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APPLICATION OF REMOTE SENSING AND GIS IN CROP MODELLING: A REVIEW

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ABSTRACT:

The crop modelling and forecasting are very important for the estimation of crop yield before the harvesting is done. This offers sufficient time to prepare for the requirement of foods to the management, decision-makers and respective government officials at district, state, and national level. The crop modelling and forecasting subsequently play a vital role in food safety, security and management. Further, the possible impact of climate change on crop yield and food security are optimised and minimised by put on the crop modelling and forecasting models. The application of remote sensing and GIS integrating with crop growth model provides the missing spatial information required from the crop growth modelling and forecasting. Numerous crop model and RS & GIS techniques had been combined to estimate the crop yield locally and globally. Studies had been carried out for estimating canopy density, biomass, canopy variables and soil properties using RS & GIS data and integrated with various crop models. In this review paper, a few important papers have been reviewed integrating RS & GIS and crop models. The models, limitations and advantages and future trends of remote sensing data and crop models have been discussed in this paper. The projected future trends are discussed, as the new and planned remote sensing platforms, developing applications of crop models and their expected enhancement to combine automatically the increasingly available remotely sensed products.

Key words: Crop model, RS & GIS, Yield prediction and forecast.

INTRODUCTION:

The crop growth modelling and forecasting convey the association of the particular crop with the soil, air, water and the environment by putting on the physical processes in a time period, daily, weekly or monthly. This gives the approximate estimation for the yield of the crop before its harvesting. The appropriate estimations of the crop are crucial for the food security, livelihood and socioeconomic factors. Since food scarcity could affect people adversely than any other factor. (Murthy, 2003).In the literature, crop models are now and then also called crop yield models or agricultural system models. Despite how numerous scientists refer to crop models, all of them agree that a model replicates the real-world conditions to obtain the most appropriate estimation (Van Ittersum and Donatelli 2003). These models play a vital role in assisting the land managers, food officers and policymakers to manage and plan accordingly for the food requirements, sustainable land practice and management. The local governing bodies and decision-makers in the rural sector acquires a reliable prediction about the upcoming production capacities of crops (Soria-Ruiz et al. 2012). In today's world, with the latest tools and technique, the factors affecting the growth and yield of crops are well known. For any crop, during the time of growing season the crop there are numerous factors or variables, genetics, soil type, soil fertility, plant population, crop management, water management and irrigation system, climate, and the integration of stress that the crop faces (Batchelor et al. 2002).

In the 1970s after the United States did a huge acquisition of wheat from the Soviet Union, crop models expected significant attention (Pinter et al. 2003). Thus, new investigation programs expected aids to generate crop models that take benefit of the abilities of remote sensing data to forecast the yield of main crops. One of the starting efforts in this path was the Large Area Crop Inventory Experiment (LACIE) that was sponsored by NASA and NOAA to develop a technique for approximating the yield of wheat globally by using LANDSAT data (Erickson 1984).

In the 1980s the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) backed by the United States Department of Agriculture developed a model for tropical environments. The major objective of this mission was to recognise how the system and its mechanisms function (Jones et al. 2003, Roubtsova 2014). The requirement to develop the models of IBSNAT more suitable concerning input data and thereafter it resulted in the proposal of Decision Support System for Agrotechnology Transfer (DSSAT) (Johnson et al. 2003).

The complicated progressions and connections of plant, soil, water and atmosphere might be changed by climate change. According to Challinor et al. 2009 the foremost challenge for upcoming researchers on the reaction of crops to climate change with the accurateness of the spatial information.

Remote sensing technique acquires geographical data scientifically for bulky areas at affordable cost and hence, it has become the major practice for acquiring natural and agricultural data surveys during the last few decades. Remote sensing resolves to some extent the ambiguity of spatial data of crop parameters that are needed for crop modelling. Numerous methods of integrating remote sensing data along with crop growth models had been proposed. The models, limitations and advantages and future trends of remote sensing data and crop models have been discussed in this paper.

Table: 1. List of the Most Common Crop Models

Crop Model	Details	Source /Link
APSIM	The Agricultural Production Systems Simulator (APSIM) is internationally recognised as a highly advanced platform for modelling and simulation of agricultural systems.	http://www.apsim.info
AgrometShell	Software for crop yield forecasting initiated by the Food and Agriculture Organizati on of the United Nations	http://www.hoefsloot.com/agrometshell.htm
Aquacrop-GIS	AquaCrop-GIS facilitates the use of AquaCrop when a high number of simulations is needed, simplifying the task of generating inputs and project files and the management of output files	http://www.fao.org/aquacrop/software/aquacrop-gis/en/
Cropsyst	CropSyst is a user-friendly, conceptually simple but sound multi-year multi-crop daily time step simulation model. The model has been	http://modeling.bsyse.wsu.edu/CS_Suite_4/CropSyst/index.html

	developed to serve as an analytic tool to study the effect of cropping systems management on productivity and the environment.	
DAISY	Daisy is a mechanistic simulation of agricultural fields developed by the Agrohydrology group at the University of Copenhagen. Daisy keeps track of water, nitrogen, carbon, and pesticides in the bioactive zone near the soil surface.	https://daisy.ku.dk/
DSSAT	Decision Support System for Agrotechnology Transfer (DSSAT) is a software application program that comprises dynamic crop growth simulation models for over 40 crops. DSSAT is supported by a range of utilities and apps for weather, soil, genetic, crop management, and observational experimental data, and includes example data sets for all crop models.	http://dssat.net/
EPIC	The Agricultural Policy / Environmental eXtender (APEX) model was developed to extend the EPIC's capabilities of simulating land management impacts for small-medium watersheds and *heterogeneous* farms.	https://epicapex.tamu.edu/
Fasset	FASSET is a whole-farm dynamic model, which can be used as a tool to evaluate consequences of changes in	http://www.fasset.dk/

	regulations, management, prices and subsidies on a range of indicators for sustainability at the farm level, e.g. farm profitability, production, nitrogen losses, energy consumption and greenhouse gas emissions.	
ORYZAv3	ORYZA is an ecophysiological model which stimulates growth and development of rice including water, C, and N balance (Bouman et al., 2001; IRRI, 2013) in lowland, upland, and aerobic rice ecosystems. It works in potential, water-limited, nitrogen-limited, and NxW-limited conditions. And it was calibrated and validated for 18 popular rice varieties in 15 locations throughout Asia.	https://sites.google.com/a/irri.org/oryza2000/about-oryza-version-3
SWAP	SWAP (Soil, Water, Atmosphere and Plant) simulates the transport of water, solutes and heat in unsaturated/saturated soils. The model is designed to simulate flow and transport processes at field scale level, during growing seasons and for long term time series.	http://www.swap.alterra.nl/

REMOTE SENSING AND CROP GROWTH MODELS:

Remote sensing is the science and art of obtaining information about objects about distance (Fischer et al. 1976). Sensors can collect data remotely while mounted on various platforms such as satellites, planes, unmanned aerial vehicles, and handheld devices (Challinor et al. 2015). In recent years, satellite imagery has proven to be a useful tool for many agricultural applications. Healthy vegetation is very strongly reflected in the near-infrared (NIR) but absorbs red wavelengths.

Therefore, the combination of these two bands provides a set of vegetation indices (VI) that helps to understand the forces of vegetation (Campbell and Wynne, 2011). VIs is the equations or mathematical ratios of spectral bands and is used to identify functional relationships between crops and other vegetation types (Wiegand et al. 1979).

Yield forecasts are based on agricultural specimens, i.e. field surveys and written inquiries. Processing all of this data is a costly and time-consuming task given the wide range of forecasts at the local, national or international level (Bouman 1992).

Neiring et al. In the DSSAT-CERES model, remote integration of LAI and soil moisture and their results showed that a combination of remote sensing data and harvesting models required data changes to estimate the performance of a time scale over a season. The researchers suggest investigating methods and other supporting data to directly correlate leaf development with grain development. LAI and evaporation equation (ET) represent two important cultural processes. LAI simulates the development of the sky affecting light blocking and photosynthesis, and ET reflects the water available to support the growth of the culture. To accurately estimate yield, it is important to improve the simulation of these variables (Huang et al. 2015).

With recent technological advances, drones (UAVs) are highly used in agriculture. The drone used in agriculture provides low-cost, timely and spatially high-resolution data along with a lightweight and inexpensive remote sensing sensor. However, due to the small size of these devices and limited battery capabilities, they are mainly used in precision agricultural applications to ensure a variety of factors affecting plant growth in the farm. The operational use of small UAVs at the local level is questioned (Jin et al. 2018, Panagiotou et al. 2018). However, due to the high costs associated with data collection and processing complexity, usability is limited. In addition to raw satellite images, products are available for a variety of biophysical parameters that can be monitored by remote sensing (Silleos et al. 2014).

The vegetation index is easy to calculate, so parameters for the condition of the roof are often used. NDVI (Normalized Difference Vegetation Index) has been the most used since the 1970s. Numerous studies have used NDVI to analyse plant growth and estimate crop yield (Lopresti et al. 2015, Bolton and Friedl 2013). In most studies, the central strategy is to use linear regression models to predict performance based on the remote detection rate obtained during the growing season (Johnson 2014, Prasad et al. 2006) and VI to calibrate the model with input model estimates like LAI parameters (Launay and Guerif 2005).

Compared to optical sensors, Synthetic Aperture Radar (SAR) offers several advantages when monitoring harvest conditions. These sensors are not affected by atmospheric conditions, but they can collect data day and night, and the SAR sensor penetrates the top of the plant (Dominguez et al. 2015).

LIMITATION AND ADVANTAGES OF USING RS GIS WITH CROP MODEL:

It should be made clear that no spatial information is expected from the crop models as such. However, you can use spatial input to work. Therefore, the main advantage of using remote sensing data with culture models is the addition of spatial information, which is often absent in dimensionless models (Thorp et al. 2010, Seidl et al. 2004). Remote sensing data can provide spatial information and, therefore, can be used to extend coverage in two-dimensional space (Launay and Guerif 2005). This spatial information is very important for various applications, including for a specific agricultural sector and food security, which face one of the most difficult tasks of monitoring and providing consistent information on yield over time and space (Azzari et al. 2017). Besides, monitoring factories and providing yield forecasts at different scales before harvest are important for decision-making in areas such as retail, logistics and insurance.

According to published data, the reported drawback of using remote sensing data is the low spatial resolution of satellites, which offer ready-to-use products with high time resolution for practical work with harvesting models. They suggested using higher resolution satellite data, such as MODIS from PROBA-V. Another advance in the implementation of time series remote sensing data in plant growth models is that frequent remote sensing data may provide missing information since plant models are often ineffective when growing conditions are poor. deviate from the optimum (for example, due to biotic or abiotic loads). The system and the quality of the results strongly depend on the quality of the data used by the model.

FUTURE TRENDS:

Future integration of plant modelling and plant breeding is not without problems. In particular, modelling a phenotype of a gene requires quantitative knowledge of the genetic effect on physiological parameters of physiological characteristics in the production process. This is not necessarily easy, as the characteristics for determining performance interact with each other. However, the ability to scale up the hybrid assessment both in space and in the environment of the target population suggests that crop modelling in future cycles will be an important complement to experiments with several environmental conditions (Wollenberg et al. 2016).

Establishing a relationship between spatial scales is not the only task for greater integration of harvesting models and remote sensing data. Agriculture around the world currently operates in a changing climate, and constant, often autonomous, adjustments are taking place. Remote sensing can play a role in monitoring these changes and related changes in land use. These changes in land use are the result of several complex factors, including climate policy and food demand. Changes in land use can also affect crop model capabilities. (Bajželj et al. 2014, Challinor et al. 2015).

Recently, more and more attention has been paid to the combination of harvest models with UAV data. With the expansion of unmanned aerial vehicle technology and the new, more sophisticated light sensors on the market, the collection of remote sensing data for unmanned aerial vehicles and harvesting models for field applications will rapidly develop. For example, (Bendig et al. 2015) combined Vis data from UAVs and hyperspectral soil data and plant height information to estimate barley biomass. Another example is the work of (Zhou et al. (2017). where multispectral and digital images were taken at critical stages of growth and were used to correlate with grain yield and LAI, to determine the appropriate time period and an optimal visual assessment to predict rice yield and to assess the possibility of multiple EPs to predict yield Using UAV images. The results showed that multispectral and digital images are reliable for both rice production and growth prediction.

DISCUSSION:

Plant models and remote sensing have undergone parallel development courses. This article describes the background and efforts to combine these two elements to improve plant modelling. It also examines the main methods of combining remote sensing data and harvesting models, the extent, impact of climate change and early warning systems for food security and plant breeding. Future trends are discussed, taking into account planned satellite remote sensing flights, alternative sources of remote sensing data and expected improvements in harvest models. The main advantages of including remote sensing data in crop models are the presentation of the lack of spatial information on them and a more precise description of the actual state of crops at different stages of the growing season. These shortcomings are related to the accuracy of the information obtained by remote sensing and the possible appearance of clouds which hamper the collection of satellite data. Plant models should be adapted to facilitate research on climate change and genotype modelling requirements. You should benefit from future trends in remote sensing, including new platforms (UAV, nanosatellites and planned satellite missions) and more sensitive image sensors (eg hyperspectral). Given the benefits and wide applicability of the combination of these two factors, it is doubtful whether the collaboration of remote sensing data with harvest models will increase with the introduction of automated methods to improve their productivity. The so-called big data revolution is the context in which this collaboration will undoubtedly take place. Data assimilation and quality control methods should be at the centre of this promising area of research to provide reliable and competent forecasts.

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