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Neural network for grain yield predicting based multispectral satellite imagery: comparative study

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Abstract

Estimations of crop yield predictions are vital in the management of agronomical matters. Such Agronomical issues affecting agriculture include agricultural management, national food policies, as well as the international crop trade-which is under the mandate of Food agriculture organization (FAO). Also, an increase in food demand due to the ever-growing population has contributed to the cultivation of large tracts of land. Thus has led to the evolution of diverse methods as well as systems deployed for prediction of crop yield including the application of satellite images. Satellite techniques are utilized due to their capacity to continuously cover large areas while providing accurate estimations of crop yields. In this context of crop yield estimations, the vegetation indices provided by the satellite sensors, as well as land surface variables such as weather elements, soil moisture, hydrological conditions, soil fertility, and fertilizer application is used. Where the convenience of data acquisition and high prediction accuracy is mandatory, many empirical models based on machine learning techniques were employed and the most successful methodology applied was the neural network. The neural network data input varied in the form of normalized histograms of a multi-spectral image bands, normalized vegetation index, absorbed active photosynthetic radiation, canopy surface, and environmental factors. Our findings indicate that the rapid advances in satellite technologies and ML techniques will provide affordable and comprehensive solutions for accurate grain prediction. Many remote sensing researches for yield estimation is needed to adjust and develop the existing methods for more accurate grain crop prediction.

Keywords: Neural network; vegetation index; machine learning; multispectral satellite imagery; crop yield prediction

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1. Introduction

The World Food Program located in Rome, Italy, indicates that 91.4 million people in 83 countries rely on donated food and as the population increases, the supply of food drops [1]. Hence a need to diversify production both locally and on a global scale (focusing on the grain which plays a major role in developing countries diet) by concern on combine of existing best agricultural practices, changing of classical habits, and depending modern digital technologies in agriculture to overcome the global challenge of feeding 9-10 billion people by 2050 [2]. Thus, digital technologies and smart agriculture have taken place as new scientific fields used to improve agricultural monitoring, productivity and food security, and one of the most important factors for achieving these challenges was grain crop production and its estimation [3, 4].

In crop yield estimation, data is forecasted using the manual surveys, crop simulation models as well as remote sensing data [5]. The manual studies involve the traditional systems of predicting crop yield. They require in-situ information about the crop, and the return is forested by comparing data from the subsequent years analyzed through rudimentary statistical tools. Additionally, crop simulation models simulate crop development throughout its pre-requisites and pre-preparation; that is, from soil properties, weather, and management practices. The system applies mathematical models and historical yield data to channel the estimates over a large area [6]. The problem of statistical and simulation models which is collecting high-quality agricultural data dataset appeared in developing countries that are suffering from lacking and unavailability of data, so many researchers other process of crop yield estimation rely on remote sensing; this is the science of observing an object without physical interaction and sourced from satellites and drones. Remotely sensed data characterized by the objective measurements and systematic, time series and spatially represented information and also large scale observation to collect well-known/non-destructive information about earth features [7]; besides, remote sensing provides images that are within a range of 2-3 spectra samples such as the vegetation indices, enhanced vegetation indices, and normalized difference water index.

Machine Learning ML has ability of high-performance computing that enables it to create new opportunities to understand and quantify data-intensive in agricultural. More recently, machine learning techniques have been applied for grain crop yield prediction. One of ML techniques is a deep neural network which belongs to the class of representation learning models that can find the underlying representation of data without handcrafted input of features and have recently been used to predict crop yield [8, 9].

The basics of precision agriculture and regional development of smart farming are summarized by [10-13]; novel Earth remote sensing technologies developed in Russia for precision agriculture and irrigation are systemized by [14]; the application of big data analysis in agriculture and smart farming are described in [3, 15]; using of Satellites Image in precision agricultural in [16], machine learning and deep learning in agriculture are presented by [8, 17, 18]. This study examines the Neural Networks models employed to the prediction of grain yield, in addition to the used multispectral satellite data sources and overall performance metrics (criteria) results achieved by the authors.

2. Methodology

The bibliographic analysis started by collect related works then review and analysis of these works. The keywords used in the search query were: [‘Artificial Neural Network’] AND [‘crop yield prediction’] AND [‘Multispectral Satellite Imagery’ OR ‘Vegetation Index’]. The scientific databases such IEEE Xplore, ScienceDirect, Scopus, Web of Science WoS and Google Scholar GS were searched for conference papers and articles. After that, the papers referring to crop yield prediction but not based on multispectral satellite imagery or not related to grain yield had been filtered out.

The selected papers were studied and analyzed according to several factors included the sources of satellite data were used, which additional data was used in prediction and how it affected the prediction results, which class and architecture of neural network were chosen and why as well as how the multispectral satellite data was preprocessed.

3. Multispectral Satellite Imagery

Satellite imagery or satellite data is information provided by man made satellites in their orbits about Earth and other planets in the space, the most important part of this data is Earth Observation EO which describe the surface and weather changes on the Earth. There is a wide range of satellite data that varies in technique (active/passive, scatterometer/ radiometer), spatial resolution, spectral range and viewing geometry [19].

The interpretation of this data is often aided by specialized techniques such as geo-statistics, image analysis and classification, and/or artificial intelligence AI.

Satellite images are more economically accessible than aviation sensing methods but they need greater efforts to valuable image interpretation. In other side, the use of unmanned aerial vehicles (drones) has virtually no limits to revisited time, while the multispectral sensors of the modern devices have spatial resolution sufficient for tracking the growth of individual plants [14, 20]. The minimal costs of the drones are ranged from to 30.000 to 80.000 US [14]. There are more than ten commercial satellites which provide data with 0.3 - 1 m resolution and revisit one surface point every 1-2 day; the cost of one image grow exponentially with resolution from 220 to 2800$ [16]. The images of Sentinel-2 (Landsat 7-8) are free to download, but it has spatial resolution of pixel of 10 (30) meters and revisited time only 5(8) day. Other open access satellite Terra and Aqua (MODIS) are viewing the entire surface of Earth every 1 - 2 days, but have a resolution of about 250 meters. The multispectral images consisting of reflectance from the visible, near-infrared NIR and mid-infrared regions of the electromagnetic EM spectrum which can be interpreted in terms of physical parameters (such as crop cover, crop health and soil moisture), So in the last decades, multispectral satellite images are widely used for agricultural applications, for examples precision agriculture that utilizes these sensor technologies for yield mapping and prediction, stress mapping, soil sensing, nutrient and pesticide application, crop diseases detection, irrigation control, etc. and the reason of their success is due to large global and temporal availability and easy accessibility [21, 22]. According to the spectral resolution of sensors, satellite images allow to detect and monitor several characteristics of crops and soil during the whole production process [16]. The availability of monitoring data and remote sensing imagery allows the relations between yield and spectral image data to be evaluated more robustly and thoroughly than the use of limited numbers of yield samples [21].

However, the thermal region of the EM spectrum has application in soil and vegetation water content evaluation [23], Short-wave infrared SWIR are able to detect, on a large scale, several soil properties as mineralogy, texture, organic carbon, and salinity [24], while NIR and visible region of the EM spectrum contributed in developed many vegetation indices VIs used effectively to monitor crop cover, crop yield and crop health in addition to soil moisture and nitrogen stress, where they mostly based on the difference between reflectance in NIR and R bands like RVI [25], NDVI [26], EVI [27] and SAVI [28], which positively correlated with crop yield, and LAI [29], fAPAR [30], which can be used to define biophysical features of vegetation [31]. These vegetation indices or spectral bands of the satellite image collected at specific times of the growing season and considered as independent variables of the prediction model, where they may be relating to the crop yield and valid for yield estimation.

It worth mentioning that, VIs data derived using the National Oceanic and Atmospheric Administration NOAA / Advanced Very High Resolution Radiometer AVHRR had been used to forecast crop yield in many countries since the 1980s, while VIs data derived using the Moderate Resolution Imaging Spectroradiometer MODIS, available through 2000 to the present, had made significant improvements addressing imperfection from AVHRR; where:

- MODIS has an accurate radiometric sensitivity, coming by separating R and NIR channels from the spectral regions of atmospheric water absorption, while AVHRR, in contrast, introduces noise due to the placement of AVHRR-NIR channel (emitted range: 0.725–1.100 μm) which overlapped within the water-vapor absorption region (emitted range: 0.9–0.98 μm); Also, MODIS-R channel is much narrower (reflected range: 620 – 670 nm) than AVHRR-R channel (reflected range: 580 - 680nm); making it more chlorophyll-sensitive which resulting in MODIS-NDVI saturation over medium to dense vegetation;
- MODIS has a high spatial resolution reach (250 m to 1 km), at variance AVHRR with a spatial resolution (1 km to 4 km); that could afford MODIS an accurate forecast in yield prediction field;
- MODIS, since 2000, has been acquiring data in 36 spectral bands; by contrast, the AVHRR has five spectral bands. This enables MODIS to provide data for applications in both vegetation and land cover mapping;
- MODIS offer geo-location accuracy and onboard radiometric calibration better than AVHRR.

Hence, it is clearly in a graphical representation that the tendency of researchers to depend on MODIS data in the studied works, Fig. 1(a).

4. Artificial Neural Network in Grain Yield Prediction

During the last three decades, development in satellite data as acquisition, data processing and interpretation of ground-based satellite observations have made it possible to couple these data with the machine learning ML technologies which also witnessed a remarkable development. Generally, Artificial Neural Network (ANN) is a simplified structure of the real biological neural network, consists of an interconnected set of nodes with associated weight for each connection. These nodes ordered in multiple layers divided as input and output layers and one or more hidden layers responsible for learning function. Typically ANNs are used efficiently for clustering, classification, pattern recognition in addition to prediction problems.

However, various successful popular open-source package and tools for modeling artificial neural networks can be used to start building ANN models rather than starting from scratch and each one has a suitable scenario for the purpose of its use and also comes with its weights pre-trained, such as tensorflow, Neural Network Toolbox in Matlab, weka, Pybrain, Neurolab, nnet, neuralnet, Scikit and FANN; as well as existed architectures such as ResNet, AlexNet, GoogleNet, CaffeNet, VGG. It is worthy to be mentioned that some problems can occur when using such framework when pre-trained on similar or small data sets. The Satellite information correlates nonlinearly with crop yield; therefore, it requires an appropriate ML model for grain crop yield prediction. The previously used methods were relied statistical models for grain yield prediction such as [6, 32-36]; but when looking to advantages of the neural network NN in term of nonlinearity, input-output mapping, generalization and fault tolerance, NN techniques can be the well-liked method for prediction model. Where, an NN is a massively parallel distributed processor has the ability for storing experimental knowledge and putting it up for use in prediction in addition to it's learning procedure which gives the ability to approximate any non-linear relationship existing between dependent and independent variables [37, 38].

The most popular techniques for grain yield prediction based ANN and multispectral satellite image data are summarized in Appendix A, which represents grain type, multispectral data source, used model/algorithm and achieved results.

4.1. ANN based satellite-derived vegetation indices

Widespread studies have been undertaken to enable grain yield prediction in agriculture that dependent variety approaches, models and algorithms either using weather/climate data, satellite data or both.

As we mention previously, there are various VIs derived from spectral (optical/ thermal) bands e.g. NDVI and EVI describing grain crop growth conditions. Some researchers used vegetation index time series in the grain yield estimation model as independent variables, focusing on the spatial, temporal or spatiotemporal behavior of data.

In [39] researchers prefer to examine various VIs combinations of the MODIS-NDVI, MODIS-EVI and NOAA-NDVI to be used as independent variables in the wheat forecasting model, well they grouped the census agricultural regions in Canadian Prairies according to the yield data using the technique of hierarchical clustering, then built Bayesian neural network BNN model with number of hidden neurons between 1 and 3 optimally determined by the inner loop. The model was trained and tested by double cross-validation scheme involved two iteration loops and used the Neural Network Toolbox in MATLAB. Bayesian NN was chosen in this study because of their short study period (2000–2011) of 12 years, and this NN characterized by its ability to address over-fitting problem without requiring validation data to determine the regularization parameter.

Furthermore, some researchers constrained a spatiotemporal analysis of satellite image time series for developing yield predicting model such [40, 41]. However, Remote Sensing spatiotemporal pattern recognition is intricate problem; where Markov models and traditional ANNs are often used with temporal information, but with spatial-spectral information they usually miscarry in obtain the integration of long temporal spatial-spectral components; that is because of ignoring the temporal dimension or oversimplify its representation [42]. Therefore, the work [43] directed into third generation of ANNs and proposed a new Spiking Neural Networks SNN computational architecture, called NeuCube to process streams of spatiotemporal brain data. However, in work [40] introduced for the first time SNN as a promising technique in spatiotemporal satellite data analysis, and adapt the use of NeuCube technique for modeling the satellite image time series for prediction of crop yield. Because of climate change is critical for yield estimation and prediction, in [41] Spatiotemporal datasets are used including climate and satellite data. Also Exploratory Data Analysis EDA was applied before using NN method to reveal the spatiotemporal patterns of correlations between (satellite data, climate data) and wheat yield. They compared result of NN with other prediction method but without giving the details of NN architecture.

As soil such as climate play a significant role in crop growth and yield, many research developed their crop yield prediction model based soil/climatic data in addition to satellite Vis [41, 44-49]. The soil is responsible for variations in grain crop yield, due to the spatial variability of soil properties and nutrient [24]. Also, the soil background signal on the optical properties of overlying canopy, have influence on incomplete canopy or canopy spectra [28]. The authors of [45] developed prediction model within field variation in wheat yield using online multi-layer soil data fused with multispectral satellite imagery for accurate prediction. Using bilinear interpolation, the derived NDVI was resampled to match the 5m X 5m grid of the soil layers. Supervised learning methods, were used to combine data about crops and soil with the isofrequency classes of wheat for a single cropping season, included three Self Organizing Map (SOM) models of counter propagation-artificial neural networks CP- ANN, XY fused Networks XY-F and Supervised Kohonen Networks SKN.

As the soil, affect the distribution of the vegetation on Earth; the weather and short-term climate elements affect the vegetation state and greenness as well as annual crop productivity. Where unfavorable weather conditions can outcome in minimum vegetation characterized by mostly dryness. Hence climate data used together with satellite imagery VIs in [48] as independent variables of feed-forward multi-layer network for predicting corn yield in the Iowa state. The model examined the seasonal sensitivities of the corn yields by using three period groups of climatic data, but didn't show the impact of climate data on the predictions. This study implemented NN as deep neural network, where generally ANNs are break down into two categories as traditional ANNs and deep learning DL which also called as Deep ANNs or Deep Neural Networks DNNs [50].

Simply the DLL is ANN with multiple hidden layers and can be classified as supervised, partially supervised, or unsupervised. However, DNN combines the advantages of traditional ANNs and ML models through a deep learning process, and overcomes the problem of local minima in training process and the problem of overfitting which seen in traditional ANN models. That is due to the ability of DNN to optimize the structure via the "back-propagation" algorithm, which integrates forward and backward optimization processes, also by the activation function, which prevents the problem of vanishing gradient-based learning functions during the back-propagation process. Recently, DL models have great success in computer vision, image recognition and complex issues that are difficult to solve with traditional ANN; therefore, it significantly improved the state-of-the-art in different field and industries including agriculture [8].

In the work [51] authors in addition to ANN they developed an optimized DNN grain crop yield prediction model using optimized inputs from satellite products and meteorological datasets. ANN model was modified using nnet package in R language, while DNN model was applied by tens or flow package in Python. In another study [52], authors developed methodology for estimating crop yields by using DL with satellite data, climate data and environmental data. Their methodology relies on using fast feature embedding (Caffe) to develop a convolutional architecture of deep learning estimation model and utilized ReLU for activation function. Same authors in another study [53], used weather data with Satellite-based VIs for developing two prediction models including DNN with six hidden layers and 4000 neurons in each, and an autoencoder NN, which is pre-training using central layer to reconstruct a high-dimensional input vector to represent more important features. In both these works [52, 53], authors concentrated on developing a crop yield prediction by utilize DL to extract features that significantly affect growth of crop and couldn't being quantified ever.

In agriculture, when working on climate and its effect on crop yield prediction, it must be addressed the phenology. The crop phenology dynamics is critical for yield variations because the crop sensitivities toward different climatic events vary with growth phases [54]. Therefore, authors of [55] developed a deep learning model based long short-term memory LSTM that integrates heterogeneous crop phenology, meteorology and satellite data (Wide Dynamic Range Vegetation Index WDRVI) to estimate crop yields. They adopted LSTM method as DL model to leverage the Recurrent Neural Network RNN structure to capture the cumulative effect of corn growth. While, in the different study [56], authors adopted vegetation health indices VHIs include vegetation condition index and temperature condition index(VCI & TCI), that describe the moisture and thermal conditions and have significant influences on crop growth, as a predictors in multi-layer feed-forward back-propagation ANN prediction model. Where the VCI/TCI indices averaged on study area to produce two time series as input of a nonlinear auto regressive with exogenous input (NARX) neural network time series prediction model. However, NARX ANN has feedback connections enclose several layers of the network for using the past values of predicted or actual time series. After training phase, the NARX ANN is converted to the parallel architecture, which is useful for multi step ahead prediction [57]. In Fig. 1(b), a graphical representation shows the ratios of uses of satellite-derived VIs in the neural network prediction models among studied works.

Although the time series of VIs often affected by noise, e.g. atmospheric variability and cloud contamination, several smoothing time-series methods were proposed among studied works to improve these data and remove noise included wavelet transform, SWETS method and moving average method.

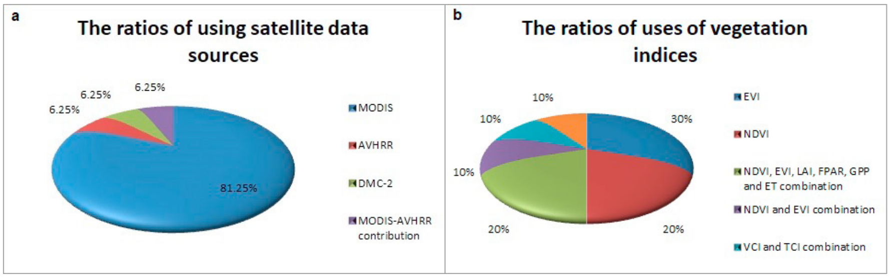

Fig. 1. (a) the ratios of using satellite data sources; (b) the ratios of using vegetation indices

4.2. ANN based raw satellite image

The approaches in the previous section used vegetation indices to predict the yield, but after the work [58] introduced their novel idea about utilize raw multispectral satellite images and especially the non-usually used bands which excessively high spatial/temporal resolution, so they contain a wealth of information on vegetation growth. But it is hard to extract features from such bands due to their high-dimensional and unstructured, therefore [58] proposed deep learning approach, which had led to massive improvements in computer vision. Well, their approach suggests that instead of averaging the VI image pixels per county or district, it uses raw satellite image and create sequences of 2D-histograms of pixel-counts for all bands in that multispectral image in the cropland areas; Then convolution neural network CNN and LSTM networks would be learnt temporal features from this histogram sequences.

The exclusive results were gotten from not limiting the use of the features found in visible wavelength and NIR bands, and use all bands in multispectral satellite image give as:

- SWIR bands reflect higher response to crop growth than traditional bands such as R and NIR;
- Land surface temperature LST reflect high correlation with crop growth, especially in early months, as improved previously by [49].

However, the first deep learning approaches to learn features of remote multispectral image for crop classification was introduced by [59] consists of two CNNs, one 2D-CNN learn spatial feature and the other 1D-CNN learn spectral feature. In general, 2D-CNN is more suitable for machine learning issues like computer vision which not need temporal dimension, while remotely sensing data typically supply dynamic or temporal information which is necessary in spatiotemporal analysis. For that [60] developed a 3D-CNN model that learn spatiotemporal features from multispectral satellite images for grain crop classification also.

Based on the foregoing, the approach of [58] overlooks spatiotemporal dependencies between data points, therefore the authors integrated the spatiotemporal information by using a Gaussian Process GP layer on top of neural network models, which making the inputs that are close in space and time produce close outputs. But their method assumes that image pixels are permutation invariant, so pixels position marks only location of farmlands and not effect on yield prediction. Indeed, the pixel positions may render useful information about soil, weather and water sources, therefore, the authors of [22] transforming multispectral images into 3D-histograms and feeding them to 3D-CNNs. In work [61] authors testing the ability of transfer a CNN-LSTM Model trained in one region to another, this is because the successful of DL models is largely dependent on the abundance of ground truth training data. Their results demonstrated that this approach can successfully learn effective features then transfer this learning with achieving improved performance. Recently, many types of research towards multispectral satellite data analysis using Deep CNN-LSTM Model with MODIS Surface Reflectance SR and LST raw bands as model predictors such as [62-64].

It is remarkable that this technique had recorded successes in other applications in the domain of agriculture, such as land-cover classification, leaf based disease detection, soil moisture contents in the field, weed identification, plant recognition, in addition to predicting future yield.

5. Accuracy metrics and criteria for yield prediction evaluation

The criteria quality of the yield prediction models being compared should characterize their forecasting effectiveness, as measured by the general population. In most articles, statistical criteria considered for quantitative forecasts, such as the mathematical expectation of mean absolute of forecast error MAE/RMSE, multiple correlation factor R/R^2.

In the development of methods of yield forecasts, it is important what benefit will be gained by farmers. Thus, the quality of models should be characterized by economic indicators provided that they are used optimally with predictive information. In this work, the most used accuracy or performance metrics for crop prediction model's evaluation in surveyed literatures, also the number of times they used are shown in Table 1. However, Root Mean Square Error (RMSE) is the most used metric in these studies as it clear from Table 1. In other side, cross-validation approach is the most used evaluation technique and the most studied models were trained using a leave-one-year-out cross validation LOOCV scheme.

Table 1. All used evaluation metrics.

Abbreviation	Measure	#Times
RMSE	Root Mean Square Error provides a general-purpose error metric of numerical prediction	11
MSE	Mean Square Error measures the average squared difference between the estimated and the actual yield	1
MAE	Mean Absolute Error represents the average of differences in estimations (in physical units), and describes the average model performance error	4
MBE	Mean Bias Error indicates whether the prediction model overestimates or underestimates the yield	3
MAPE	Mean Absolute Percentage Error measures the deviation from the actual yield in terms of percentage	3
RE(%)	Relative Error refers to persistent prediction error represents the ratio of error to ctual observed value	4
R/ R2	Correlation Coefficient/ Coefficient of Determination measures the linear relationship between predicted and real values of the yield	5 / 6
SS	Skill Score determines the skill of a forecast model by comparing to a reference or base model	1
Average accuracy	Average prediction accuracy = 100 − RE(%)	2

6. Conclusion

The crop yield processes changes with time and they are highly complicated and non-linear (on occasion linear) because of the participation of many associating factors. Recent studies show that ML algorithms especially Deep algorithms have improved the capability in displaying linear or non-linear relationships in the field of grain yield moreover to their exceptional prediction proficiency. With the notable rapidly development in the satellite data, which provide cost-effective and more comprehensive datasets, combined with more sophisticated algorithmic solutions; this will promise in a new path that significantly alters the field of smart farming and industry.

Although ANNs are widely used with multispectral satellite data to predict grain crop yield, they have some limitation with selection of the number and size of hidden layers, learning rate, the need for a large training dataset and overfitting problem. Therefore, in last decade researchers towards deep learning algorithms, because of its ability to automatic engineer features, capture high - dimensional, multimodal data distributions and uncovering features beyond current knowledge.

In general, there are two classes of deep ANNs that provide a lot of flexibility, useful and reliable in a range of predictive modelling problems with many frames and architectures to work with a multi temporal/spatial/spectral data derived from a time series of multispectral satellite images; consist of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs). However, CNNs have a benefit with spatial data analysis due to their ability to learn position in variant structures in the satellite images, while LSTM, which is the most well-known RNN networks, have a benefit with long and complex temporal analysis of data by recursion and extract dynamic spatiotemporal features. A state-of-the-art model didn't used CNN or RNN alone, but these types of networks are used as layers in hybrid type of deep neural network architecture model in the form of CNN-LSTM architecture.

The ability of transfer learning which existing generally in DL techniques will provide the ability to achieve successful crop yield predictions in developing countries with fewer available data by fine-tuning pre-trained models from countries where data is more easily available. This alongside with overall advantages of DL which promising for further use in smarter, well-managed sustainable agriculture and secure food production.

Appendix A. Surveyed publications-based ANN and satellite imagery for grain yield prediction

Article	Grain Crop	Multi-spectral Data	Model	Accuracy
39	Barley and Wheat	MODIS NDVI, EVI; AVHRR NDVI	BNN	For barley: SS (MAE) = 0.248 For wheat: SS (MAE) = 0.245
40	Winter wheat	MODIS NDVI	SNN	Average accuracy= 95.64%, RMSE=0.28 t/ha, MAE=0.23 t/ha, R= 0.81, MBE=-0.0009t/ha.
41	Wheat	MODIS EVI	ANN	$R^2 = 0.73$
45	Wheat	UK-DMC-2; NDVI	CPANN, XY-F, SKN	Average overall accuracy for SKN = 81.65%, CP-ANN = 78.3%, XY-F = 80.92%
48	Corn	MODIS NDVI, EVI, LAI, FPAR, GPP, ET	DL	MAE =0.608, MAPE (%)=6.5,RMSE = 0.787, MBE= -0.059, r = 0.800
51	Corn and Soybean	MODIS NDVI, EVI, LAI, FPAR, GPP	ANN, DNN	DNN results / For corn: r=0.945,MAPE=7.6, RMSE=0.765,MAE=0.582,MBE=0.029 DNN results/ For soybean: r= 0.901,MAPE=7.8, RMSE= 0.285, MAE=0.222,MBE=-0.016 ANN results/ For corn: r= 0.926,MAPE=9.8, RMSE= 0.928, MAE=0.705,MBE=0.024 ANN results / For soybean: r=0.853, MAPE=9.7, RMSE= 0.340, MAE=0.270,MBE=-0.016
52	Corn	MODIS EVI	DL	RMSE = 6.298, r = 0.810
53	Corn	MODIS EVI	ANN, DNN	DNN results: RMSE =18.5, R^2= 0.773 ANN results: RMSE =19, R^2 =0.759
55	Corn	MODIS WDRVI	LSTM	RMSE = 0.87 Mg/ha, R^2= 0.76
56	Boro Rice	AVHRR VCI, TCI	Dynamic ANN	R = 0.977, MSE = 0.0165
58	Soybean	MODIS SR, LST	CNN, LSTM	RMSE = 5.55, MAPE = 3.37
22	Soybean	MODIS SR, LST	CNN, LSTM	RMSE= 7.53
61	Soybean	MODIS SR, LST	LSTM	Argentina : $0.54<RMSE<0.73$, $-0.13<R^2<0.57$ Brazil: $0.23<RMSE<0.62$, $-2.03<R^2<0.57$ Brazil(transfer learning from Argentina): $0.26<RMSE<0.52$, $-1.75<R^2<0.66$
62	Maize	MODIS SR, LST	LSTM	$R^2 = 0.63$
63	Soybean	MODIS SR, LST	CNN, LSTM	RMSE = 0.81, ER(%)= 2.70
64	Soybean	MODIS SR,LST	CNN, LSTM	end-of-season : RMSE = 329.53, R^2 = 0.78 ,RE%<10 early prediction: RMSE = 353.74, R^2 = 0.74, RE%<10

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