

Application of Remote Sensing Data in Crop Yield and Quality: Systematic Literature Review

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ABSTRACT

Purpose: Covering current state of the art in the field of application of remotely sensed data in crop quality improvement.

Methodology/Approach: Systematic literature review using novel text mining techniques.

Findings: Relevance of topic, measured by number of relevant studies, is rising, best performing input data types and modelling techniques are identified.

Research Limitation/Implication: Review to a certain point of time in a rapidly evolving field of research.

Originality/Value of paper: There was no similar review article on the topic at the time of conducting this research.

Category: Literature review

Keywords: satellite imagery; crop growth model; remote sensing; crop yield quality; precision agriculture

1 INTRODUCTION

Precision Agriculture (PA) is changing aspects of agriculture around the world through several potential benefits, such as profitability, productivity, sustainability, crop quality, environmental protection, and rural development (Liaghat and Balasundram, 2010). According to Cisternas et al. (2020), one of the most used technologies in PA is Remote Sensing (RS).

Jensen (1996) defined RS as “a scientific discipline discussing the acquisition and interpretation of information obtained by sensors that are not in physical contact with an observed object”. This field of science includes aerial, satellite

and cosmic observations of the surfaces and atmospheres of the planets of the solar system, with the most frequently studied object being the planet Earth. RS technologies are usually limited to methods that detect electromagnetic energy, including visible and invisible radiation that interacts with surface materials and the atmosphere (Liaghat and Balasundram, 2010).

Data obtained by RS techniques can be used in variety of sectors besides agriculture: from urban and natural resources planning and natural disaster prevention (Solemane et al., 2019) to creating tools that help optimizing global supply chains, such as Global Copper Smelting Index.

RS technologies have biggest impact on crop quality. According to Munnaf et al. (2020), the key indicator of crop growth and productivity is crop canopy and its geometric characteristics. It has been proven by many researchers, that crop canopy is a potential crop yield indicator (Villalobos et al., 2006). From the perspective of remotely sensed agricultural data, satellite-derived vegetation indices are often used to monitor crop quality and predict crop yields.

2 METHODOLOGY

The goal of this study is to summarize models, input data and crop types researched in the relevant studies in the field of crop yield quality estimation (CYE). We conducted this study as a systematic literature review by adapting the framework of Kitchenham and Charters (2007).

Firstly, we created a plan for the review, which consists of composing research Questions (Q), defining sources of articles, and search and review protocols:

Q1: What are the most researched crop types?

Q2: What models are used in CYE?

Q3: What input data are used in CYE?

2.1 Search Protocol

First step was to extract keywords. Simple text mining tool was developed using Python programming language and Natural Language Processing packages, with full text of 15 previously found and highly relevant case studies as base data collection. In the next step, we performed text processing which consists of removing undesirable information (stop words), stemming and lemmatization. Finally, we evaluated the most frequent one-, two- and three-word terms.

Based on text analysis, we identified “remote sensing”, “satellite imagery”, “crop yield estimation” and “crop growth model” as the most relevant keywords. Selected terms were then combined into search queries (Table 1). Dataset of collected studies consists of 378 papers (after removing 43 duplicates).

Table 1 – Search Queries, Journal Repositories and Number of Studies

Repository	Search query	Papers
Web of Science	(TS=((("remote sensing") OR ("satellite imagery")) AND ("crop yield estimat*") OR("crop growth model")))) AND DOCUMENT TYPES: (Article)	132
IEEE Xplore	((("remote sensing") OR ("satellite imag*")) AND ("crop yield estimat*")OR("crop growth model))	80
Science Direct	("remote sensing" OR "satellite imagery") AND ("crop yield estimation" OR "crop growth model")[Journals]	209
Total		421

2.2 Review Protocol

Firstly, we defined 3 degrees of Relevance (R):

- R1: Papers that are relevant for this research, but do not represent the main source of knowledge (e.g., RS technologies overview in general);
- R2: Papers that are moderately relevant and adequate (e.g., previously conducted literature review on application of RS);
- R3: Papers that are very relevant and adequate: actual case studies on application of RS data in CYE.

We decided to include every publication with Relevance 3 to this research; excluded were publications with Relevance 1 and 2. Subsequently, we reviewed abstracts of each publication to further relevance consideration.

By conducting this research, we found 108 highly relevant publication, that were subjected to further in-depth review. We reviewed full text of each publication to address all research questions.

3 RESULTS AND DISCUSSION

This section summarizes the results of the research. Firstly, we present general findings. After that, every research question is addressed.

The results shown that importance of RS and PA techniques used in crop yield prediction is increasing, based on the rising number of conducted case studies (relevance R3), as shown in Figure 1.

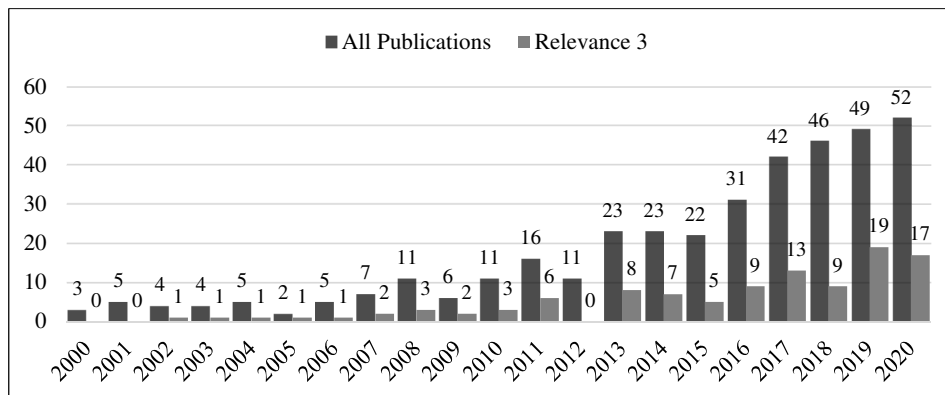


Figure 1 – Distribution of Publications per Year

Amid the selected publications, 52 were researching CYE models in Asia, with China (40) being the most researched Asian country, followed by India (5) and Pakistan (2). Second most researched continent is America, USA appeared in case studies 23 times and Canada four times. Fewer studies were conducted in Europe (13), Africa (13) and Australia (3).

3.1 Crop Types

It has been observed that seven publications did not explicitly indicate a specific type of crop. On the other side, 14 reviewed publications researched more than one crop at once.

We have identified a total of 16 different crop types. The most frequently researched crops were wheat, corn, rice, soybean, and cotton. This could be related to the researched countries, since, according to UN FAO statistics, China, India, and USA are amongst the biggest wheat and corn producers in the world. Results are shown in Figure 2.

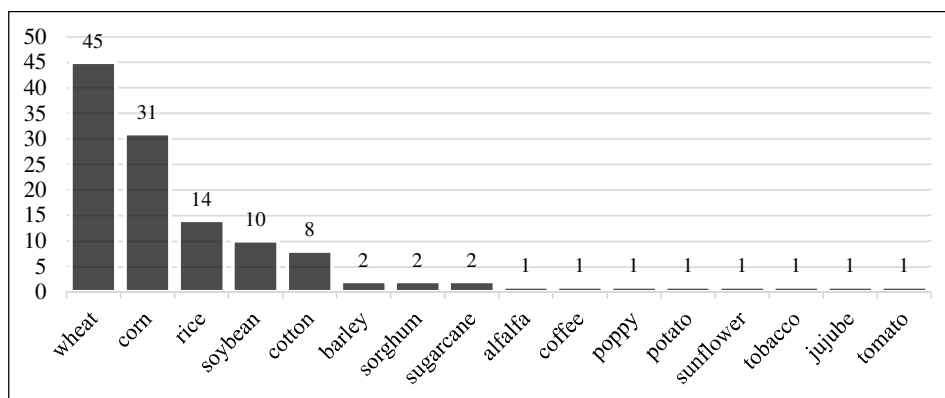


Figure 2 – Crops Mentioned in Reviewed Publication

3.2 Models

We have identified 19 different CYE models. Two main groups of estimation models were defined: existing models and custom models. Former group represents models, such as World Food of Studies (WOFOST) or Crop Environment Resource Synthesis (CERES), that simulate crop growth response to climate data, soil data, crop genotypes and field management across locations throughout the world (Basso, Liu and Ritchie, 2016).

Custom models are developed directly by researchers, using mainly regression analysis (REG) and machine learning techniques (ML). We have discovered that majority of researchers decided to develop their own model, with regression analysis being the most frequent one. However, as technology advances, more researchers are implementing machine learning techniques to estimate crop yield more precisely, as shown in Figure 3.

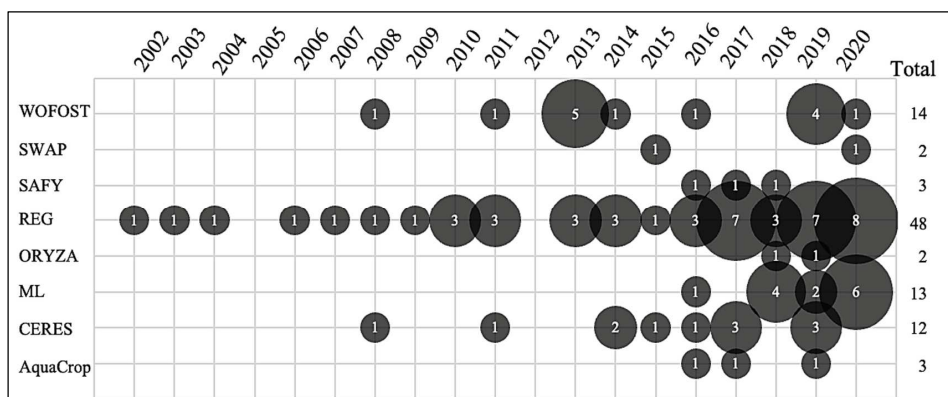


Figure 3 – Models Used in Reviewed Publications per Year

3.2.1 Regression models

We have identified linear regression and time series analysis as the most frequent approach to estimate crop yield.

Prasad et al. (2006) developed piecewise linear regression method with breakpoint for corn and soybean, considering Normalized Difference Vegetation Index (NDVI), soil moisture, surface temperature and rainfall data of Iowa state as input variables. To minimise inconsistency and errors in yield predictions, non-linear Quasi-Newton multi-variate optimization method is utilized, resulting in R^2 of 0.78 for corn R^2 of 0.86 for soybean crop.

Wang et al. (2010) discovered that linear regression yield prediction model based on canopy reflectance (represented by NDVI) of rice at booting stage in Taiwan was not significantly different from the 1:1 line. Although this model showed Mean Average Error (MAE) of 7.7 per cent for the first crop season and 13.1 per cent for the second season, authors state that the relation between spectral indices and CYE needs to be further verified.

Sakamoto, Gitelson and Arkebauer (2013) developed linear regression maize yield estimation model based on MODIS-WDRVI (Wide Dynamic Range Vegetation Index), which was assimilated with MODIS-based crop phenology detection Shape Model Fitting method (SMF). Additionally, correlation between MODIS-WDRVI and grain yield ($R^2 = 0.83$) was higher than the one based on ground observed green Leaf Area Index (LAI) ($R^2 = 0.66$). The best correlation was observed 7 to 10 days before silking stage of maize.

Holzman and Rivas (2016) created linear model for maize yield prediction in Argentina's humid large, cultivated areas using Temperature-Vegetation Dryness Index (TVDI) index data from MODIS/Aqua Enhanced Vegetation Index (EVI) products that was evaluated against official statistics. The authors claim that model can predict maize yield with reasonable accuracy (Root Mean Square Error – RMSE – from 12 to 18 per cent) 8 to 12 weeks before harvest.

Paul, Saha and Hembram (2020) developed regression model of rice yield prediction in India with self-constructed vegetation indices based on NDVI and EVI. Study revealed that the rice yield can be predicted with reasonable accuracy 30 to 60 days before harvesting.

3.2.2 Machine Learning Models

13 publications of 108 reviewed case studies implemented ML techniques in CYE models. As the most frequent ML technique we have identified Random Forest (RF), which appeared in nine publications.

Ngie and Ahmed (2018) developed CYE model using RF technique for maize yield prediction in South African fields with accuracy of $R^2 = 0.92$ adopting Soil-adjusted vegetation index (SAVI) and NDVI data. Results have shown that maize yield prediction was more accurate earlier on in the season (in March during the vegetative growth stage) in comparison to reproductive stage in June. As a possible explanation authors state the correlation between green pigment in corn leaves and its yields through photosynthetic activities.

Yu and Shang (2018) estimated annual maize and sunflower yield in China, implementing RF technique and vegetation indices. Eight models were developed: the most optimal model was based on NDVI time series data from the 120th day to the 201st day (with 10 days' interval). Optimal model for sunflower was identified as the combination of NDVI and phenological characteristics. The most important conclusion of this case study is that the yields of both crops could be well estimated 50 days before crop harvest. The accuracies (Adjusted R^2) of both estimation models varies from 0.80 to 0.90 at pixel level, and from 0.43 to 0.48 (maize) or from 0.61 to 0.68 (sunflower) at the county level, respectively.

In four publications, we have discovered usage of Neural Networks (NN). Koller and Upadhyaya (2005) predicted daily LAI values using artificial NN model, which were used as an input of analytical model for CYE of tomato. However, researchers discovered, that the correlation between actual and predicted yield maps was not very high ($R^2 = 0.29$). Reason for that might be the fact, that the

ANN model developed by researchers used only 1 neuron. Important to add, this study was conducted in 2005, NN as well as computational power have been developing significantly since.

More accurate results were accomplished by Bose et al. (2016). Researchers compared different modelling methods: Linear Regression, K-nearest neighbour algorithm (KNN), support vector regression (SVR) and spiking neural networks (SNN) with NeuCube computational architecture. As the best performing modelling method have been discovered SNN with correlation coefficient (R) of 0.81, RMSE of 0.29 and MAE of 0.24.

Peng et al. (2020) compared five ML algorithms: least absolute shrinkage and selection operator regression (LASSO), ridge regression (RIDGE), Support Vector Machine (SVM), RF and ANN. Results revealed, that nonlinear algorithms (RF, SVM, ANN) outperformed the linear algorithms (LASSO, RIDGE) for maize and soybean yield prediction. Sun et al. (2020) proposed model employing convolutional neural network (CNN) and recurrent neural network (RNN). Although CNN cannot learn temporal patterns and RNN can barely learn spatial characteristics, both techniques can be adopted in a multilevel deep learning network (MLDL) model to extract both spatial and temporal features, including time series RS data and soil data to predict crop yield. Researchers evaluated model in U.S. Corn Belt states: MLDL model outperformed deep neural network (DNN) as well as LASSO, RF and RIDGE models with R^2 up to 0.78.

Leroux et al. (2019) compared linear and nonlinear (RF) statistical model for corn fields with RF technique being more accurate thanks to ability to account underlying eco-physiological processes in vegetation development. In addition, soil data (such as soil moisture) contributed to improving RF corn model. Similar results were accomplished by Sakamoto, Gitelson and Arkebauer (2013) for corn and soybean in USA.

Jiang et al. (2019) compared deep learning long short-term memory (LSTM) model performance with LASSO regression and RF technique for annual yield estimation across the U.S. Corn Belt. The main advantage of LSTM model is the ability to estimate yield under extreme weather events, such as historically low values of precipitation or killing degree days occurred in 2012 in researched area. LSTM model achieved the highest R^2 of 0.66, in comparison with LASSO ($R^2 = 0.63$) and RF ($R^2 = 0.58$).

According to Shao et al. (2015), selection of model (linear regression or ML techniques) depends on number of variables. If the number of variables is limited, linear regression model may work well. When the number of variables increases, the model becomes more complex and using ML techniques (such as RF) is recommended. However, authors did not identify the exact breaking point in number of variables.

3.2.3 Crop Growth Models

Our research revealed, that the most frequently used existing model was WOFOST. According to Yuping et al. (2008), WOFOST model provided more accurate estimates of winter wheat yield when remote sensing data are included during the growing season. Similarly, Ma et al. (2013) accomplished more accurate results implementing MODIS-LAI instead of simulated LAI inputs, although one of the disadvantages of MODIS-LAI approach is the residual error resulted from the mixed pixel effect.

CERES is an eco-physiological model that simulates crop phenology, total above ground biomass and yield using carbon, nitrogen, and water balance principles. Base CERES model uses similar inputs as WOFOST: weather, soil, and cultivar data. Case studies have shown that best results are accomplished when using both MODIS-, MERIS- or ASAR-derived LAI and vegetation indices such as EVI or NDVI (Dente et al., 2008; Fang, Liang and Hoogenboom, 2011; Jin et al., 2016a; Ban, Ahn and Lee, 2019).

AquaCrop is a water-driven crop growth model aimed at improving crop water management strategies in irrigation regions. Inputs are meteorological data, soil data, crop parameters and field management data. Jin et al. (2016b) researched winter wheat yield prediction using AquaCrop model and discovered, that the best performing spectral index was Normalized difference matter index (NDMI). Luciani, Laneve and JahJah (2019) used NDVI time series derived phenological data in AquaCrop model with $R = 0.699$ for corn and $R = 0.723$ for wheat. However, authors stated, that model performances could be unsatisfactory in severely water-stressed environment.

CROWRAYEM is an abbreviation of Crop water requirement analysis yield estimation model, based on CROPWAT modelling software, which uses climatic data and the crops' yield response to estimate yield (Eze et al., 2020). The research has been conducted in Ethiopia for sorghum and barley. Both crop types performed relatively well, with R^2 coefficient of 0.85 (sorghum) and 0.86 (barley).

3.3 Input Data

We have identified 11 types of vegetation indices that were used as an input in various CYE models. The most frequent vegetation index is NDVI, which appeared in 75 of 108 publications, followed by LAI (53 publications) and EVI (18 publications). Results showed that the importance of NDVI and LAI is increasing in recent years, with both indices being used in more studies published in recent years (Figure 4).

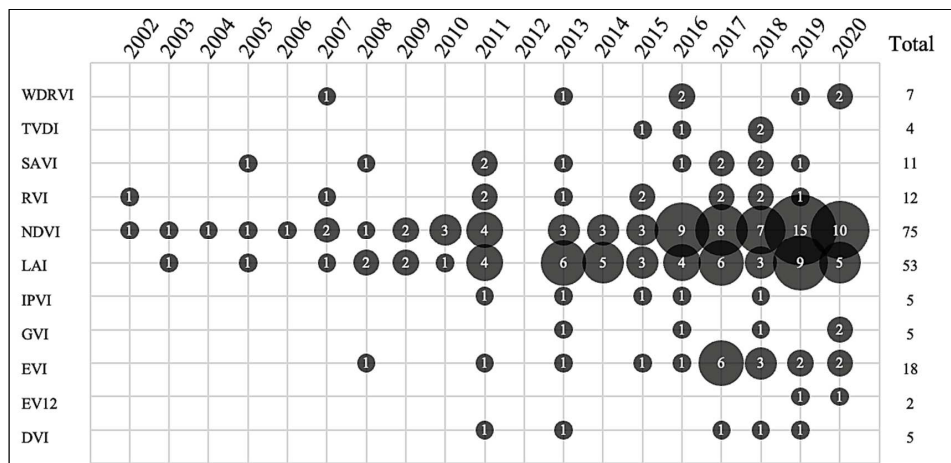


Figure 4 – Distribution of Input Data per Year

Gontia and Tiwari (2011) developed two linear regression models to estimate wheat yield in India using NDVI and SAVI as inputs. Results revealed that SAVI-based model could predict crop yield more accurately compared to that based on NDVI. Reason for that might be ability of SAVI values to adjust the soil reflectance.

Noureldin et al. (2013) compared different vegetation indices in rice yield estimation regression models for the season 2008 and 2009. Validation analysis of each model showed, that using multi-regression model of LAI as one input and NDVI or any other vegetation index calculated from red and near infrared spectral reflectance during the period of the maximum vegetative growth accomplished the best results. However, to achieve the best accuracy of model, using high resolution satellite imagery is necessary.

Holzman and Rivas (2016) studied relationships between the TVDI and corn yield. Statistical significance was found, although the strength of the correlation in analysed counties of Argentina varied with the agroclimatic zone. The values were 0.73 (semi-arid area) and 0.83 (humid area), respectively.

Liaqat et al. (2017) compared spectral indices SAVI, MSAVI, NDVI and EVI in linear regression model for wheat in Pakistan. SAVI developed the best relationship which previously reported wheat yields amongst studied indices. Furthermore, researchers studied accuracy of SAVI obtained from Landsat 8 satellite and MODIS database. Evaluation of Landsat 8 images illustrated better relation ($R^2 = 0.743$) compared to model yield estimation by MODIS ($R^2 = 0.63$).

Shrestha et al. (2017) developed regression model with NDVI as an independent and corn yield dependent variable to predict corn yield loss due to the flood in studied area. Results showed that NDVI can estimate corn loss in flooded areas with high accuracy.

4 CONCLUSION

PA is one of the most important trends in the direction of the food sustainability and quality improvement. As the population of the Earth grows, so do the food requirements. PA offers many frameworks and tools that help achieve this goal, with remote sensing being one of the most important. Usability of remote sensing technology is extensive: from urban and natural resources planning and natural disaster prevention to agriculture industry optimization.

This study provides knowledge on the state of the art regarding the crop yield estimation using remote sensing technologies as well as identifies current trends in research. Firstly, we have identified 3 main research questions:

- What are the most researched crop types?
- What models are used for CYE?
- What input data are used in CYE?

We have implemented a novel approach using Python's natural language processing packages to extract keywords from previously found case studies. By inserting extracted keywords into search machines, we have found 378 articles in total. As our research revealed, this scientific field has grown in importance in recent years: while 20 years ago were three studies published, in 2020 alone we have found 52 publications on the topic.

As our research showed, there has been exponential rise of research over the years on CYE using RS data. This can be observed through the amount of publication that we found using relevant keywords.

Researchers study many different crop types with wheat and corn being the most frequent; develop different regression models and engage machine learning and artificial intelligence techniques to predict crop yields more and more accurately. On the other side there are many existing crop yield/growth models that report reasonably accurate estimations, such as WOFOST or CERES, that can be modified to fit the specifics of a crop type to further enhance the accuracy of forecast.

We have discovered, that remotely sensed data emerged as variations of spectral vegetation indices, that are more unified and more usable in crop yield forecasting. Different vegetation indices report different accuracy for different crop types, even in different parts of the world. We have identified the most important spectral vegetation indices, that can be used to predict crop yield, as well as potential sources.

The results of the systematic literature review allow to identify multiple future work research in context of CYE using RS data. Namely, focusing on crop types that have not been researched as often, such as barley, sugarcane, potato, or sunflower or creating model that is able to identify type of crop and automatically suggests needed input data. This can be done by implementing

convolutional neural networks, that are able to extract spatial and temporal features from multispectral images. Another important aspect that future research should focus on is the impact of predicted yield and estimated health of crop on global supply chains. This can lead to optimization of pesticide use and hence to better food quality.

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CONFLICTS OF INTEREST

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