Machine Learning for Human Intelligence
2023, Vol. 1, Issue 1

Research Article

Digital Agriculture: Transforming Yield Prediction with Deep Learning and Multispectral Data

Muhammad Ali[1,⋆] and Nisar Ali Khan[2]

[1,2]Faculty of Information Technology, University of Sargodha, Sargodha, Pakistan.; Email: m.ali@su.edu.pk, nisarali@su.edu.pk
[⋆]Corresponding author: Muhammad Ali (m.ali@su.edu.pk)

Article History

Academic Editor:
Dr. Muhammad Sajid
Submitted: January 03, 2023
Revised: February 19, 2023
Accepted: March 1, 2023

Keywords:
BTriticum; Yield Assessment; Multispectral Methodology; Normalized Difference Vegetation Index (NDVI)

Abstract

Automation is becoming essential across diverse professions and sectors, including agriculture. Remote sensing for wheat yield estimation has become a more effective alternative to conventional yield prediction techniques. Traditionally, measuring wheat output required labor-intensive and time-consuming destructive sample methods. Accurate and timely yield estimates are essential for decision-making processes, including crop harvesting plans, milling, marketing, and forward selling strategies, thereby improving the efficiency and profitability of the worldwide wheat sector. Currently, growers or productivity officers, frequently financed by mills, utilize destructive or visual sampling methods to evaluate wheat yield throughout the growing season. There is an increasing demand for rapid and effective problem-solving techniques. This study seeks to demonstrate and compare the efficacy of employing satellite earth observation data for monitoring agriculture, specifically in wheat production. Various predictor variables are employed to compare multiple regression models. The research includes wheat yield estimation methodologies, including regression models, time series analysis of vegetation indices, remote sensing, phenological observations, and the normalized difference vegetation index (NDVI). Artificial intelligence methods, such as Random Forest and ordinary least squares, are utilized to formulate a proposed method that precisely correlates ground-measured data. This study presents an innovative technique for estimating wheat output, which markedly enhances forecasting precision and offers potential for improving decision-making in wheat cultivation practices.

1 Introduction

The economies of least developed nations (LDNs), including Pakistan, are mostly dependent on agriculture, with Pakistan's economy being primarily agriculture-based. The agricultural sector significantly contributes to Pakistan's GDP, accounting for 21% and demonstrating an annual growth rate of 2.7%. Approximately 44% of the labor force is involved in agriculture, supplying 62% of rural inhabitants with their principal source of income. Agriculture occupies a pivotal position at the convergence of lifestyle and commercial innovation, fulfilling several functions within the economic framework, especially in emerging countries. Wheat, as a staple crop in Pakistan, possesses significant economic value.

The significance of wheat production to the economy is threefold: it is an essential source of food and raw materials for national industries; it generates revenue from international markets; and it supports the supply of products and services both domestically and globally. Historically, individuals have planted crops on their lands to satisfy their dietary requirements, with any surplus frequently helping animals and birds as well. Agriculture globally encompasses around 5 billion hectares, accounting for roughly 38% of the total land area.

This introduction underscores the significance of wheat farming in Pakistan's agriculture, highlighting its crucial impact on the economy, food security, and international trade.

2 Determinants of Agriculture

Due to several causes, agricultural risk management necessitates meticulous attention. Agriculture is an industry where crop cycles are intricately connected to natural phenomena and are entirely contingent upon climatic conditions, which subsequently influence risk levels in diverse ways depending on the unique locale. Crop cultivation and development are influenced by changes in human and environmental resources. Various factors affect wheat yield, defined as the quantity of agricultural produce at a certain location. These variables can be categorized into three primary groups: technical (agricultural practices, management decisions), biological (insects, pests, weeds, diseases), and climatic (temperature, soil fertility, terrain, water quality), among others.

2.1 Agricultural Challenges

The nation is experiencing significant issues with food supply shortages due to conventional agricultural methods and insufficient implementation of modern technologies. The average yield significantly varies from the production [1]. The fast population growth significantly jeopardizes the nation's nutritional strategies. The economic framework of Pakistan is predominantly agricultural, hindered by challenges such as inadequate water supply infrastructure, diminished agricultural productivity, illicit water distribution, insufficient agricultural technology, limited arable land, soil salinity and moisture issues, sluggish growth of related commodities, suboptimal yield per acre, among various other factors.

3 Agriculture and Remote Sensing

The healthy production of food and resource management are two interconnected subjects strongly influenced by agriculture and remote sensing. Remote sensing involves the collection of data regarding the Earth's surface without direct contact, utilizing satellites, aircraft, drones, and other advanced technology. Remote sensing profoundly influences agriculture by enhancing agricultural techniques, optimizing crop yield, and monitoring environmental conditions. Crop monitoring and management are among the primary applications of remote sensing in agriculture. Remote sensing may collect comprehensive data regarding crop health, vegetation indices, and growth patterns through various sensors, including multidimensional or hyperspectral cameras. This data helps identify optimal irrigation and fertilizing approaches, diagnose diseases, pests, or nutritional deficiencies, and assess the overall health of crops. Farmers can avert production loss and enhance resource allocation by the early identification of problematic areas and timely intervention [2].

Remote sensing is furthermore utilized for precision agriculture and land use planning. It provides valuable information for delineating and classifying agricultural land, assessing soil composition and moisture content, and examining topographical characteristics. This knowledge enables farmers to select crops, schedule plantings, and utilize agricultural inputs such as insecticides and herbicides more effectively. Precision agriculture techniques facilitated by remote sensing allow for targeted resource application, reducing waste and negative environmental impacts while enhancing production. Moreover, remote sensing facilitates the administration and oversight of agricultural natural resources. It assists in assessing water availability, monitoring alterations in water bodies, and detecting drought conditions. Farmers and water managers can develop efficient water management strategies and implement precise irrigation techniques by integrating remote sensing data with geographical information systems (GIS) [3].

Remote sensing has demonstrated its immense use in monitoring agricultural crops. Satellite imagery provides comprehensive coverage and superior temporal accuracy, yielding valuable data on crop development, vegetation indices, and other significant attributes. It enables the identification of both regional and temporal variations in agricultural circumstances, facilitating crop yield predictions. Predicting crop productivity with artificial intelligence methodologies, including machine learning algorithms and deep learning models, has shown promising outcomes. These strategies leverage the correlation between actual yield measurements and remote sensing data to train models capable of accurately predicting future yields [4]. Commonly employed AI methodologies encompass decision trees, random forests, support vector machines (SVM), convolutional neural networks (CNN), and recurrent neural networks (RNN).

In conclusion, remote sensing technology and agriculture engage in a symbiotic relationship that enhances agricultural productivity, resource efficiency, and environmental sustainability. Farmers may enhance their operations, make informed decisions, and contribute to a more resilient and sustainable food system by leveraging the capabilities of remote sensing.

4 Artificial Intelligence

The development of computer technology capable of doing activities that typically necessitate human intelligence is known as artificial intelligence (AI). It encompasses a diverse array of methodologies and strategies aimed at enabling computer programs to replicate or simulate cognitive capabilities including as memory, reasoning, problem-solving, cognition, and judgment. Artificial intelligence (AI) systems are designed to collect and interpret data, learn from patterns and contexts, and subsequently predict outcomes or take action. They can rapidly process vast quantities of data, see trends and patterns, and formulate astute decisions or responses. AI encompasses several significant subfields, including Robotics, Deep Learning (DL), Natural Language Processing (NLP), Computer Vision (CV), and Machine Learning (ML).

4.1 Artificial Intelligence in Agronomy

Artificial intelligence (AI) systems are designed to collect and interpret data, learn from patterns and contexts, and subsequently predict outcomes or take action. They can rapidly process vast quantities of data, see trends and patterns, and formulate judicious decisions or responses. Subsequently, novel robotic techniques were devised. The most recent procedures provided sustenance for the entire world while creating employment for billions of individuals. Artificial intelligence has initiated a new era in agriculture [5]. This strategy has safeguarded agricultural productivity from various factors, including population growth, employment challenges, and food security issues.

Artificial intelligence (AI) has emerged as a transformative technology in agriculture, fundamentally altering various farming practices, growing techniques, and harvesting processes. Significant applications of AI in agriculture include Crop Tracking and Management, Precision Agriculture, Crop Forecasting and Optimization, Herb and Pest Management, Farm Automation, Livestock Tracking and Management, Field Management Systems, and Logistics Optimization. Artificial intelligence is transforming agriculture into a more efficient, lucrative, and sustainable sector through data-driven decision-making and technological advancements.

5 Wheat Field

Wheat, a fundamental crop of considerable importance in global agricultural commerce, is essential for supplying food and feed to worldwide populations. Wheat, a crucial cereal grain of the Triticum genus within the Poaceae family, originates from areas ranging from mild temperate to tropical climates. It often varies in height from 0.5 to 1.5 meters, distinguished by slender, hollow stems that produce grains abundant in carbohydrates. In contrast to sugarcane, wheat does not undergo cross-pollination, and its cultivars generally display limited hybridization. The cultivation of wheat spans countries located in several latitudinal zones, featuring climates that vary from temperate to subtropical. Wheat covers over 220 million hectares worldwide, yielding over 700 million tons per year.

5.1 Wheat Production in Pakistan

Wheat, intricately linked to Pakistan's agricultural legacy, has its cultivation origins in antiquity, nurtured by the fertile soils of the Indus River and its tributaries. The historical region of the Indus Valley Civilization possessed knowledge of wheat cultivation, a practice that continues to influence the cultural landscape with staples such as "Roti" and "Naan." Wheat farming thrives in areas situated between latitudes 24 and 34 degrees north, characterized by irrigated subtropical zones with mild temperatures favorable for its growth.

Of Pakistan's 22.0 million hectares suitable for cultivation, wheat occupies roughly 16.0 million hectares, representing a substantial 72.7% of the irrigated area. The country's water resources, comprising reservoirs, total approximately 135 MAF (million acre-feet), which is inadequate to satisfy the crop's projected demand of roughly 10 MAF. Notwithstanding these issues, Pakistan's wheat sector continues to be resilient, functioning at approximately 70% capacity. Annual wheat output in Pakistan ranges from 25 to 30 million tons, driven by factors such as irrigation availability and precipitation patterns [6].

Government support, such as elevated aid prices for wheat producers, incentivizes farmers to prefer wheat cultivation over other crops. Wheat agriculture occurs in three provinces of Pakistan, with Punjab accounting for 68% of production, Sindh for 24%, and Khyber Pakhtunkhwa (KPK) for 8%. Prominent wheat cultivation areas encompass the Punjabi division of Bahawalpur and the Sindhi division of Sukkur.

5.2 Ecological Considerations in Wheat Cultivation

5.2.1 Photosynthetic Productivity

Wheat, an essential cereal crop, demonstrates modest photosynthetic efficiency, transforming solar energy and atmospheric carbon dioxide into biomass. Although less efficient than sugarcane, wheat's C3 photosynthetic pathway allows it to harness roughly 1% of incident solar energy for biomass generation. The photosynthetic rate generally varies from 6 to 8 µmol $CO2/m^2/sec$; wheat is a crucial component of food and agricultural systems, yielding grains vital for human consumption and livestock feed.

5.2.2 Climatic Conditions

Wheat agriculture flourishes in temperate to subtropical areas, with a minimum of 400 mm of yearly precipitation for maximum development. Wheat agriculture in Pakistan spans multiple biological regions, including the northwestern, central, and southern areas of the country. Lower Sindh, distinguished by its hot and humid climate, provides very conducive circumstances for wheat cultivation. The climate of Pakistan varies from temperate arid to semiarid, with average temperatures ranging from 4°C in December and January to 38°C in June and July.

5.3 Influence of Biotic and Abiotic Factors on Wheat Growth

Millions of households depend on agriculture for their livelihoods, as it is anticipated to be a lucrative endeavor. Agriculture in Pakistan encompasses both principal and secondary crops, including cotton, sugarcane, rice, maize, and wheat. The low wheat output in Pakistan is attributable to various factors, including inadequate soil fertility, insufficient seed rates, inferior seed quality, conventional planting methods, and suboptimal farm management [7].

Insect and pest infestations are key issues that substantially limit wheat yield. In Pakistan, insect infestations are diminishing cane productivity, with various pests identified as the principal agents responsible for production decreases [8]. Pesticides are essential to the Integrated Pest Management approach. Integrated Pest Management (IPM) strategies incorporate chemical, biological, cultural, mechanical, pheromone, and light trapping methods.

6 Literature Review

The wheat industry relies significantly on wheat cultivation; therefore, accurate forecasting of wheat production is crucial for optimizing crop management practices, ensuring efficient resource distribution, and facilitating informed decision-making within the wheat sector. An effective instrument for calculating agricultural yields has developed, integrating remote sensing with artificial intelligence (AI) techniques. This literature review aims to examine and consolidate existing information on AI-driven remote sensing models for predicting wheat yields.

Numerous studies have focused on developing remote sensing and AI-based models for forecasting wheat yield. These algorithms extract relevant factors for yield prediction utilizing various remote sensing data, including multispectral or hyperspectral imagery. Various vegetation indicators, such as the Green Chlorophyll Index (GCI), Enhanced Vegetation Index (EVI), and Normalized Difference Vegetation Index (NDVI), have been employed to assess vegetation health and predict wheat yields [9].

The advancement of unmanned aerial vehicles (UAVs) has introduced a novel way for remote sensing, facilitating the capture of high spatial-temporal resolution imagery at a regional scale [10]. The development of a time series comprising high spatial resolution multispectral imaging has been explored in many studies that integrate a high spatial resolution panchromatic image with a lower spatial resolution multispectral image from one or multiple sources.

Yield remains the paramount characteristic sought, and dependable yield evaluation for breeding lines is essential for the incorporation of novel crops into production strategies [11]. The assessment of crop characteristics, such as plant height, chlorophyll content, leaf area index, disease susceptibility, moisture sensitivity, nitrogen concentration, yield, and others, has heavily relied on remote sensing imagery.

Various methodologies for interpreting satellite- and airborne-derived imagery continue to be proposed and assessed. Recent advancements in satellite photography and Artificial Intelligence (AI) have enabled precise measurement of field-scale genetic information and the integration of big data into conservative and predictive management systems.

7 Problem Statement

Wheat is a crucial agricultural commodity, supplying sustenance to a substantial segment of the global populace. The problem of precisely and promptly estimating wheat yields remains a significant concern. Traditional wheat yield estimation techniques, dependent on antiquated methods and historical data, often lack the precision and promptness required to address the intricacies of modern agriculture.

The matter presents multiple dimensions. The challenges confronting regional farmers, agricultural consumers, and policymakers are evident; in the absence of precise and reliable production predictions, they must make critical decisions regarding crop management, resource distribution, and market projections [12].

8 Research Objectives

The aims of this research are:

- To obtain the most significant characteristics utilizing a multispectral dataset
- To create a preprocessing model for the removal of outliers in the multispectral dataset
- To construct a deep learning model for the estimation of wheat yield

We employ diverse techniques for creating predictor variables and evaluate them according to their efficacy in estimating yield. The initial technique employs NDVI alongside time series data from additional vegetation indices (VI). The second strategy entails computing measures for phenology [13].

9 Methods for Development of Predictor Variables

Several methodologies can be considered in the development of predictor variables for wheat yield using remote sensing data:

9.1 Vegetation Indices

Compute widely used vegetation indices such as the Enhanced Vegetation Index (EVI), Normalized Difference Red-Edge Index (NDRE), and Normalized Difference Vegetation Index (NDVI). The assessments of vegetation's greenness, vigor, and health are essential indicators of agricultural development and productivity.

9.2 Spectral Bands

Utilize spectral bands from remote sensing data that are connected with wheat yield. The near-infrared (NIR) and red-edge bands are often important in assessing the biomass and chlorophyll content of vegetation [14].

9.3 Radiometric Transformations

Improve specific attributes or correlations with wheat yield by implementing radiometric modifications to the spectral bands, including logarithmic or exponential transformations.

9.4 Temporal Features

Consider temporal elements by analyzing many time points or seasonal variations in the remote sensing data. To analyze the temporal dynamics and growth patterns of wheat over time, calculate statistical metrics such as mean, standard deviation, or rate of change.

10 Materials and Methods

10.1 Study Area

The selected district for this study in Punjab Province is Dera Ghazi Khan. It accounts for over 30% of Punjab's overall wheat production. Southern Punjab is classified as an agricultural district, as the predominant portion of its population is engaged in agriculture. It is a productive region that yields a diverse array of crops, including wheat, cotton, maize, sugarcane, and mangoes.

10.2 Data Sources

Collecting precise in-situ crop data (yield, biomass, and other biophysical variables) requires substantial resources, yet it is crucial for reliable crop modeling. This study employs the autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) forecasting models to predict the production and yield of Pakistan's two principal cash crops, cotton and wheat [15].

10.3 Remote Sensing Information

We documented the wheat cultivation period for 2022–2023 utilizing multi-temporal Sentinel-2 Level-2A data from the ratooning phase (April 2023) to the harvest phase (December 2022). The cultivation period of wheat in Pakistan averages 10 to 12 months. Three distinct vegetation indicators (VIs) were calculated: the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Red Edge 1 (NDRE1), and the Chlorophyll Index Red Edge (CIRE), utilizing atmospherically corrected Sentinel-2 surface reflectance (Level-2A) data.

Table 1: Selected Vegetation Indices for the Examination

Vegetation Index	Definition
NDVI	Normalized Difference Vegetation Index, sensitive to vegetative biomass
NDRE1	Normalized Difference Red Edge 1, exhibiting reduced susceptibility to saturation within
CIRE	Chlorophyll Index Red Edge, sensitive to plant foliage chlorophyll and mesophyll hydratio

10.4 Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI), a widely used vegetation index, assesses vegetation density and health based on the reflectance of near-infrared (NIR) and red light bands. The processing of NDVI entails the subsequent steps:

Data Preparation: Acquire the necessary near-infrared and red bands from the satellite image. The near-infrared band is designated as Band 8 (B08) in Sentinel-2, but the red band is identified as Band 4 (B04).

Calculation of NDVI: Calculate the NDVI with the formula:

$$NDVI = \frac{Band8 - Band4}{Band8 + Band4} \tag{1}$$

10.5 Normalized Difference Red-Edge Index 1 (NDRE1)

The Standard Deviation Red-Edge Index 1 (NDRE1) is a vegetation index that assesses chlorophyll content and plant health utilizing the red-edge band. Calculate NDRE1 using the formula:

$$NDRE1 = \frac{Band6 - Band5}{Band6 + Band5} \tag{2}$$

10.6 Canopy Chlorophyll Index Red-Edge (CIRE)

The Canopy Chlorophyll Index Red-Edge (CIRE) serves as an indicator of vegetation, providing data on chlorophyll levels and photosynthetic activity. Calculate the CIRE using the formula:

$$CIRE = \frac{Band7}{Band5} - 1 \tag{3}$$

11 Regression Algorithms for Crop Yield Estimation

Various methodologies are employed to predict yield at both regional and field scales. Regression algorithms can anticipate wheat yield based on many input variables for crop yield estimation. The following regression techniques are frequently employed for agricultural yield estimation: Linear Regression, Multiple Linear Regression, Decision Trees, Random Forest, Support Vector Regression (SVR), Gradient Boosting, and Neural Networks.

11.1 Random Forest (RF)

Each tree within a random forest relies on the values of a randomly sampled vector, uniformly distributed over all trees in the forest. As the quantity of trees in a forest rises, the generalization error approaches a limit. The robustness of each individual tree within the forest and their interrelationships dictate the generalization error of a forest of tree classifiers [19].

The out-of-bag (OOB) error encountered during training is utilized to estimate the error of the random forest. The ability of Random Forest to accommodate non-linear relationships, a substantial number of input variables, and proficiently address missing data are merely a few of its advantages for wheat yield estimate.

11.2 Gradient Boosting

Gradient Boosting enhances data analysis by iteratively amalgamating weak learners, commonly in the form of decision trees. This ensemble technique constructs models in succession, with each subsequent model rectifying the flaws of its predecessors [20]. The Gradient Boosting method identifies the model that most accurately represents the provided data points by reducing the loss function via gradient descent optimization.

11.3 K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a commonly employed non-parametric technique for estimating wheat yield. KNN employs the concept of proximity to forecast the dependent variable's value based on the values of the k-nearest neighbors within the feature space. The procedure is simple: it computes the distance from the point to be forecasted to all other points, identifies the k-nearest points, and forecasts the value based on the average (or majority) of these neighbors.

11.4 Neural Networks

Neural Networks aim to identify a correlation between one or more independent variables or predictors and a dependent variable, such as wheat yield. This is accomplished via a network of interconnected nodes (neurons) organized into input, hidden, and output layers. Every connection possesses a corresponding weight, and the network acquires knowledge by modifying these weights to reduce the loss function, generally via backpropagation.

12 Results

Diverse regression models, such as Random Forest (RF), K-Nearest Neighbors (KNN), Gradient Boosting, and Neural Networks, are commonly utilized in remote sensing-based wheat yield prediction models that incorporate artificial intelligence. These models possess distinct characteristics and can offer significant insights into the correlation between remote sensor data and wheat production.

The Random Forest algorithm is a robust machine learning method that constructs an ensemble model by aggregating the predictions of several decision trees. It excels at managing nonlinear relationships and capturing complex interactions among predictor variables [21]. The RF regressor has been employed in models for predicting wheat production from remote sensing data because to its capacity to manage the multidimensional and multi-temporal nature of such data.

12.1 Model Performance Comparison

The bar chart analysis reveals the R^2 ratings of various machine learning models employed for wheat yield estimation:

- Decision Tree: R^2 score of 0.21
- Random Forest: R^2 score of 0.67
- Neural Network: R^2 value of 0.85
- K-Nearest Neighbors (KNN): R^2 score of 0.61

The Neural Network model demonstrated the highest accuracy among all tested models [22].

12.2 Time Series Variables Analysis

Given that the CIRE (Canopy Index Recovery) exhibited superior performance compared to other vegetative indices (VIs) in predicting wheat production, we concentrated on it in our research. We employed linear regression analysis, specifically the ordinary least squares (OLS) method, for each time step of the CIRE to ascertain the optimal dates for wheat yield estimation [23].

Our analysis of the CIRE period sequence revealed a specific pattern in the R^2 scores throughout the different stages of the wheat development cycle. The R^2 marks consistently increased during the green-up phase, reached their zenith at the season's conclusion, and subsequently declined during the senescence period.

12.3 Variable Importance Analysis

This study employed the Random Forest (RF) algorithm to do a SHAP (Shapley Additive Explanations) analysis of the phonological variables. The SHAP study revealed that many phonological parameters significantly influenced the model's performance. The maximum NDVI value, indicative of the season's peak (POS), has emerged as a crucial predictor [24].

Three critical variables that significantly influence yield estimation are:

- Growth rate
- Senescence rate
- The cumulative NDVI values

13 Discussion

The preliminary estimating capabilities of the proposed framework require enhancement and validation through further study utilizing advanced remote sensing technologies and machine learning methods. By enhancing our comprehension of and ability to forecast wheat yield dynamics, we can facilitate more effective and efficient wheat production, thereby bolstering overall food security and agricultural sustainability.

The OLS regressor consistently yielded the highest R^2 scores, signifying a superior match between predicted and observed values, and the lowest root mean squared error (RMSE), indicating minimal variances between anticipated and observed values [25]. This indicates that, according to the selected feature sets, the OLS regression model provides the most precise and accurate estimates of wheat yield.

Our findings underscore the trade-offs between model complexity and performance. The OLS repressor had superior overall model fit and error estimates compared to the RF regression model, which exhibited the ability to capture non-linear correlations in the data. The OLS regression model is an attractive choice for predicting wheat output because of its transparency and interpretability.

14 Conclusion

Our study demonstrated a clear correlation between wheat yield and the predictive parameters (mean CIRE, senescence rate, and growth gradient). The efficacy of these variables as indicators of wheat productivity is indicated by the positive association between mean CIRE and yield, alongside the negative correlations observed for senescence rate and growth gradient [26].

These findings enhance our understanding of the factors influencing wheat yield and can inform agricultural management strategies aimed at optimizing crop productivity and ensuring sustainable wheat production. Future research may explore supplementary visualizations and innovative approaches to analyze the relationships among phonological parameters, their intensities, and their impacts on wheat output forecasts in greater depth.

The preliminary estimating capabilities of the proposed framework require enhancement and validation through further study utilizing advanced remote sensing technologies and machine learning methods. By enhancing our comprehension of and ability to forecast wheat yield dynamics, we can facilitate more effective and efficient wheat production, thereby bolstering overall food security and agricultural sustainability.

References

[1] Mostafaeipour, A., Fakhrzad, M. B., Gharaat, S., Jahangiri, M., Dhanraj, J. A., Band, S. S., ... & Mosavi, A. (2020). Machine learning for prediction of energy in wheat production. Agriculture, 10(11), 517.

[2] Ahmad, I., Singh, A., Fahad, M., & Waqas, M. M. (2020). A remote sensing framework to forecast and evaluate the interannual variability of maize yields in Pakistan utilizing Landsat images. *Computers and Electronics in Agriculture*, *178*, 105732.

[3] Arab, S. T., Noguchi, R., Matsushita, S., & Ahamed, T. (2021). Forecasting grape yields with time-series vegetation indicators utilizing satellite remote sensing and a machine learning methodology. *Remote Sensing Applications: Society and Environment*, *22*, 100485.

[4] Ashapure, A., Jung, J., Chang, A., Oh, S., Yeom, J., Maeda, M., Maeda, A., Dube, N., Landivar, J., & Hague, S. (2020). Creating a machine learning framework for estimating cotton yield utilizing multi-temporal UAS data. *International Journal of Photogrammetry and Remote Sensing*, *169*, 180-194.

[5] Callier, P., & Sandel, O. (2021). Overview of Artificial Intelligence. *Advances in Psychology*, *60*, 18-20.

[6] Canata, T. F., Wei, M. C. F., Maldaner, L. F., & Molin, J. P. (2021). Mapping sugarcane yield via high-resolution imaging data and machine learning techniques. *Remote Sensing*, *13*, 232.

[7] Cao, J., Zhang, Z., Luo, Y., Zhang, L., Zhang, J., Li, Z., & Tao, F. (2021). Predictions of wheat yield at both county and farm levels utilizing deep learning, machine learning, and Google Earth Engine. *European Journal of Agronomy*, *123*, 126204.

[8] Chen, Y., Lee, W. S., Gan, H., Peres, N., Fraisse, C., Zhang, Y., & He, Y. (2019). Prediction of strawberry yield via a deep neural network with high-resolution aerial orthoimages. *Remote Sensing*, *11*, 1584.

[9] Cooper, N., Panteli, A., & Shah, N. (2019). Linear estimators for biomass yield mapping to enhance biomass supply chain optimization. *Applied Energy*, *253*, 113526.

[10] Deng, Q., Wu, M., Zhang, H., Cui, Y., Li, M., & Zhang, Y. (2022). Estimation of Winter Wheat Yield Utilizing an Optimal Weighted Vegetation Index and the BHT-ARIMA Model. *Remote Sensing*, *14*, 1994.

[11] Dubey, S. K., Gavli, A., Yadav, S., Sehgal, S., & Ray, S. S. (2018). Yield forecasting for sugarcane (Saccharum officinarum L.) in India with remote sensing technology. *Journal of the Indian Society of Remote Sensing*, *46*, 1823-1833.

[12] Feng, H., Tao, H., Fan, Y., Liu, Y., Li, Z., Yang, G., & Zhao, C. (2022). Evaluation of winter wheat yield estimation utilizing near-surface hyperspectral and UAV hyperspectral remote sensing data. *Remote Sensing*, *14*, 4158.

[13] Feng, L., Wang, Y., Zhang, Z., & Du, Q. (2021). Geographically and temporally weighted neural network for predicting winter wheat yield. *Remote Sensing of Environment*, *262*, 112514.

[14] Zhao, Y., Potgieter, A. B., Zhang, M., Wu, B., & Hammer, G. L. (2020). Forecasting wheat yield at the field level through the integration of high-resolution Sentinel-2 satellite imagery and crop modeling. *Remote Sensing*, *12*, 1024.

[15] Gillard, X., Coppé, V., & Schaus, P. (2021). Enhancing the filtration of the branch-and-bound MDD solver. In *International Conference on the Integration of Constraint Programming, Artificial Intelligence, and Operations Research* (pp. 231-247). Springer.

[16] Tucker, C. J. (1979). Red and photographic infrared linear

[17] Pantazi, X. E., Moshou, D., Alexandridis, T., Whetton, R. L., & Mouazen, A. M. (2016). Wheat yield prediction using machine learning and advanced sensing techniques. Computers and electronics in agriculture, 121, 57-65.

[18] Segarra, J., González-Torralba, J., Í. A. J. L. Aranjuelo, S. C. J. R. S. Kefauver. (2020). Assessing wheat grain yield with Sentinel-2 imagery while examining the influence of topography characteristics and precipitation on wheat productivity in Navarre, Spain. *12*, 2278.

[19] Shafique, M., Khan, M.A., Khan, W.S., Ahmad, W., & Khan, S.J.J.O.N. (2017). Manufacture, characterisation, and in vivo assessment of famotidine-loaded solid lipid nanoparticles to enhance oral bioavailability. *2017*, 7357150.

[20] Sharma, N., Saxena, S., Dubey, S., Choudhary, K., Sehgal, S.J.T.I.a.O.T.P. Ray, Remote Sensing and S.I. Scientific disciplines. (2019). Evaluation of Sugarcane Cultivation Area and Yield Projections Obtained from Remote Sensing Data and Alternative Hybrid Methodologies within the Fasal Project. *42*, 157-163.

[21] Lafarge, T. A., & Hammer, G. L. (2002). Predicting plant leaf area production:: shoot assimilate accumulation and partitioning, and leaf area ratio, are stable for a wide range of sorghum population densities. Field Crops Research, 77(2-3), 137-151.

[22] Singla, S.K., Garg, R.D., & Dubey, O.P.J.R.D.I.A. (2020). Utilization of Ensemble Machine Learning Techniques for Estimating Sugarcane Yield Using Remote Sensing Data. *Thirty-four*.

[23] Su, J., Liu, C., Hu, X., Xu, X., Guo, L., Chen, W.-H.J.C., & E.I. Agriculture. (2019). Spatiotemporal surveillance of wheat yellow rust via UAV multispectral imaging. *167*, 105035.

[24] Szulczewski, W., A. Żyromski, W. Jakubowski, M.J.R., Biniak-Pieróg, S.E. Evaluations. (2018). A novel approach for estimating the biomass production of gigantic miscanthus (Miscanthus giganteus) during the growing season. *82*, 1787-1795.

[25] Tiruneh, G.A., Meshesha, D.T., Adgo, E., Tsunekawa, A., Haregeweyn, N., Fenta, A.A., & Reichert, J.M.J.P.O. (2022). Modeling crop productivity in Northwest Ethiopia based on leaf reflectance. *17*, e0269791.

[26] Wolanin, A., Mateo-García, G., Camps-Valls, G., Gómez-Chova, L., Meroni, M., Duveiller, G., Liangzhi, Y., & Guanter, L.J.E.R.L. (2020). Assessing and comprehending crop output with interpretable deep learning in the Indian Wheat Belt. *15*, 024019.