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Editorial

Crop Yield Prediction in Precision Agriculture

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Abstract: Predicting crop yields is one of the most challenging tasks in agriculture. It plays an essential role in decision making at global, regional, and field levels. Soil, meteorological, environmental, and crop parameters are used to predict crop yield. A wide variety of decision support models are used to extract significant crop features for prediction. In precision agriculture, monitoring (sensing technologies), management information systems, variable rate technologies, and responses to inter- and intravariability in cropping systems are all important. The benefits of precision agriculture involve increasing crop yield and crop quality, while reducing the environmental impact. Simulations of crop yield help to understand the cumulative effects of water and nutrient deficiencies, pests, diseases, and other field conditions during the growing season. Farm and in situ observations (Internet of Things databases from sensors) together with existing databases provide the opportunity to both predict yields using "simpler" statistical methods or decision support systems that are already used as an extension, and also enable the potential use of artificial intelligence. In contrast, big data databases created using precision management tools and data collection capabilities are able to handle many parameters indefinitely in time and space, i.e., they can be used for the analysis of meteorology, technology, and soils, including characterizing different plant species.

Keywords: crop models; artificial intelligence; big data; IoT; yield influencing variables; yield forecasting; data fusion

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1. Introduction

The concept of this Special Issue is based on the practice and scientific results of crop yield prediction in precision farming. The definition of precision farming according to the ISPA (International Society for Precision Agriculture) is the following: "Precision Agriculture is a management strategy that gathers, processes and analyses temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production" [1]. Precision agriculture needs to have more efficient and clearer results related to the topic of yield prediction. This Special Issue published eight research papers and one review article. This Special Issue's aim was to discuss various yield prediction methods, the adaptation of big data, and the use of interseason databases from different platforms in crop yield forecasting. Studies focused on applications regarding prediction methods, data fusion, and the adaptation of big data were submitted.

2. Papers in the Special Issue

The review paper of this issue aims [2] to identify the alternatives to traditional estimation methods in vineyard forecasting. Articles were reviewed using PRISMA as a guideline based on the research topic, methodology, data requirements, and practical applications. Relevant scientific works already published on the topic were searched for in the Scopus, Web of Science, ScienceDirect, IEEE, MDPI, and PubMed databases. The vineyard yield estimations mainly depend on the computer visions, image processing algorithms, data-driven models based on vegetation indices, and pollen data and on relating climate, soil, vegetation, and crop management variables that can support dynamic crop simulation modelling. The methods have advantages and shortcomings, but they still lack real application in a commercial production. The authors' opinion is that the methods must be as simple as possible and use as little data as possible, preferably with data the producers can access quickly, easily, and cheaply. The synergistic use of proximal and remote sensing with artificial intelligence (AI) can be one of the best alternatives to estimating a vineyard's yield. Other options for vineyard yield estimations are laser, radar, radio frequency, and ultrasonic data. Despite these methods, the most critical parameters are the spatial variability and heterogeneity in decision making.

The second paper [3] in the Special Issue shows different sensors that can be merged with other systems to improve fusion methods, such as optical, multispectral, hyperspectral, thermal infrared, light detections, and radar. The study highlights different platforms that can be used as a source of the fusion of technologies, e.g., robots, satellites, and aerial monitoring systems. The study's aim was to present the data fusion techniques for site-specific crop parameter monitoring, such as nitrogen, leaf area index, biomass, chlorophlyll content... etc. This study reviewed 250 research articles which explored the spatio-temporal data fusion on combining data with fine spatial resolution. Nowadays, the fusion of sensor technologies efficiently classifies the crop type, the phenological status, and parameters for site-specific crop monitoring. The authors concluded that the major constraint of data fusion is the multimodality of data from different types of sensors, systems, noise, poor resolution, or flaws. However, the assessment of the advanced models for crops is still in the development stages.

A linear model has been created based on multiple linear regression analysis (MLR), and a non-linear model has been built using artificial neural networks (ANN) to predict the potato yield of very early varieties [4]. Phytophenological and meteorological data were used for modelling. The authors used some forecast error metrics such as global relative approximation (RAE), root mean square error (RMS), mean absolute error (MAE), and mean absolute percentage error (MAPE) in the validation stage. The MAPE value for the neural model, amounting to 7.2%, proved the high prediction quality in the implementation of forecasts. However, the authors highlighted the influence of the independent variables, and a greater number of experiments should be carefully considered and taken into account to increase the dataset. For building models, it is recommended to adapt the full database of experiments.

The objective of the study [5] was to assess the effect NP fertilizer placement depth, in conjunction with the year, on the number of maize plants after emergence using the additive main effects and a multiplicative interaction model. The number of plants after emergence per unit area decreased along with the increase in NP fertilizer placement depth in each of the examined years. The results obtained from the additive main effects and multiplicative interaction (AMMI) analyses are very useful in terms of the development and recommendation of the most optimal NP (and starter) fertilizer placement depths concerning the productivity in maize's growing season. These agrotechnological management practices could be regularly employed in the future to delineate predictive, more rigorous recommendation strategies.

Moreover, the AMMI method was used to identify the stability of maize hybrids and optimized site-specific precision nutrient strategies [6]. The results of the ANOVA showed that genotype, year, and fertilizer levels had various effects on grain yield, oil, protein, and starch content. FAO340 had the maximum grain yield on different fertilizers (NPK and N), and FAO350 had the maximum protein content. To gain the best performance and maximum yield of maize in terms of protein and oil content, FAO350 is recommended for protein and FAO340 for oil content. The parameters of grain yield, oil content, protein content, and starch content affected by NPK fertilizer provide the stability of grain yield parameters. Depending on the given fertilizer application, farmers can use the various hybrids to obtain a stable yield.

The sixth paper developed a new Fresh Fruit Bunch Index (FFBI) model [7] based on the monthly oil palm fresh fruit bunch (FFB) yield data, which correlates directly with the Oceanic Nino Index (ONI), to model the impact of pas El Nino events in Malaysia in terms of production and economic losses. The FFBI derived monthly FFB yields from 1986 to 2021, in the same way the ONI is obtained from monthly sea surface temperature. The FFBI showed significantly higher correlation with ONI compared to FFB yields (adjusted R-squared of 0.93 and 0.83), while the FFBI model had a smaller error based on residual analysis. The developed method provides an improved model to measure the impact of El Nino events in the oil palm industry.

One of the most important issues in crop yield predictions is temporal and spatial yield variation at the within-field scale. The seventh paper in this SI shows 48 wheat yield monitor maps from 23 fields to build linear-mixed models for predicting yield, which were tested using leave-one-field-out cross-validation [8]. The authors selected many vegetation indices in this work, but they concluded that there were only marginal differences in the performance of the different indices tested. This paper clearly describes that the predictions using longer-term average yields are generally more accurate than predictions of yield for single years. Data from the peak stage were given the best performance. Combining data from the same vegetation index but from multiple stages did not improve the predictions. Most indices showed good performance of the spatial pattern of wheat yield, but only modest accuracy in terms of predictions of actual yield within field.

The objective of the eighth paper was to access the ability of the Ceres-Maize model to predict yields in long-term experiments at different nitrogen rates [9]. The model was calibrated with data from a long-term experiment field trial. The range of the predicted data of maize yield was between 6671 and 13,136 kg ha^{-1}. In several cases, the DSSAT-CERES Maize model accurately predicted yields, but it was sensitive to seasonal effects and estimated yields inaccurately. The simulated results of the model followed the increase in yields with increasing nitrogen dose.

The final published paper [10] presents a pumpkin yield estimation method using images acquired by a UAV (unmanned aerial vehicle). The algorithm is fully automated and robust. This work consists of an orthomosaic generation, a colour model collection using a random subset of the data, coluor segmentation, and counting of pumpkin blobs, together with assessing the number of plants. The lowest F1 score (0.970) for the validation process shows the high efficiency and precision of the method. Moreover, the UAV images can be used for yield estimations of pumpkin, but it requires choosing the optimal growth stage(s) to be able to count the plants reliably.

3. Conclusions

The articles presented in this Special Issue cover a wide range of yield prediction methodology of various crops in precision agriculture. The new, innovative perspective of the crop yield prediction is based on artificial intelligence with big data [11], which can help to model the spatial distribution of site-specific yields and to explore the influencing factors at different seasonal impacts. Future developments, such as of intelligent and autonomous systems, are a major necessity for the expansion of technology and data fusion to provide precise data and more accurate yield estimation over the forecasted years. Precision farming, which takes into account fine spatial and temporal resolution management units, requires accurate and reliable crop yield models [9]. We can conclude that the predictions over multiple years are valuable for spatial patterns in yield [8]; however, there is a limited number of tools to help make more accurate management decisions.

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References

1. ISPA. ISPA Precision Agriculture Definition. 2019. Available online: https://ispag.org/ (accessed on 26 September 2022).
2. Barriguinha, A.; de Castro Neto, M.; Gil, A. Vineyard yield estimation, prediction, and forecasting: A systematic literature review. *Agronomy* **2021**, *11*, 1789. [CrossRef]
3. Ahmad, U.; Nasirahmadi, A.; Hensel, O.; Marino, S. Technology and data fusion methods to enhance site-specific crop monitoring. *Agronomy* **2021**, *12*, 555. [CrossRef]
4. Piekutowska, M.; Niedbala, G.; Piskier, T.; Lenartowicz, T.; Pilarski, K.; Wojciechowski, T.; Pilarska, A.A.; Czechowska-Kosacka, A. The application of multiple linerar regression and artificial neural network models for yield prediction of very early potato cultivars before harvest. *Agronomy* **2021**, *11*, 885. [CrossRef]
5. Szulc, P.; Bocianowski, J.; Nowosad, K.; Bujak, H.; Zielewicz, W.; Stachowiak, B. Effects of NP fertilizer placement depth by year interaction on the number of maize (*Zea mays* L.) plants after emergence using the additive main effects and multiplicative interaction model. *Agronomy* **2021**, *11*, 1543. [CrossRef]
6. Bojtor, C.; Mousavi, S.M.N.; Illés, Á.; Széles, A.; Nagy, J.; Marton, C. Stability and adaptability of maize hybrids for precision crop production in a long-term field experiment in Hungary. *Agronomy* **2021**, *11*, 2167. [CrossRef]
7. Khor, J.F.; Ling, L.; Yusop, Z.; Tan, W.L.; Ling, J.L.; Soo, E.Z.X. Impact of El Nino on oil palm yield in Malaysia. *Agronomy* **2021**, *11*, 2189. [CrossRef]
8. Ulfa, F.; Orton, T.G.; Dang, Y.P.; Menzies, N.W. Developing and testing remote-sensing indicies to represent within-field variation of wheat yields: Assessment of the variation explained by simple models. *Agronomy* **2022**, *12*, 384. [CrossRef]
9. Zelenák, A.; Szabó, A.; Nagy, J.; Nyéki, A. Using the Ceres-Maize model to simulate crop yield in a long-term field experiment in Hungary. *Agronomy* **2022**, *12*, 785. [CrossRef]
10. Midtiby, H.S.; Pastucha, E. Pumpkin yield estimation using images from a UAV. *Agronomy* **2022**, *12*, 964. [CrossRef]
11. Nyéki, A.; Kerepesi, C.; Daróczy, B.; Benczúr, A.; Milics, G.; Nagy, J.; Harsányi, E.; Kovács, A.J.; Neményi, M. Application of spatio-temporal data in site-specific maize yield prediction with machine learning methods. *Precis. Agric.* **2021**, *22*, 1397–1415. [CrossRef]