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Crop yield prediction using satellite remote sensing based methods

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Abstract

Agriculture plays an important role in a nation's economic progress by not only feeding its population but also by providing rural employment, agriculture related export and fetching foreign exchange. Adoption of new technologies and interdisciplinary management approaches has significantly improved the agricultural produce. This study provides an insight into the application of several satellite remote sensing-based models that are used to quantify the crop yield. Further, it emphasizes on the need to develop a single or hybrid problem specific and user-friendly model. This may facilitate agriculturists and other stakeholders to identify the most reliable technique to ascertain the crop yield.

Keywords: crop yield estimation, crop simulation, regression based models, satellite remote sensing based model, yield prediction

Introduction

Humans and their live stocks are dependent on the agricultural produce to sustain their food necessities. With the ever-increasing numbers there is an immense pressure for a significant raise in the agricultural productivity. According to a food and agricultural organisation report 70% increase in the food production is required to satisfy the food demand of the world population by the year 2050 which is expected to be around nine billion (FAO, 2017) [8]. Food security is one of the several agendas of Sustainable Development Goals (SDGs) of United Nations. To add to the already existing woes, the unprecedented attacks of corona virus and the mass migration of workers during lockdown has impacted the agricultural sector. Specifically, the post-harvest crop management has taken a severe toll.

Globally, the lack of any standard dataset due to different agroclimatic conditions, crops and agricultural techniques makes the crop management even more difficult. All the intrinsic qualitative and quantitative parameters affecting the yield are known by use of several methods and thereby eliminate several unnecessary times and cost consuming processes. The authors through the current review shed light on some of the most commonly used satellite remote sensing-based methods of crop yield prediction and critically analyse their strengths and weakness.

Satellite Remote Sensing based methods

In 1970s the Satellite Remote Sensing approach was the newest technique on the block and was seen as a potential method to enhance the agricultural statistics world over. Remote sensing (RS) data is an assemblage of the several atmospheric, geometric and field data taken remotely from a high position above ground. The data is stored and analysed to gain agronomically important biotic and abiotic information like the nutrient status of the field, weed or pest infestation, water status, damages due to winds hail and chemical. The analysis is done by comparing the spectral signatures of crop species in the study area with that of a healthy plant. The spectral signature is based on the vegetative index, the most common being the NDVI i.e. the normalised difference vegetative index. The spectral, spatial, radiometric and temporal resolutions influence the selection of the remote sensing system.

Among the various methods to estimate the crop yield of satellite remote sensing based methods are gaining popularity. Though it is not a very new concept but to attain precision and accuracy several operational models were proposed from time to time. In 1960s the aerial remote sensing techniques were bettered by the satellite remote sensing with Explorer, Television Infrared Observation satellites (TIROS series) corona and series of Landsat's (Lettenmaier *et al*., 2015) [22]. Major agricultural crops like rice, wheat, sugarcane and maize are monitored for their productivity via the space borne satellite remote sensing. Various morphological, biochemical and biophysical factors are studied as crop growth parameters called the vegetation indices. The satellite remote sensing generated spectral data has been utilised in agricultural programmes for several crop studies, problems associated with crop inventories and accurate yield predictions and development of models (Sahai *et al*., 1988) [34]. The remote sensing methods relied on the weather forecasts, clouds, radiations of various wavelengths focusing on the development of algorithms.

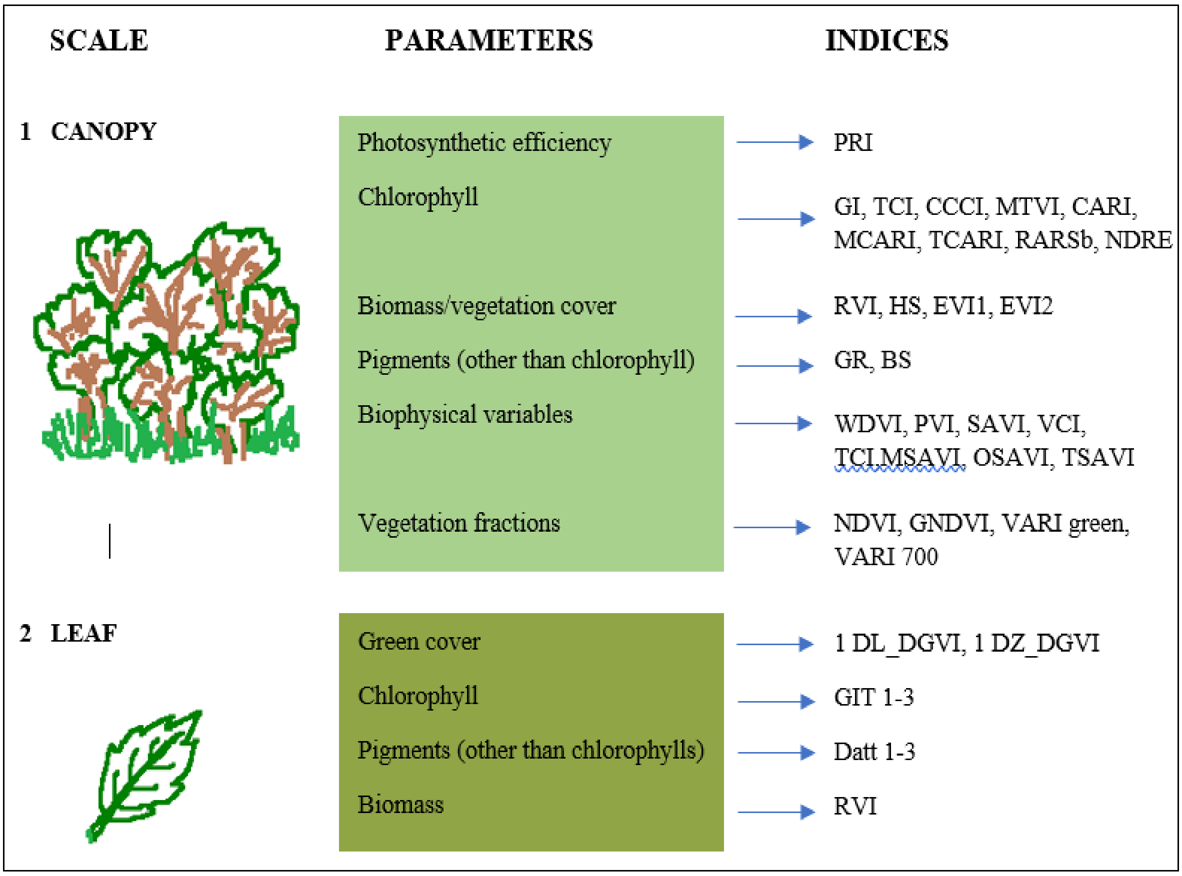

Fig 1: Various vegetation indices used for estimation of different parameters developed for canopy and leaf scale. PRI-photochemical reflectance index, GI- green index, TCI- temperature condition index, CCCI-Canopy chlorophyll Content Index MTVI- Modified triangular vegetation index, CARI- Chlorophyll absorption reflectance index, MCARI- Modified CARI, TCARI- Transformed CARI, RARSb- Ratio reflectance of reflectance spectra, NDRE-normalised difference red edge RVI- Ratio vegetative index, HS-Hansen & Schjoerring, EVI- Enhanced Vegetative Index, EVI2- Enhanced Vegetative Index 2, GR- green ratio, BS-Blackburn & Steel, WDVI- weighted Difference vegetation index, PVI- Perpendicular vegetation index, SAVI-soil adjusted vegetation index, MSAVI- modified SAVI, OSAVI- optimised SAVI, TSAVI- transformed SAVI, VCI- vegetation condition index, NDVI- normalised difference vegetative index, GNDVI-, VARI green- Visible atmospherically resistant index, VARI 700- Visible atmospherically resistant index 700 nm, DL_DGVI- First order derivative of the green vegetation index using local baseline, DZ_DGVI- First order derivative of the green vegetation index using zero baseline, GIT 1-3- Gitelson1-3, Datt 1-3 (Cammarano, 2014) [5]

In the recent years, the focus shifted towards data use. A comparison of satellites with optical/thermal sensors, satellites with active microwave sensors satellites with passive microwave sensors, satellites that measure the gravity field on the basis of special and temporal resolutions was performed to studying their impacts on various agriculture aspects (Karthikeyan *et al*., 2020) [19].
The remote sensing-based methods can further be classified into methods as described in the following subsections.

1. Regression based methods
Literature shows that vegetable indices give an idea about crop's expected yield on the basis of accurate and reliable data processing. The estimation using this technology rely on reliable and accurate quantitative processing of the data like type of crop, edaphic and climatic factors via regression and machine learning techniques(Fang *et al*., 2019) [7]. A regression relationship is drawn between the crop yield and vegetable indices which can then be used in future yield indications using fresh data from the vegetative features (Karthikeyan *et al*., 2020) [19].
The gross primary productivity GPP, Net primary productivity, leaf Area Index LAI, Solar Induced Chlorophyll Fluorescence SIF are indicators of crop growth and yield. NDVI is the most common index. Some other indices are also used by different researchers like EVI-Enhanced Vegetation Index (Liu *et al*., 1995) [24], NDVI-Normalized Difference Water Index (Gao 1995) [10], EVI2-two-band EVI (Jiang *et al*., 2008) [16],GRVI-Green-

Red Vegetation Index (Motohka *et al*., 2010) [29], MODIS NDVI data with air temperature values from MERRA2 reanalysis product (Skakun *et al*., 2019) [35] and spatio-temporal variations in the crop frequency using MODIS NDVI and EVI data along with ancillary information (Tao *et al*., 2017) [37].

Different workers have compared different vegetative indices and have preferred one over the others for their respective crops. From NDVI (Lai *et al*., 2018) [21], AVHRR (Advanced Very-High-Resolution Radiometer) NDVI(Quarmby *et al*., 1993) [32], AVHRR VCI Vegetation Condition Index (Liu and Kogan, 2002) [25] to use of Landsat 8 Operational Land Imager (OLI) NDVI values (Mirasi *et al*., 2019) [28] have been used for wheat yield prediction. Of various techniques like partial least square regression (Hansen and Schjoerring, 2003) [13], ANN- artificial neural networks (Johnson *et al*., 2016) [17], support vector machines (Tuia *et al*., 2011) [41] and random forests was adjudged the best to predict the LAI of rice (Wang *et al*., 2018) [42]. On the basis of past works it may be concluded that the shortcoming of this method is its site dependency that is suitable and effective for local studies with study of few variables.

2. Physics based method

The physics-based methods adopt the biophysical processes like the leaf optics for the modeling purpose. Jacquemoud and Baret (1990) used a radiative transfer PROSPECT model that utilises the information such as the leaf anatomy, amount of pigment, water and dry matter. This model simulates the leaf optics in the 400nm to 2500 nm range of wavelength. Now its modified versions PROSAIL-4 and PROSAIL-5 are also available (Feret *et al*., 2008) [9]. The oversight in the data is minimized by involvement of model inversion (Li *et al*., 2015) [23]. Despite its advantages in applicability over a greater scale, this method too has its limitation in the form of equifinality that leads to optimality. Several scientists propose the inclusion of prior knowledge to solve this problem.

3. Assimilation of RS data in crop simulation models

A hybrid of physics-based model and the crop simulation model can come to the rescue for the problems specific to either model if used alone. The former employs soil parameters for a particular crop. On the other hand, the later not only uses the agronomic and edaphic conditions but also relies on the meteorological data and farming practices.

Several crop simulation models have been used spanning last few decades. Hoogenboom and co-workers (2019) recently used DSSAT-decision support system for agrotechnology transfer. WOFOST- World food **st**udies(Diepen *et al*., 1989) [6], EPIC- Environmental Policy Integrated Climate Model (Williams *et al*., 1989) [43], CERES- Crop environment resource synthesis (Ritchie *et al*., 1989) [33], Daisy model (Abrahamsen and Hansen, 2000) [1], Aqua crop model (Steduto,2009) [36], SWAP model- Soil, Water, Atmosphere and Plants (Kroes *et al*., 2009) [20] and MONICA- model for nitrogen and carbon dynamics in agroecosystems (Nendel *et al*., 2011) [30]are some of the other commonly used techniques.

The application of crop models has its own challenges when used for large fields as huge data is required. These problems can be handled using remote sensing methods. These two can be assimilated for an efficient output in the following two ways- either the crop growth variables maybe substituted by the simulated variables or the former maybe used to tweak the later, thereby altering the output.

Under heavy cloud conditions the remote sensing models prediction based on optical images maybe compromised. Now-a-days better signals from a multi satellite missions like Sentinel, Sentinel-2 etc. provide better optical and radar images though with their own limitations like saturation effect in calculating various vegetation indices (Thenkabail, 2000) [38]. Assimilating the crop variables based on the satellite images with the crop simulation models researchers have estimated the crop yield in several crops. The predictions are subject to the environmental conditions of the region, the farming practices employed, the biophysical variables considered. The major limitations being that the analysis is based on the data accumulated over a period of different developmental stages using multiple VI's which may not be optimal individually for all the stages (Kamenova and Dimitrov, 2020) [18]. The authors while using Sentinel-2 data concluded that inadequate temporal and spatial resolution of data limits its crop productivity predictions. They advised to use these data sets with appropriate care and indicated preference for UAV (unmanned aerial vehicle) based approaches to assess the Sentinel-2 data.

4. RS of plant photosynthetic activity

Satellite remote sensing has enabled crop monitoring over large areas. It uses different spectrum wavelengths. The inference related to the GPP is based on the correlation between the structure of the plant and reflectance. Since the biomass is an integral part of the yield therefore any parameter indicating towards it may be utilised for yield predictions. The vegetative indices based on optics may lead to a calibration error and thus flawed yield projections. In the ecosystems that have seasonal variation in light use efficiency and that show variation with respect to the carbon assimilation due to climate change, predicting the productivity is quite challenging. Therefore, several remote sensing parameters like LST (Land surface temperatures), NDVI, EVI (enhanced vegetation index) and NIRv (near infra-red reflectance of vegetation) fail to detect the GPP seasonal variation.

The SIF- Solar Induced Fluorescence data, being a measure of photosynthetic activity, is considered a promising option to indicate crop productivity (Guan *et al*., 2016) [11]. The physics-based models like SAIL (Miller *et al*., 2003) [27] and its modification SCOPE- Soil Canopy Observation, Photochemistry and energy fluxes model can retrieve the SIF data (Tol *et al*., 2009) [40]. Another light use efficiency model to which SIF is related is the fPAR-fraction of photosynthetically active radiation. It gives the estimates of CO_2 fixed through photosynthesis and is derived from satellite remote sensing. fPAR can be obtained from whole canopy or from the leaves (Bastiaanssen and Ali, 2003) [2]. Though the estimation based on the two would be quite different. To get precision, the fPAR needs to be coupled with other model that could enhance the GPP-Gross Primary productivity. GPP is critical for understanding the C-cycle and ecosystem functions. SIF is indirectly used as a measure of the GPP as it is capable of capturing the seasonal variance in gross primary productivity (Magney *et al*., 2019) [26]. Peng and coworkers (2020) used high resolution SIF to predict maize and soybean yield. They suggested the need of improved SIF data with better resolution and quality for yield estimations as according to the authors in its present state satellite based high resolution SIFs role in yield estimation is ambiguous and not much better than other remote sensing approaches. Recently, Cai and group (2019) employed SIF products to estimate the yield of wheat and found out that due to coarse resolution in the satellite-based SIF results it was inferior to the EVI input which performed better. Therefore, it would be an exaggeration to credit this method as the one with better projections of crop yield while benchmarking it against many other available methods.

5. Microwave data-based methods

The microwave data uses microwaves for the environment forecasting with wavelengths between 1mm to 1m which can penetrate the cloud, haze, dust and fog cover, thus making it possible to obtain data in any weather condition except in heavy rains. These are of two types-the active microwave and the passive microwaves. The active captures the radiations emitted by the objects surface in daytime and the passive are the transmitted ones and independent of the light source. The two can be complementary to each other as one is based on the backscattering and the other is based on the optical depth of vegetation (Guan *et al*., 2017) [12]. The passive microwaves find use in hydrology meteorology and oceanography (Calla, 1990) [4]. Several researchers from the 1990s to the first decade of the twenty-first century have used the microwave - based determination of primary productivity that indicates the crop yield. The morphology and canopy variables play a vital role in this model. But as is the case with most models this also have its weaknesses. The major being the coarser resolution and impact of vegetation on measurements.

Conclusion

The crop yield estimation is an important aspect of farming. Globally various crop yield estimation techniques are being used. Nevertheless, there is no consensus amongst the researchers on any one method that fulfils all requirements and can serve as a universal model. Each method comes with its own operational constraints. The selection of a method is based on specific objectives, area under consideration and the precision required.

Remote sensing-based models with variations in the supplementary methods are the most promising of all. Despite its own lacking, it is still the most favoured technique. The compensation for the low resolution is offered by several others like statistical and mathematical models. Artificial Intelligence algorithms are assisting and improving the present-day methods and providing the farmers and stakeholders a better insight into the agricultural systems. The authors through this work highlight the need to generate more informative and hybrid model(s) that will probably eliminate the local, regional and global biases in precise yield prediction.

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Conflict of interest

The authors declare there is no conflict of interest.

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