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Current Approaches and Future Perspectives in Methods for Crop Yield Estimation

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ABSTRACT
Food security is one of the most pressing challenges of 21st century. The shrinking cultivable land, ever increasing population, man-made narrowing crop diversity and changing climate are some of factors contributing to the concern. Technology laden agricultural resource management strategies try to stabilize the situation by extracting the maximum benefits and minimizing unnecessary and avoidable losses. Food security has drawn attention of all branches of sciences and researchers have come up with various methods that may help in determining the damages and predicting overall yield before harvest. In the current study, the authors have prepared a narrative review based on some most commonly used and validated methods for crop yield estimation. Based on the analysis it was proposed to integrate the data derived from various approaches to obtain a near real yield estimation. The various aspects of artificial intelligence, satellite remote sensing, crop simulations, statistical and mathematical technique based models hold great promise in bridging the gap between the real and the predicted.
***Keywords**: Crop yield estimation, mathematical models, remote sensing, crop simulation*

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INTRODUCTION

India is a developing country that mostly uses traditional methods of farming. Lack of use of sophisticated farming equipment and advanced technology, decreasing agricultural areas due to urbanisation, reduced crop yield due to pest infestations, drought, flood and other factors due to climate change pose a threat of food security on the nations face. Adoption of precision and sustainable farming holds the key to address the universal problem. By 2050, at global level 70% increase in the food production is required to satisfy the food demand of the world population which is expected to be around nine billion [1].

Agricultural scientists, specifically the agro-economists are exploring simple yet effective techniques for yield prediction as it is an important feature of the management aspect. It forecasts the quantity of farm product and helps in preparing for the logistics management that includes the storage, marketing, transport, insurance against yield losses. In a nutshell, it impacts not only the individual growers' finances but also the nation's economic development. The traditional manual methods of yield estimation are strenuous, take lot of time and are not very accurate. It requires manpower and monetary investment. The modern methods involving use of scientific and mathematical approach are robust, stable and accurate. Generally, all process need calibration followed by operational application [2].Several aspects of crop like its growth, yield, disease, irrigation etc can be monitored using various techniques that may provide precise and accurate yield forecast and thus enable the growers to plan and manage a sustainable produce.

In the present review, an attempt has been made to understand the role of various methods of yield estimation with a preconception that prediction of crop yield might prepare the agriculturists to assess and manage the necessary manpower, irrigation, marketing strategies and storage facilities. A comprehensive analysis may help the stakeholders to understand the benefits and limitations of these methods and provide an insight into adoption of the most effective yet less complicated method of crop yield estimation.

METHODS OF CROP YIELD ESTIMATION

Forecasting the field produce has been one of the most intricate features of agriculture. It prepares the farmer to make necessary logistic and economic arrangements. From the farmers eye prediction to the use of cutting-edge technologies like artificial intelligence and deep learning the yield estimation is progressing towards automated, rapid and precise methods.

MECHANISTIC MODEL

The mechanistic models simulate specific outcomes by using some important fundamental soil and plant processes such as soil water dynamics, photosynthesis, biomass partitioning, and respiration [3]. Some complex models were developed based on this approach. The EPIC plant growth model evolved to measure soil productivity was exploited to predict the crop yield by simulation[4]. This model simulated variables associated with biomass production to predict the soil productivity. In the same year, Diepen and coworkers[5] came up with a simulation model WOFOST (World Food Studies) to analyse the crop growth and productivity. Holzworth and fellow workers[6] reviewed and critically discussed a range of applications of the various models available at that time for food security, climate change and adaptations advising farmers of efficient resource use, policy assessment and yield gap analysis to name a few. The drawbacks of these applications were that these models were not able to predict plant responses to the increasing temperature and carbon dioxide levels. The uncertainties in the model parameters and meteorological aspects hampered their performance. The mechanistic models may ignore some very important parameters defining the productivity therefore they end up with prediction errors. The need for new ICT based algorithms and new models cropped up to address global challenges.

COMPUTER VISION-BASED SYSTEM

To overcome the disadvantages of the conventional methods of yield forecast which are inefficient, inaccurate and time consuming, the computer vision-based method is employed for rapidity and accuracy. Computer vision-based technology is used in precision farming in India for real time weed control [7] and monitoring plant's phenotypic changes [8]. It is dependent on two camera stereo rig launched on a platform to for getting images and automatic data collection. To avoid the daylight variations, it works in darkness of night with controlled artificial illumination. The yield is estimated on the basis of images scanned by the computer cameras while moving on a vehicle. It has been used in fruit orchards where the fruit count is done on the basis of series of images by scanning the sides of trees detected by computer vision algorithm[9]. Advances in the field of Machine learning is accelerating and automating the image analysis. Though the computer vision system is offering automation to the agriculture system, it also has its share of challenges. For example, with advancement comes technological issues and the need for experts to extract right information[10].

STATISTICAL METHODS

The statistical algorithms provide a better yield estimation in comparison to the Multiple linear regression (MLR) in the crops where multiple factors like the biological, cultural and climatic are important[11]. Most often used statistical algorithm is ANN- artificial neural networks. Together with satellite based remote sensing, ANN is very effective in land mapping and retrieval of surface parameters[12]. Though the statistical methods are difficult to interpret, they are still widely used due to comparatively low performance of physical model-based methods[13, 14, 15]. ANN is an ML- machine learning approach in which ML algorithms are used to predict accurate yields[16]. It is considered as a mathematical model that is similar to the linear regression statistical method[17]. A hybrid MLR-ANN model predicts the yields with better accuracy with the same datasets[18].

The statistical yield models are relying on the environmental or satellite data. The augmentation of the environmental data to the satellite data improves the yield predictions and project more precise forecast[14]. The later maybe based on the VIs-vegetative indices[19, 15] LST-land surface temperatures[20, 21],fPAR- fraction of photosynthetically-active radiation[22], GPP-gross primary productivity[23], active and passive microwave based[24]. The quality of the factors decides the performance of the yield prediction model. Therefore, more sophisticated approaches are being employed and a gradual shift towards upscaling the meteorological and satellite data is done. Despite its applicability in large scale predictions the statistical methods are complicated and cannot be easily interpreted.

MATHEMATICAL MODELING

In the twenty first century, the throne of manual calculations and predictions is on the head of mathematical modelling. In this method, real time situations are converted into mathematical models using mathematical concepts and language by applying necessary constraints[25]. Fields like physics, chemistry, biosciences, economics, commerce, engineering, social sciences etc do use this method for solving their real time problems. Modeling of crop growth in order to develop, crop type, environmental, climatic conditions specific mathematical models dragged the attention of agro-scientists since last mid-century. The problem after identification is simplified using some conditions and is converted into a model. The solution of this model is interpreted in the context of real physical problem. Due to some ideal assumptions taken during modelling, these models give approximate solutions. These analytical or numerical solutions are highly capable of predicting near to accurate and more precise agriculture produce. Mathematical models available in literature are listed as linear, non-linear, implicit, explicit, static, dynamic, discrete, continuous, probabilistic, deterministic, inductive, deductive, strategic and non-strategic.

Static models are often used to analyse the experimental data. However, these models exhibit limited generality. This was used to study the response of crop produce towards weeds population[26]. A deterministic model was used to forecast the crop produce under given atmospheric conditions and spatial conditions of water, soil and irrigation[27]. Hochmuth and co-workers[28] presented a case study on lettuce and applied three mathematical models named as logistic, linear plateau and quadratic models with the objective of estimating proper fertilization so as to optimize the crop produce. A dynamic model named as InfoCrop for estimating crop produce was capable of assessing the losses caused by pests, and response of agro-eco systems in tropical regime[29]. Both inductive and deductive models were applied by others to study the causal parameters for changes in land use[30]. A probabilistic model was developed to give the estimation for probability distribution values of crop produce[31]. The climatic conditions like precipitation and soil moisture values were used to derive the model. Another model predicted a new pattern of cropping in Egypt for increasing the crop return value[32]. A discrete model was developed with the objective of controlling the weeds population[33]. The model favours weeds control at the initial stage instead of usual matured weeds control by herbicides. This will help in reducing weeds population and improving crop produce to its optimal value. Thus, in brief, mathematical modelling makes the life of research world easy in agriculture regime.

SATELLITE REMOTE SENSING BASED METHODS

Satellite Remote Sensing methods are in use since 1970sand it revolutionized agriculture world over. Remote Sensing information is a synthesis of aerial data taken from various sources like atmospheric, geometric and field data. It focuses on development of algorithms based on information from weather forecasts, clouds and radiations. The data is analysed generally by comparing the spectral signatures of healthy plant with the plants in the area of study. Several vegetative indices are utilised for the spectral signature. The radiometric, spatial, spectral and temporal resolution is important to select the remote sensing system. It can be used in combination with other mentioned crop yield estimation methods for better precision and accuracy [34]. Several agricultural research studies have used the spectral data generated by satellite remote sensing for accurate yield predictions and development of models[25, 35].

CONCLUSION AND FUTURE PERSPECTIVES

Crop yield prediction is one of the most important aspect in the agricultural management system. The timely yield estimation may help the farmers to get their crops insured on a personal level and the authorities to plan for food security in developing economies at government level. Various methods of yield determination are employed within a range of precision but each one comes with some limitations as well. Even after decades of work, each single method is incomplete on its own and needs complementation from other robust technology-based methods to be adopted.

The available methods are reasonably good at yield determination but from past studies, it can be derived that multiple methods used in hybrid mode give the best and most precise estimation for all scales. For a particular application, a thorough discussion on the merits and demerits will help in selecting the most suitable approach that has the potential to be as near to the real as possible with minimum prediction error or a new model could be developed that address the particular situation. This review emphasizes the potential importance of interdisciplinary approach to bridge the gaps present in the available methods and recommends further research explorations to develop universal methodology that encompasses the genotypic, physiological and ecological parameters.

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CONFLICT OF INTEREST

The authors declare there is no conflict of interest.

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