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From Satellites to Sensors: The New Science of Predicting Crop Yields

*Piyush Dogra[1], G.D. Sharma[1], Sandeep Manuja[1], Sanjay Kumar[1], Ashish Kumar[1], Krishna[1] and Tarun Sharma[2]
[1]Department of Agronomy, CSK HPKV, Palampur, HP, India
[2]Amity Institute of Organic Agriculture, Amity University, Noida, Uttar Pradesh, India
*Corresponding Author's email: piyushdogra1177@gmail.com

Ensuring global food security under climate variability and resource constraints requires accurate, timely crop yield prediction which is a complex outcome of genotype × environment × management (G × E × M) interactions. Traditional methods such as crop cutting and surveys are reliable but labor-intensive and limiting real-time use. Advances in digital agriculture - integrating remote sensing (e.g., NDVI, EVI), GIS-based spatial analysis, crop simulation models (DSSAT, APSIM) and AI/ML techniques- enable continuous, large-scale monitoring and improved predictive accuracy by capturing complex, non-linear relationships among weather, soil and crop variables. Emerging tools such as UAVs and IoT sensors, combined with cloud computing and big data analytics, further enhance high-resolution, real-time forecasting. Collectively, these technologies support precision agriculture, climate-smart decision-making and sustainable food production.

Keywords: Artificial intelligence (AI), Climate-smart agriculture, Crop yield prediction, Precision agriculture and Remote sensing

Introduction

Crop yield prediction has become increasingly important as agriculture faces the dual challenge of feeding a growing population while coping with climate variability and limited natural resources. Yield is not determined by a single factor but by the complex interaction of genetics, environment, and management practices (G × E × M), which makes accurate prediction difficult yet essential. For farmers, timely yield information helps in making better decisions about inputs, harvesting, and marketing, while at a larger scale it supports food security planning and price stabilization. However, traditional methods such as crop cutting experiments and field surveys are time-consuming, costly, and often provide results only after harvest, reducing their usefulness for real-time decision-making (Jabed et al. 2024).

With the rise of digital agriculture, new technologies are transforming how crop yields are estimated and forecasted. Tools like remote sensing, GIS, and crop simulation models now allow continuous monitoring of crop growth over large areas, providing valuable insights into crop health and productivity. More recently, artificial intelligence and machine learning have taken this a step further by analysing large datasets and identifying complex patterns that were previously difficult to capture. These advancements are enabling faster, more accurate, and real-time yield predictions, supporting precision agriculture and climate-smart farming. The integration of modern data-driven approaches is significantly improving our ability to predict crop yields under changing environmental conditions.

What is crop yield prediction?

Crop yield prediction simply means estimating how much crop will be produced from a field before it is actually harvested. In everyday terms, it helps answer a very practical question for farmers: "What kind of output can I expect this season?" This estimate is influenced by several factors such as weather conditions, soil fertility, crop variety, and the way the crop is managed. While earlier farmers relied mostly on their experience and visual assessment, today this process has become more scientific with the use of modern tools and data-driven approaches.

For farmers, knowing the expected yield in advance can make a big difference in planning. It helps them decide how much fertilizer or water to use, when to harvest, and how to manage storage or sales. This not only reduces uncertainty but also improves income stability. At a broader level, policymakers depend on yield predictions to make informed decisions about food supply, pricing, and agricultural policies. These forecasts also play a key role in crop insurance schemes, helping assess risks and provide timely support to farmers in case of poor production.

Crop yield prediction is closely linked to food security because it gives an early indication of how much food will be available in the future. This allows governments and agencies to prepare in advance for shortages or surpluses, ensuring that food reaches people on time and at stable prices. It also helps in market planning by guiding traders and supply chains to manage storage, transportation, and distribution efficiently. With the help of modern technologies, yield prediction is becoming more accurate and timely, strengthening the overall agricultural system.

Limitations of Traditional Methods

Traditional crop yield estimation methods largely depend on field surveys and manual observations, where data is collected directly from farms through sampling techniques like crop cutting experiments. While these methods have been widely used for many years, they often depend heavily on human judgment and field conditions. This can introduce errors due to differences in observer skills, sampling bias, or incomplete data collection. In many cases, it becomes difficult to represent large and diverse agricultural areas accurately using limited field samples.

One of the major challenges in traditional yield estimation is the unpredictable nature of weather. Sudden changes in rainfall, temperature, or extreme events like droughts and floods can significantly affect crop growth. Since conventional methods do not effectively incorporate real-time weather variability, their predictions may not reflect actual field conditions (Lobell et al. 2010). As a result, yield estimates can become less reliable, especially under changing climate scenarios.

Traditional methods are often slow and labor-intensive, requiring extensive fieldwork, data collection, and processing. Crop cutting experiments, for example, involve multiple visits to the field, manual harvesting, and detailed measurements, which take considerable time and effort. Because of this, yield estimates are usually available only after the crop has been harvested, limiting their usefulness for early decision-making and timely interventions.

Advanced Technologies in Yield Prediction

1. Remote Sensing

Remote sensing has become a game-changer in agriculture by allowing crops to be monitored from space and air using satellites and drones. Instead of relying only on field visits, farmers and researchers can now observe large agricultural areas in real time. Tools like vegetation indices (e.g., NDVI) help assess crop health, canopy cover, and biomass, giving early signals about crop performance. This makes it easier to detect problems and estimate yield well before harvest.

2. Artificial Intelligence (AI) & Machine Learning (ML)

Artificial intelligence and machine learning are transforming how agricultural data is used. These technologies analyse large amounts of data- such as weather patterns, soil conditions, and satellite images to predict crop yields more accurately. They are especially useful in identifying hidden patterns and complex relationships that are difficult to detect using traditional methods. As a result, AI-based models are helping improve decision-making and making yield predictions more reliable.

3. Internet of Things (IoT)

The Internet of Things (IoT) brings smart farming to the field by connecting sensors and devices that continuously collect data. Sensors placed in the soil can measure moisture levels, nutrient status, and temperature in real time. This constant flow of information helps farmers monitor crop conditions more precisely and take timely actions, such as irrigation or fertilizer application, leading to better yield outcomes.

4. Unmanned Aerial Vehicles (Drones)

Drones provide a closer and more detailed view of crops compared to satellites. They capture high-resolution images that can reveal variations within a field, such as pest attacks, nutrient deficiencies, or water stress. With early detection of these issues, farmers can respond quickly and minimize losses. Drones are especially useful for precision agriculture, where small-scale variations can significantly affect yield (Wolfert et al. 2017).

5. Geographic Information Systems (GIS)

GIS helps in organizing and analysing spatial data related to agriculture. It combines information such as soil type, weather conditions, topography, and crop data to create maps and identify patterns across regions. This makes it easier to understand yield variability and supports regional-level yield forecasting, as well as site-specific farm management.

6. Big Data & Cloud Computing

Modern agriculture generates a huge amount of data from satellites, sensors, weather stations, and farm records. Big data analytics and cloud computing make it possible to store, process, and analyse this information efficiently. By integrating data from multiple sources such as weather, soil, and crop conditions, these technologies enable more accurate and scalable yield prediction models, accessible even in real time.

Figure 1. Technologies for crop yield prediction

Benefits of Advanced Yield Prediction

- Improves farmer decision-making through timely and accurate yield insights (Jeong., 2016).
- Enhances efficient use of fertilizers and water, reducing input wastage

- Supports risk management by providing early warnings for droughts and pests
- Aids market planning by stabilizing prices and predicting supply trends

Challenges and Limitations

Despite the rapid advancement of technologies in crop yield prediction, several challenges remain. High initial costs of tools such as drones, sensors, and AI platforms limit their adoption, especially among small and marginal farmers. In addition, a lack of technical knowledge and awareness further restricts effective use in real-world conditions. Another major issue is the availability and quality of data, as inaccurate or incomplete datasets can reduce prediction reliability. Moreover, poor internet connectivity and digital infrastructure in rural areas hinder real-time data access and the seamless functioning of these advanced systems.

Future Prospects

The future of crop yield prediction lies in the integration of advanced and emerging technologies. The use of nano-sensors can provide highly precise, real-time information on soil and crop conditions, improving prediction accuracy. At the same time, AI-powered precision agriculture will enable automated and intelligent decision-making for optimizing inputs and maximizing productivity. These innovations will also play a crucial role in promoting climate-smart farming by helping farmers adapt to changing environmental conditions and reduce the impact of climate risks.

Conclusion

Crop yield prediction is becoming increasingly important for ensuring food security, improving farm efficiency, and reducing agricultural risks. The integration of technologies such as remote sensing, AI, IoT, and big data is transforming traditional farming into a more precise and sustainable system. Moving forward, efforts should focus on making these technologies affordable, accessible, and user-friendly, while strengthening research and data systems. This will empower both farmers and researchers to adopt smarter approaches and ensure sustainable agricultural development in the future.

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