



Wheat Yield Prediction Models: A Review of Methodologies and Influencing Factors

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ABSTRACT

It is necessary to look at wheat productivity in the light of global food security, optimal utilization of inputs and formulating policies in view of the prevailing conditions. The present paper deals with advanced understanding of wheat yield forecasting through the use of process based crop models, machine algorithms and their hybrid approaches. This study considers the benefits and limitations of these forecasting methods in terms of climate change, soil characteristics or even self-forecasting. The review aims at enhancing effective yield prediction and in the process pinpoint areas which have not been covered in the existing literature for further investigation.

Keywords: Wheat yield prediction, machine learning, crop modeling, climate variability, precision agriculture

1 Introduction

The growing global demand for wheat makes the need for accurate yield prediction important. This is necessary for balancing agricultural planning with food availability. However, predicting wheat yields is a daunting task because of the intricate interplay of environmental, genetic, and management factor. But with the improvements of computational methodologies and sensor technologies, the more advanced models that integrate conventional agronomy with machine learning (ML) and remote sensing have been developed. This paper analyzes the methods used in the prediction of wheat yield, explaining how they are used and achieved, their level of performance, and what other variables affect the efficacy of the model.

2 Recent Works

2.1 Process-Based Crop Models

Process-based models, like APSIM, simulate crop growth by incorporating modules for climate, soil, and management factors, which influence wheat yield. According to Hao et al. (2021), these models can simulate growth processes over time, allowing researchers to assess how specific management decisions and environmental conditions impact yield. They are effective in evaluating the effects of long-term climate change when integrated with seasonal forecasts (Marletto et al., 2007).

2.2 Machine Learning Approaches

ML models have become popular in yield prediction due to their ability to handle complex, non-linear relationships. Pantazi et al. (2016) demonstrated that models like Supervised



Kohonen Networks (SKN), CP-ANNs, and XY-fused Networks perform well in predicting yield using soil and crop data. SKN, for instance, achieved over 91% accuracy in predicting low-yield classes, showcasing its effectiveness in capturing complex yield-limiting factors.

2.3 Hybrid Models

Hybrid models combine elements of simulation and ML, leveraging the strengths of both approaches. For example, Marletto et al. (2007) applied the WOFOST model with downscaled seasonal weather forecasts to predict wheat yield in Italy. This approach capitalizes on both observed and forecasted weather data, yielding robust predictions that align closely with actual field observations.

3 Proposed Work Explanation

Climate Variability

Climate factors such as temperature and precipitation significantly impact yield. For instance, studies by Bell and Fischer (1994) showed that rising temperatures in Mexico's Yaqui Valley led to a reduction in wheat yield over time, suggesting that prediction models must account for such changes to provide accurate forecasts.

Soil Characteristics

Soil properties, including moisture content and nutrient availability, affect crop growth. Proximal soil sensing technologies enable high-resolution soil data collection, improving the accuracy of yield predictions (Pantazi et al., 2016). These technologies are particularly valuable for within-field yield variability analysis.

Model Structure and Activation Functions

In neural network-based models, factors like activation functions and learning rates influence prediction accuracy. Bhojani and Bhatt (2020) introduced new activation functions in MLP models, achieving improved yield prediction accuracy. The study highlights the need to optimize model parameters to handle complex, agriculture-specific datasets effectively.

4 Conclusions

This review highlights that while process-based models and machine learning techniques offer promising tools for wheat yield prediction, hybrid approaches that combine the two may deliver superior performance, especially when enhanced with high-resolution soil and climate data. Factors such as climate variability, soil characteristics, and model parameters significantly impact prediction accuracy. Future research should focus on developing models that integrate real-time data with adaptive algorithms to enhance reliability under changing environmental conditions. Additionally, interdisciplinary collaborations are needed to refine yield prediction models and support sustainable agricultural practices.



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