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MODELING DRIP-IRRIGATED RICE YIELD USING NORMALIZED DIFFERENCE VEGETATION INDEX: A PRELIMINARY STUDY

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Abstract

Rice is one of the major food crops with a growing demand on the global market. The need for water-saving and environmentally friendly technologies presses current agricultural science to look for alternative ways of rice irrigation. The most prospective one is drip irrigation. Yield prediction is also of great importance for sustainable agriculture. The goal of the study was to create a pilot model for drip-irrigated rice yield prediction in the conditions of the South of Ukraine using spatial normalized difference vegetation index. The index values were taken from OneSoil AI platform for the drip-irrigated rice cultivated in 2016-2017 within the framework of cultivation technology studies. The highest index value was recorded in the stage of "tillering-heading" and applied for the regression and neural network-based models. It was established that the performance of various regression models was quite similar in fitting quality and accuracy, while neural network-based one provided significantly higher precision. It is reasonable to simulate drip-irrigated rice yield with a good accuracy (MAPE<15%) using simple linear regression model. Further improvement of predictions is expected through the increase of the sample size.

Key words*: artificial neural network, regression, remote sensing, statistics, yielding scale.*

INTRODUCTION

Yield prediction is a valuable branch of modern agricultural science with a growing demand in practice of precision agriculture. Timely prediction of a crop yield is essential for economic planning of agricultural production; besides, it is necessary to identify and correct possible weak places in the cultivation technology in advance to avoid yield losses, and for this purpose modern farmers can use the latest achievements of yield simulation in various decision support systems. Some of them are integrated with geoinformation systems and remote sensing data, such as vegetation indices, which are widely implemented to characterize growing conditions of plants cultivated in the field. Normalized difference vegetation index (NDVI) proposed by Rouse et al. (1974) is among the most frequently used in these purposes due to its wide availability on various online platforms, both paid and free (Pettorelli, 2013). Most crop yield prediction models are based on the vegetation index, which is applied as the only input or in combination with additional inputs to simulate crop yield. There are crop yield prediction models almost for every crop, cultivated in Ukraine, for example, sweet and grain corn, beans, grain sorghum, soybeans, wheat, barley, major oil crops, etc. (Becker-Reshef et al., 2010; Franch et al., 2019; Lykhovyd, 2020; Vozhehova et al., 2020; Lykhovyd, 2021; Lykhovyd, 2022; Lavrenko et al., 2022). On the global scale, NDVI-based models for yield prediction are developed to some extent almost for every major crop, with the greatest focus on such valuable ones as wheat, corn, and rice.

Rice is one of the major staple food crops in the world. It is cultivated in more than 100 countries with a gross yield exceeding 450 million tons per year. Although rice is one of the most cultivated crops in the world, there is still lack of provision with this crop because of extremely fast increase in the population. As it is estimated, the provision of rice should be at the level of 700 million tons, therefore, now there is a discrepancy of nearly 250 million tons between the proposal and demand on the global market (Bhandari et al., 2017). Therefore, an enhancement of rice productivity is of a great relevance for current agricultural science.

Rice is on the list of cereals cultivated in the South of Ukraine, mostly concentrated in Kherson and Odesa regions. The areas are about 30,800 ha, mostly - paddy rice, cultivated by high-input and extremely costly (especially, in the initial stage) technology with high freshwater uptake. In the modern conditions of the global freshwater scarcity in all the branches of economy, it is necessary to develop the technology for water saving during rice cultivation. In this regard, notwithstanding the fact of biological mismatching, drip irrigation could be a prospective technology for rice cultivation, therefore, drip-irrigated rice grows more and more popular among the leading crop producers and scientists in South Asia, India, China, and also Ukraine (Sharda et al., 2017; Parthasarathi et al., 2018; Osinnii et al., 2020; Xu et al., 2020). One of the tasks is not only to improve the crop cultivation technology, but also to provide novel reliable tool for the yield prediction in advance to harvesting. In this regard, remote sensing combined with geoinformation technologies could serve a good service.

The main goal of this study is to provide a preliminary result on the estimation of drip-irrigated rice yield, cultivated in the South of Ukraine, using the highest NDVI value as the only input for the crop productivity estimation. This prospective study is aimed to determine main regularities of yield prediction under novel cultivation technology, and provide an assessment of the maximum attainable crop productivity under such conditions.

MATERIALS AND METHODS

Models for drip-irrigated rice yield prediction using normalized difference vegetation index (NDVI) were developed by the yielding data collected in the field trials with the crop conducted within 2016-2017 at the fields of "Raiz-Pivden" farm located in the Oleshky district of Kherson region, Ukraine (geographical coordinates of the experimental field are 46°28'22.52" N 33°09'38.60" E; altitude 13 m). The drip-irrigated rice was cultivated using common cultivation technology, apart from the factors of tillage (skimming at 10-12 cm; chisel plowing at 30-32 cm), fertilization (N_0P_0; $N_{90}P_{30}$; $N_{120}P_{45}$; $N_{150}P_{60}$), and irrigation (120, 140, 160% of ETc adj). The experiment was performed in four replications, therefore, in general, we had 192 different rice plots with different yield levels for the two years of the study. The study was conducted with the variety Flahman (var. *italic* Alef). The field was monitored using NDVI from the OneSoil AI platform (combined Sentinel ½ images) with the resolution 250 m. Only cloud-free images were used for computation of NDVI. The highest values of the vegetation index were used for yield simulation. This falls to the phenological phase "tillering-heading", specifically, July 24th in 2016, and July 11th in 2017. The grid of experimental plots was superposed over the NDVI images and NDVI values were correspondingly extrapolated and assigned for each plot. Average yield and vegetation index values for every plot were further used in the crop modelling.

Crop modelling was performed using standard algorithms of various regression functions (Freund et al., 2006). The calculations were performed in BioStat v.7 software, add-in for Microsoft Excel 2019. Models' accuracy was estimated by the value of mean absolute percentage error (MAPE), while fitting quality – by the value of coefficient of determination R^2. Combined model of regression and neural network was created through the method of simple superposition and adjustment coefficient computation by the method proposed in the work of Lavrenko et al. (2022). Pure artificial neural network-based model was developed using Tiberius XL software, which is a back-propagation neural network tool with the generalized delta rule training algorithm, with the following parameters: 48 samples, 5 hidden neurons, 1000 epochs, learning rate 0.80 (Adamowski, 2008). Figure was created in Microsoft Excel 2019.

RESULTS AND DISCUSSIONS

The input data for drip-irrigated rice yield modelling are generalized in the Table 1. The results of regression modelling by seven different approaches are represented in the Table 2. It is evident that the models do not significantly differ from each other in terms of prediction accuracy with MAPE amplitude of 0.3951%. The same is true for the fitting quality, assessed by the values of R^2 coefficient. The best fitting is in cubic regression function, while the worst one is attributed to functional regression. However, we must admit that the difference between all the applied regression approaches is so subtle that it could be neglectable. This is explained by relatively small sample size, where complicated non-linear regression computations had no opportunity to show their superiority over simple linear regression analysis (Frost, 2020). As all the developed models fall under the criteria of good forecast by the magnitude of prediction error MAPE (Blasco et al., 2013), and are classified as moderate or strong correlation between the crop yield and NDVI by various interpretations of correlation coefficient used in modern science (Taylor, 1990; Akoglu, 2018), it is reasonable to create a scale for rough drip-irrigated rice yield estimation based on a single chosen model among the developed ones. Therefore, the basis for the development of rice yield scale in connection with NDVI values in our study is the linear model as the simplest one but not inferior in quality.

Table 1. Data on rice yields and corresponding NDVI values in the field trial

Sample number	Yield, t ha^{-1}	NDVI	Yield, t ha^{-1}	NDVI
	2016		2017	
1	3.14	0.55	3.12	0.50
2	3.79	0.60	4.32	0.56
3	4.58	0.65	5.11	0.59
4	4.06	0.62	4.62	0.57
5	3.73	0.59	3.76	0.53
6	4.56	0.65	5.29	0.60
7	5.61	0.72	6.33	0.65
8	5.17	0.70	5.92	0.63
9	3.44	0.57	3.44	0.52
10	4.20	0.63	4.88	0.58
11	5.00	0.68	5.57	0.62
12	4.59	0.65	5.12	0.59
13	3.93	0.61	4.70	0.57
14	5.02	0.68	6.24	0.65
15	5.61	0.73	6.90	0.68
16	5.14	0.70	6.31	0.65
17	4.76	0.67	5.58	0.62
18	6.03	0.76	7.54	0.71
19	6.90	0.82	8.57	0.76
20	6.51	0.79	8.15	0.74
21	4.56	0.65	5.24	0.60
22	5.59	0.72	7.00	0.69
23	6.25	0.77	7.65	0.72
24	5.84	0.74	7.11	0.69

Table 2. Results of regression analysis and models of the drip-irrigated rice yield correspondence to the NDVI values at the stage of "tillering-heading"*

Model type	Regression statistics and equations			
	R	R^2	MAPE (%)	Equation for rice yield derivation from NDVI
Linear	0.7525	0.5662	14.5368	$13.2552x - 3.2919$
Quadratic	0.7571	0.5732	14.4264	$-17.1049x^2 + 35.7071x - 10.5670$
Cubic	**0.7593**	**0.5765**	14.4479	$-124.9179x^3 + 229.3117x^2 - 124.7109x + 23.8913$
Power	0.7462	0.5568	14.4886	$10.7582x^{1.6767}$
Functional	0.7354	0.5408	14.7219	0.9797×12.9214^x
Logarithmic	0.7560	0.5716	**14.3268**	$9.0982 + 8.6334 - \ln(x)$
Hyperbolic	0.7559	0.5713	14.5176	$13.9147 - 5.5128/x$

*The best performance by each statistical index is marked with bold font.

Visual assessment of the linear model for drip-irrigated rice productivity prediction is presented in the Figure 1. It is obvious that the best fitting quality is attributed to the samples with median productivity of the crop, while with the increase in the crop yield, as well as with its decrease, the discrepancy between the lines becomes more distinct.

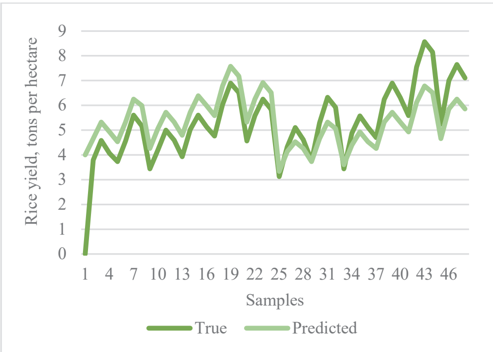

Figure 1. Visual Approximation of the Drip-Irrigated Rice Yield Prediction Model

The scale for drip-irrigated rice yields is represented in the Table 3. We used 0.05 step of NDVI values, starting the scale with the minimum of 0.50, and ending with the maximum of 0.85 (as the values of NDVI exceeding 0.85 are uncommon for OneSoil AI platform). The yield is given ± possible dispersion (taking into account the MAPE of the linear model).

Table 3. Drip-irrigated rice yield depending on the NDVI values at the stage of "tillering-heading"

NDVI	Yield, t ha^{-1}
0.50	3.34±0.49
0.55	3.99±0.58
0.60	4.66±0.68
0.65	5.32±0.77
0.70	5.99±0.87
0.75	6.65±0.97
0.80	7.31±1.06
0.85	7.98±1.16

For better understanding yield dynamics with better crops condition reflected by NDVI values we provide a graphical visualization of the developed scale in the Figure 2. As the prediction model testifies, the highest expected productivity of drip-irrigated rice is about 9.0-9.2 t ha^{-1}.

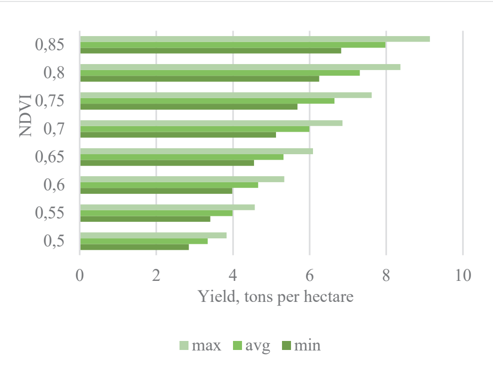

Figure 2. Drip-Irrigated Rice Yield Simulated by NDVI Values at the Stage of "Tillering-Heading"

The developed scale is the first one created to predict rice yields in the conditions of drip irrigation on the basis of remotely sensed NDVI. Most similar models are developed to predict paddy rice yields. Some of them are of comparable accuracy, and some (mostly complex, not pure NDVI-based ones) are superior to ours. For example, Huang et al. (2013) developed more accurate (overall relative error averaged to 5.82%) rice yield model based on NDVI, but it is used for paddy rice. Korean scientists developed integrated NDVI-Meteorological model for paddy rice yield prediction (Na et al., 2012). The model is more complicated than pure NDVI-based ones, but it provided somewhat higher accuracy comparing with our model: correlation coefficient 0.7840 vs. 0.7525. Another successful complex paddy rice yield models involved a combination of NDVI, enhanced vegetation index (EVI), leaf area index (LAI), and weather data. Performance of the models was very high - R^2 values were within 0.70-0.82 (Hong et al., 2012). Therefore, inclusion of additional inputs apart from NDVI is a useful strategy to improve predictive quality of mathematical models for drip-irrigated rice yield estimation. Though, some scientific groups achieved incredibly high accuracy of regression models (correlation coefficient up to 0.94) for rice prediction even at using NDVI as the only input (Faisal et al., 2019; 2020). Good prediction model for rice yield estimation in the conditions of Egypt with R^2 0.85 was proposed by Noureldin et al. (2013). At the same time, NDVI-based regression models for rice yield assessment developed by Harrell et al. (2011) are inferior to ours with R^2 0.36-0.42. We suppose that model quality strongly depends on the factors of the input's quality (from what platform and satellites NDVI imagery is derived and what GIS software is used to pre-process them), presence of additional inputs (such as meteorological data), total number of data pairs (sample size), and mathematical algorithms applied. The complex model with the best quality of inputs, large sample size will provide the best prognostic performance under the proper mathematical processing.

Apart from the complexity level and sample size, good results could be achieved through the usage of modern computation techniques. We have tried to enhance the model quality through the combination of artificial neural network (ANN) approach with linear regression analysis, as it had a success in case of the yield modelling for beans (Lavrenko et al., 2022). However, in this study the combined model (with the following equation 14.2136x - 3.5299) was inferior in prediction quality even to the simple linear one, notwithstanding the fact that the pure ANN-based model showed significantly better results (Table 4). Unfortunately, "black box" nature of the ANN-based model makes it impossible to derive the way of achieving the crop yields, so this one is unsuitable for use in practice. Therefore, the model for drip-irrigated rice yield prediction through NDVI data needs further improvement mainly through the enlargement of the sample size.

Table 4. Comparison of the simple, combined linear regression models and ANN-based one for drip-irrigated rice prediction using the NDVI values at the stage of "tillering-heading"

Statistics	Simple linear model	Combined linear model	ANN-based model
Correlation coefficient R	0.7525	0.7525	0.9999
Determination coefficient R^2	0.5662	0.5662	0,9998
Mean absolute percentage error MAPE (%)	14.5368	15.7500	5.0434

CONCLUSIONS

It is possible to predict drip-irrigated rice yield with a good accuracy (MAPE<15%) using simple linear regression model. Better performance in yield prediction is attributed to neural network-based model (MAPE<10%), but its use is limited in practice. A combination of regression and neural network did not result in significant performance improvement. Yield scale was developed based on the simple linear regression model. The scale is of use both in science and practice for drip-irrigated rice yield prediction using remote sensing data on normalized difference vegetation index in the period of "tillering-heading" of rice. Further improvements in the model are expected through the enlargement of the sample size.

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