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Editorial

Predictions and Estimations in Agricultural Production under a Changing Climate

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1. Introduction

In the 21st century, agriculture is facing numerous challenges. First, a changing climate is modifying farming conditions and increasingly influencing how agricultural production is carried out. For example, dynamic agricultural adaptation to rising temperatures is necessary to maintain farm profitability and, most importantly, ensure the continuity of food production. It is important to remember that the faster climate change occurs, the more difficult adaptation will be. Admittedly, some climatologists stress that climate change may be beneficial, if only through a theoretical increase in crop yields. Conversely, it is speculated that climate change will lead to visible shifts in the start and end of the growing season, a limited supply of water resources, and changes in the species composition of locally resident plant and animal species. It is worth noting that it is easier for agriculture to adapt to a slow change in average air temperatures or precipitation totals rather than the currently observed weather anomalies and extreme events [1].

Currently, there are many techniques conducive to adapting agriculture to the changes occurring in the Earth's climate. The main goals behind such measures are to maintain high and stable productivity and environmental functionality while sustaining profitable production and food security. Among the most promising agricultural production methods resilient to climate change are agroecology, which are systems based on soil conservation, natural methods of plant protection, and soil biologization [2]. Great importance is attributed to the development of precision and digital agriculture. These tools allow for the monitoring and optimization of agricultural production processes through the involvement of digital techniques. Precision farming methods are primarily based on a combination of new technologies using sensors, satellite navigation and positioning, and the Internet of Things. In mitigating the effects of climate change on agricultural production, prediction and estimation tools come to the rescue, allowing accurate prediction of certain events during the growing season. Making predictions of yields, input consumption, and storage space facilitates the day-to-day management of farms. In turn, predicting extreme weather events, water resources, etc., allows for more informed planning regarding crop rotation, including cover crops and irrigation [3].

Considering the above arguments, developing systems for reliable monitoring and prediction of multi-stage agricultural production is valuable. This will allow, among other things, researchers to estimate the achievable production effects in both abnormal years and standard conditions in advance. Agricultural prediction tools include classical statistical models, machine learning, GIS tools, satellite and aerial remote sensing, the Internet of Things, and big data [4–6]. Although they already well-integrated into agricultural practices, they are constantly evolving with advances in genetics, breeding, and the market for active substances.

The purpose of this Special Issue was to publish high-quality research articles that cover issues related to the use of prediction and estimation tools in agriculture challenged by the effects of climate change. Below are the most important articles published in this Special Issue.

2. Papers in this Special Issue

In the first article [7], the authors attempted to predict corn yield in the Czech Republic using extreme machine learning. The advantage of the yield prediction approach presented in the article, compared to the classical approach, was the division of the entire growth period of corn into individual months. This resulted in accurate models predicting the yield of corn grown for silage and grain. The authors worked on a large dataset collected from 2002 to 2018 for the entire county. The data concerned meteorological conditions and corn yield levels. Extreme learning machine (ELM) was used to build models. Satisfactory model accuracy results were obtained, i.e., the coefficient of determination R2 reached values in the range of 0.641–0.716.

In the second article, the authors predicted yields of rice grown in the most agriculturally intensive regions of India [8]. The two-step STRAMA (autoregressive moving av-erage) approach, referred to as STRAMA-II in this paper, was used to achieve the research objective. The use of the above method made it possible to obtain a lower absolute percentage of errors in predictive models compared to the results obtained using classical linear and nonlinear spatio-temporal time series models. The STRAMA-II method provides opportunities to create accurate forecasting models in the medium and long term.

The third article published in the presented SI also deals with rice cultivation, but the research topic presented is related to forecasting the occurrence of the main pest in this crop—Asian rice gall midge (*Orseolia oryzae* (Wood-Mason)) [9]. A six-year study on the existence of this pathogen was conducted in rice plantations in four different agroecosystems in India. The starting material for the construction of predictive models was climatic data and weekly information on the abundance of gall midge populations. The study used and compared two prediction tools: the time series method (integer-valued generalized autoregressive conditional heteroscedastic—INGARCH) and machine learning (artificial neural network—ANN; support vector regression—SVR). Finally, it was shown that the ANN model with an exogenous variable (ANNX) outperformed the INGRACH model with an exogenous variable (INGRCHX) and the SVR model with an exogenous variable (SVRX) in the accuracy of the predictions made. The presented results will allow more effective management and protection of rice from this dangerous pest.

In the fourth article, the authors presented a method for effectively and accurately predicting the effect of environmental conditions on the grain yield of maize varieties belonging to different maturity groups [10]. The presented experiment concerned the analysis of several important environmental parameters in terms of the yield efficiency of three groups of corn varieties in VCU (value for cultivation and use) experiments in Croatia. It was possible to achieve the research objective by using a linear mixed model to estimate fixed and random effects. The research conducted did not unequivocally identify a reference variety among the tested earliness groups. The analysis of the best linear unbiased predictions (BLUP) led to the conclusion that the effect of environmental effects on yield was stronger with more mature varieties. The authors stressed the need for further research on this phenomenon.

The fifth article saw the authors attempt to identify the factors with the greatest impact on the yield and digestibility of sward in Poland based on a three-year field study [11]. Nine neural predictive models were tested. The extraction of the most significant factors determining the quantity and quality of green fodder yield was possible via the sensitivity analysis of neural networks. Very interesting results were obtained, indicating the predominance of the following factors (ranked in order of importance): average daily air temperature, total precipitation, and percentage of legumes.

The sixth article dealt with estimating the area under cultivation and yield of rice in the Cauvery delta zone in Tamil Nadu, India. The study was conducted during the samba season (August–January) in 2020–2021 [12]. Sentinel 1A Synthetic Aperture Council satellite data were the input data for the construction of forecast models. Various methods of spatial yield estimation were used for analysis: classical regression analysis using spectral indices, a semi-physical approach, and an integrated remote product system with a DSSAT crop growth model. The results of the study showed that methods integrating spectral data with the DSSAT decision support system and regression analysis generate very accurate results (agreement of about 90%), and so developing such techniques for the spatial estimation of crop area is necessary.

In the seventh article, the authors dealt with the evaluation of methods for the spatial correction of ordinal data using the example of chlorosis symptoms resulting from iron deficiency in soybean crops [13]. Corrections for autocorrelation were carried out with the involvement of eight different models. Three groups of models were identified: group I, moving average grid fitting; group II, geospatial autoregressive regression (SAR) models; and group III, tensor product of penalized P-splines. The results of the above studies suggested that the quality and effectiveness of the generated models were most affected by the variability of the field, the irregularity of the chosen pattern, and the type of model used. It was shown that models belonging to Group II outperformed the other models in terms of prediction accuracy.

In the eighth article, the authors attempted a detailed assessment of the impact of current climate change on the production performance of the oil patch in Costa Rica in terms of available water resources [14]. The study proposed three scenarios of probable climate change, feasible in time periods: simulation in the base period 2000–2019; 2040–2059 (CCS1); and 2080–2099 (CCS2). The model for the analyses performed used irrigated crops. APSIM modeling was conducted in the simulations. The projections made indicated large decreases in crop yields in the following time intervals, i.e., by 7.86% (CCS1) and 37.86% (CCS2) in relation to the base period.

The ninth article dealt with the development and validation of innovative models for predicting the scale of mite infestation (DPM) on date palm fruit [15]. The scale of the appearance of the pest population in the crop is assessed via visual observation of spider webs on unripe fruit. Meteorological data and physical and chemical properties of date palm fruit were used as the input variables of two predictive models (linear regression (LR) and decision forest regression (DFR)). The DFR model produced a more accurate predictions of the occurrence of DPM compared to LR, and the R2 coefficient of determination of the DFR model was over 0.9. The selected model offers great utility and may have substantial implementation significance.

The final, tenth article of the presented SI dealt with the application of two algorithms used to forecast wheat yield in Turkey: CHAID and MARS [16]. The study additionally determined the correlation between some morphological traits of different wheat crop species. A total of 26 genotypes were analyzed. The results of the analyses described above showed that the MARS model was the best model for predicting wheat grain yield at this particular research site. Moreover, this algorithm accounted for and described as much as 95.7% of the variability in grain yield among wheat. The selected research method is a great support for breeders of new varieties, as it allows them to accurately describe the complex and intersecting interactions of $G \times E$, etc.

3. Conclusions

The research presented in this Special Issue provides an excellent overview of the current state of knowledge on the involvement of various research methods in agriculture. Most of them use techniques of precision agriculture, digital agriculture, machine learning, etc. Implementing the results of such analyses provides an opportunity for faster and more effective adaptation of this important sector of national economies to the observed climate changes.

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