Review on Yield Sensing Technologies for Horticultural crops

ABSTRACT

The economic production capacity of a farm could be effectively ascertained with the aid of crop map. With the help of yield maps farmer could benefit by increasing the effective placement input management and better map their profitability. While this yield sensing technology is being used for field crops but very few examples are observed for horticultural crops. So, in spite of many conventional technologies new inventions have been done for sensing yields of horticultural crops. This paper presents different review for examining yields that can be bifurcated in Proximal and Space Borne Sensors Sensing System. It gives us a better prediction about the yield of different crops prior to harvest. Basic principles of both the approaches (proximal & space borne sensors sensing) has been discussed as well as applications for different crops. This review also demonstrated the need for more solutions to be explored in future for yield sensing of different crops.

INTRODUCTION

Farm yield is an important issue for the farmers as it directly impacts on their financial position. The information of each crop on their field will affect their decision during the crop growing season and to enhance management measures for subsequent season [1]. Conventional yield monitoring systems of early 1990's could not work at satisfactory level because of that new yield monitoring systems came in vogue [2]. Presently, there are several global challenges i.e. increasing population pressure, limited land and water resources, deterioration in climatic conditions, therefore improvement in crop yield is necessary [3-6]. Uncertainty in agriculture requires knowledge about production efficiency within each farm to maintain sustainability. Thus, if the farmers will have the information on farm yield during the growing season, help them in taking management measures for subsequent season [7].

One of the best technologies in the present time is spatial yield mapping or geographical information system based georeferenced crop yield data that helps to draw spatial yield maps, which further improved to go for sensing systems to predict crop yield [8]. In many countries combine harvester mounted system yield sensors are being widely used to prepare yield maps [9]. Moreover, other yield monitoring sensing systems (sensors mounted on unmanned aerial vehicle and satellite) are also available in present time [10]. Yield assessment of horticultural crops using sensing technology is still in infancy stage, in spite of lot of spatial variability in crop yield [11]. The following section explains different advantages of crop yield estimation.

1. Advantages of crop yield estimation

1.1 Necessity of yield sensing

During the growth period of crop, the management measures adopted and climatic conditions are reflected as yield of the crop [12,13]. This is further realized that, this output of crop yield when, shown in the form of spatial map shows variability of crop yield in each field [14]. This yield monitoring helps the decision makers in strengthening the supply chain and storage of crop yield [15]. In case of horticultural crops, it is more important as the horticultural crops are highly perishable in nature [16]. Therefore, storage of these crops should be done at the proper time before they deteriorated in quality [17]. In addition, how much yield volume the horticultural crops are bringing will help the factories plan their management strategies.

1.2 Finding areas of low and high yield

For finding out the different causes, the areas giving low or high yield are very important that can be shown by yield map only [18]. Therefore, the further investigation can be carried out in these areas that what type of soil is there in low or high yielding areas. This helps further that particular crop can be grown only in particular areas, which are giving better yield. Therefore, yield map will help to draw a strategic plan [19].

1.3 Determination of management zones

Spatial yield pattern can be found out based on previous years yield maps [20]. This will help to find the different zones for planning and developing the management zones [21].

1.4 Nutrient removal from the crop

Crop nutrients like nitrogen, phosphorus and potash removal can be measured in the form of spatial variation map utilizing yield maps of the area [22]. If phosphate and potash content of harvested crop is known either by any analysis or from any sampling method, which can be utilized to prepare a nutrient uptake map by the crop [23]. Therefore, there are several benefits of yield mapping of horticultural crops and latest technologies should be followed to improve the yield mapping of their cropping system [24]. Different technologies and techniques are available at present time to predict or assess the yield of horticultural crops [7]. The objective of this review paper is to provide an overview of different available technologies for estimating or assessing the yield of different crops using different sensing methods/principles/approaches.

2. REVIEW OF YIELD ESTIMATION TECHNIQUES IN DIFFERENT CROPS

Yield estimation techniques can be broadly categorized as i.e. proximal and remote sensing (aerial and space borne sensors) approach.

2.1. Proximal remote sensing approach

Proximal remote sensing is a technique in which sensors are used to detect the characteristics of plant in the close vicinity of plant [25-27]. In proximal remote sensing approach two techniques are used such as computed tomography and magnetic resonance imaging. Proximal remote sensing has provided observations of plants from the cell [28] to the population [29], from above ground [30] to underground [31], and from indoor (controlled) environments to field conditions on multiple spatial [25,32,33] and temporal scales [34-36]. Over the last ten years, these technologies helped the breeders for characterizing genotypes performance in different environment [37] growth of plant and yield monitoring [38] and, crop yield forecasting [39]. The progress of proximal remote sensing in interdisciplinary applications is witnessed in some of the article. These attempts mainly related to improvement of proximal remote sensing sensors [40] different platforms like unmanned aerial vehicle [41]. The development and popularity of proximal remote sensing has led to the crop yield sensing.

A study was conducted on non-destructive water stress for different crops that can be determined by using thermal and hyper spectral data by Camoglu *et al.* [42]. This study is aimed to find out water stress not visible from the naked eye. The optimum threshold to initiate irrigation and also to estimate yield of pepper (*Capsicum annum* L.) utilizing thermal imaging and hyperspectral data at different level of water stress. The findings show that chlorophyll content, relative water content and pepper yield reflects that thermal and spectral indices were affected adversely by water stress. Therefore, these indices can be successfully used to determine water stress. Ahmed *et al.* [43] utilized visible NIR spectroscopy to assess various internal characteristics like colour, firmness, vitamin C, β carotene and moisture content for carrot. 400-1000 nm and 900-1700 nm spectral range were used for the crop to find out characteristics of carrot (*Dacus carota*). Abbas *et al.* [44] utilized the potential of proximal remote sensing technique to find out variables responsible for crop yield of potato (*Solanum tuberosum* L.). In some of the field of Atlantic Canadian provinces of Prince Edward Island and New Brunswick for the year 2017-18. The data of soil and crop properties collected through proximal remote sensing were analysed by different machine learning algorithms. Weng *et al.* [45] successfully employed potential of proximal remote sensing to find out drought of tomato (*Solanum lycopersicum* L.) using the multi features of hyperspectral imaging and subsample fusion for tomato crop. Marino and Alvino [46] applied proximal remote sensing on drip irrigated tomato field. This study was aimed to evaluate different vegetation indices like NDVI, WI (water index) and TSAVI (Transformed Soil Adjusted Vegetation Index) and to correlate VIs with tomato yield. Hamdane *et al.* [47] involved proximal remote sensing to compare the RGB and multispectral data collected during 2016 to 2020 of melon (*Cucumis melo*), tomato, eggplant (*Solanum melongena* L.) and peppers to study plant health using hand held sensors like SPAD and Duelex, portable spectroradiometer, porometer and infrared thermometer. For high production of horticultural crops N management is important. Optimal N status of vegetable crops whether it is deficit adequate or excessive is very important because this will affect the yield of crop [48-53].

Proximal remote sensors can provide rapid and periodic assessment of crop nitrogen [54]. N content in plant tissue cannot be directly measured with the help of optical sensors but provide indices of radiation measurement and indirect measurement of indicator compound that are sensitive to the crop N status [55-57]. Many studies have reported linear relationship between chlorophyll meter value versus crop/leaf N content for measurements made at a particular time or growth stage [58-62]. However, some studies have reported a plateau response, where, at relatively high N content, the linear relationship tends to “flatten out” [63,64].

2.2. Remote sensing (aerial and space borne sensors) approach

Proximal remote sensing has its limitations as it gives instantaneous data to generate yield maps of a small field only [65]. This scale of data collection is however cumbersome and error prone especially for water status measurement of large areas at the same time affect the yield prediction [66]. Therefore, to monitor and observe farms at a large spatial scale, several earth observation satellite systems are operating at an altitude of 180–2000 km [67-71]. Manned high altitude aircraft (operating within few km) and more recently unmanned aerial vehicle (operating under 120 m) drastically filled the spatial gap between high resolution ground measurements and relatively low-resolution satellite measurements [72,73]. For water status estimation of horticultural crops and their yield, the entire above aforementioned remote sensing platform are utilized depending on the used requirements [74-76]. Each remote sensing platform has its own advantages and disadvantages.

Therefore, satellite manned aircraft and unmanned can be useful for regional scale characterization.

In order to explore method of calculating number of flowers in each apple (*Malus domestica*) tree based on aerial multispectral image Xiao *et al.* [77] used multispectral camera mounted on unmanned aircraft. This study explored a simple and effective method based on multispectral images to estimate the number of flowers on apple tree in blossom, and it could contribute through flower thinning and fruit production forecasting in the future.

Horton *et al*. [78], in their study, investigated development of an image-processing algorithm to detect peach (*Prunus persica*) blossoms on trees. Aerial images of peach trees were acquired with the help of unmanned aerial vehicle system equipped with multispectral camera. Result of this study showed that image-processing algorithm could detect peach blossom with an average detection rate of 84.3% and demonstrated good potential as a monitoring tool for orchard management.

Moechel *et al.* [79] conducted their study in Bengaluru, India, for estimation of vegetable crop parameter by multi-temporal unmanned aerial vehicle-borne images. The objective of their study was to assess the applicability of unmanned aerial vehicle imagery for capturing crop height information of three vegetables i.e. eggplant, tomato, cabbage (*Brassica oleracea var. capitata*) with the complex vegetation canopy surface during a complete growth cycle to infer biomass. The results of the study demonstrated that point cloud generated from unmanned aerial vehicle based RGB imagery can be used effectively to measure vegetable crop biomass in larger areas by applying some biomass prediction models.

Mango mapping was done using unmanned aerial vehicle required imageries by Sarron *et al.* [80] in Niayes region, West Senegal. Three structure parameters (height, crown area, volume) of spices and mango (*Mangifera indica*) cultivars were measured using unmanned aerial vehicle photogrammetry, and geographic object based image analysis. This procedure reached and average overall accuracy of 0.89 for classifying tree species and mango cultivars and their yield.

The wild tomato species (*Solanum pimpinellifolium* L.) was evaluated by Johansen *et al*. [81] through field and unmanned aerial vehicle based assessment of 600 control and 600 salt treated plants. The aim of this research was to determine if unmanned aerial vehicle based imagery collected one, two, four, six, seven and eight weeks before harvest could predict fresh shoot mass, tomato fruit numbers and yield mass at harvest and if predictions varied for control and salt treated plants. A random forest approach was used to model biomass and yield. This research demonstrated that it is possible to predict biomass and yield of tomato plants up to four weeks prior to harvest and potentially earlier in the absence of severe weather events.

Di gennaro *et al.* [82] developed an automated early yield estimation system (5 weeks before harvest) using high resolution RGB images, acquired through an unmanned aerial vehicle (UAV) platform in a representative zone of vigour variability of the whole vineyard. An unsupervised recognition algorithm was applied to drive the number of clusters and size, which have been used to estimate production. This fast and accurate methodology, which operate with a low cost setup, has shown high accuracy in yield prediction providing interesting potential to support grape production management in vineyard.

A low altitude unmanned aerial vehicle (UAV) was used to acquire RGB and hyperspectral imaging data for a potato crop canopy at two growth stages to estimate the above-ground biomass and predict crop yield by Li *et al*. [83]. Crop yield was predicted using four narrow band vegetation indices and crop height with imagery data obtained 90 days after planting. A Partial Least Squares regression model based on the full wavelength spectra demonstrated improved yield prediction ($r^2 = 0.81$). This study demonstrated the merits of UAV-based RGB and hyperspectral imaging for estimating the aboveground biomass and yield of potato crops, which can be used to assist in site-specific crop management.

Suarez *et al.* [84] studied Proximal and remote sensors, which have proved their effectiveness for the estimation of several biophysical and biochemical variables, including yield, in many different crops. Evaluation of their accuracy in vegetable crops is limited. This study explored the accuracy of proximal hyperspectral and satellite multispectral sensors (Sentinel-2 and WorldView-3) for the prediction of carrot root yield across three growing regions featuring different cropping configurations, seasons and soil conditions. Above ground biomass (AGB), canopy reflectance measurements and corresponding yield measures were collected from 414 sample sites in 24 fields in Western Australia (WA), Queensland (Qld) Tasmania (Tas), and Australia. The optimal sensor (hyperspectral or multispectral) was identified by the highest overall coefficient of determination between yield and different vegetation indices (VIs) whilst linear and non-linear models were tested to determine the best VIs and the impact of the spatial resolution. The optimal regression fit per region was used to extrapolate the point source measurements to all pixels in each sampled crop to produce a forecasted yield map and estimate average carrot root yield (t/ha) at the crop level. The latter were compared to commercial carrot root yield (t/ha) obtained from the growers to determine the accuracy of prediction. Hence, this method of yield forecasting offers great benefit for managing harvest logistics and forward selling decisions.

There is enormous scope and prospective of crop yield prediction at finer scale for farm-level crop management at gram panchayat (GP) level in India [85]. Now with the advent of satellite sensors like the MSI from Sentilnel-2 with fine spatial resolution, the possibility of generating frequent information on crop condition at field scale is increasing. This study demonstrated the combined use of high-resolution data from Sentinel-2 (10 m and 20 m); moderate-resolution data from MODIS (500 m) and coarser-resolution radiation data from INSAT-3D (4 km) for estimating yield of three major crops of India at GP and taluka level using a semi-physical model based on crop-specific radiation use efficiency. The novelty of this study lies in the data fusion approach using parameters from multiple spatial resolution of Geostationary and Lower Earth Orbiting satellites within the basic semi-physical model framework. The study concluded that high resolution remote sensing data would be of immense use for finer scale yield estimation, which can be aggregated at GP and taluka level with satisfactory accuracy ($p = 95\%$).

CONCLUSION

Yield sensing and the availability of yield map present several advantages and opportunities for horticultural crop growers, thus justifying the continued development of monitoring approaches to generate reliable yield maps. The advent of digital agriculture and precision agriculture, which relies on crop management, environment, and production data to optimize the use of resources is highly dependent on yield maps and reliable yield monitoring technologies will enable horticultural crop production to fully embrace this new paradigm. Yield sensing or monitoring approaches either proximal or space borne sensor has their own limitations and advantages. The choice of right yield estimation method or approach is linked to different context for each crop and should consider multiple factor such as adaptability, reliability, precision and accuracy. The digital agriculture revolution for horticultural crops remain contingent upon the development of reliable and ubiquitous yield monitoring system.

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