Data-Driven Soil Analysis and Evaluation for Smart Farming

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Food shortage issues affect more and more of the population globally as a consequence of the climate crisis, wars, and the COVID-19 pandemic. Increasing crop output has become one of the urgent priorities for many countries. To raise the productivity of the crop product, it is necessary to monitor and evaluate farmland soil quality by analyzing the physical and chemical properties of soil since the soil is the base to provide nutrition to the crop.

soil analysis soil quality evaluation crop identification irrigation cycle

1. Introduction

Soil is a common material seen on Earth, and a natural material composed of solids (e.g., minerals and organic matter), liquids, and gases according to the definition by the Natural Resources Conservation Service (USDA, n.d.). The soil's contribution in agriculture leads to the fact that the soil is highly coupled with human daily life. According to the Food and Agriculture Organization of the United Nations in 2015, approximately 95 percent of food is directly or indirectly produced from the soil, which raises the importance of soil since food is the essential energy and nutrition source for humans. The efficiency of food productivity draws more attention globally due to food supply and insecurity issues; smart agriculture helps us maintain soil health with more accurate nutrition to the crop. As a result, soil analysis via deploying smart agriculture techniques is crucial to maintaining the sustainability of soil in producing food and crops regularly.

Smart agriculture is an emerging field that introduces new technologies such as big data, IoT, satellites, and drones to help farmers optimize farming results. The benefits of smart agriculture include a reduction in manual labor, an increase in productivity, and a decrease in costs. While lack of unification is still one challenge for agriculture researchers and farmers, most agriculture research and applications focus on one specific area such as physical features, chemical features, or biological properties.

2. Data-Driven Soil Analysis and Evaluation for Smart Farming

Table 1 shows the technical evolvement of crop identification. In the early stage (1969 to 1990) of crop identification, temporal-spectral data was used to calculate the vegetation index and to analyze the light of crop via building the crop growth and yield model. An alternative approach is to identify the lighter or darker tones of an image based on the field boundary and ground data. From 1991 to 2000, statistical analysis of the polarimetric multifrequency was getting popular, SAR data (the polarimetric C-, L-, and P-band from the AIRSAR system, as well as the X-band from the E-SAR system), sometimes combined with the pixel distributions of each agricultural plot, was used to calculate the crop's wavelengths. Starting from 2000, vegetation indices such as NDVI, EVI, MSAVI, and NDWI were analyzed as spectral features in statistical approaches [1]. In the meantime, feature selection models were developed to improve the accuracy of the approach. From 2011 to now, various machine learning models, such as Random Forest and Support Vector Machine, have been deployed in crop identification by evaluating the spatiotemporal multispectral bands from satellites [2][3]. Moreover, deep learning models such as convolutional neural networks start to process the laudatory images with image feature capture [4][5].

Table 1. The literature survey for crop identification.

ID	Year	Focused Problem	Approaches	Accuracy	Datasets
[1]	2009	Crop Identification	Statistical analysis about temporal series of indices	91%	MODIS data
[2]	2019	Crop Identification	Support vector machine	91.8%	NDVI feature
[3]	2021	Crop Identification	Decision Tree, KNN, Random Forest, SVM	79%(DT), 88% (RF), 88%(SVM)	Vegetation indices from satellite images
[4]	2022	Crop Identification	Gaussian Bayesian models, Neural Network	83.8, 80.7	Pixel spectra of crops from NASA Hyperion satellite
[5]	2022	Crop Identification	Efficientnet-B0 network architecture in Darknet	99%	Crop images

In the consideration of the irrigation prediction system from **Table 2**, Mohammad Reza et al. [6] used a combination of decision tree algorithm and particle swarm optimization (PSO) for times series prediction for wastewater with an r-squared score of 95%. Istiak et al. [7] built an integrated irrigation network, by measuring the volumetric percentage of soil sample water content. The raw soil moisture data is collected by a moisture sensor. Shilpa [8] first classified the soil type under the KNN approach with humidity, temperature, and soil moisture as the parameters. Then, the authors calculated the water needed for the crop by using The Blaney−Criddle formula. Remilekun Sobayo et al. [9] created a CNN-based soil measurement by combining thermal images with the measurements of the farm area. The moisture level is valued by the soil temperature represented in it.

Table 2. The literature survey for irrigation prediction.

ID	Year	Focused Problem	Approaches	Accuracy	Datasets
[6]	2019	Irrigation Prediction	Decision Tree, Particle Swarm Optimization	95% (r-squared)	Moisture sensor data

ID	Year	Focused Problem	Approaches	Accuracy	Datasets
[7]	2020	Irrigation Prediction	Soil moisture weight function, NPK derived from pH collection	Observations with no accuracy result	Moisture sensor data NPK sensor data
[8]	2021	Irrigation Prediction	KNN for classification, Blaney–Criddle method for water required	Observations with no accuracy result	Moisture sensor data
[9]	2020	Irrigation Prediction	CNN	0.0184(RMSE), 0.093(MARE), 0.98(R2)	thermal images
[10]	2018	Fertilizer Prediction	RF and Simple Linear Regression (SLR)	33.2%(RMSE)	hyperspectral camera data and RGB camera data
[11]	2019	Fertilizer Prediction	convolutional neural network(extraction of features)	83%	RGB crop field images
[12]	2021	Fertilizer Prediction	Random Forest	86%	RGB crop images

Niko et al. [10] estimated the crop biomass and nitrogen content in the soil by extracting features from hyperspectral and RGB cameras. The methodology is based on Random Forest and simple linear regression. H. J. Escalante et al. [11] deployed a deep convolutional neural network to extract features from RGB images and then feed those features into predictive models. Diego et al. [12] also obtained the vegetation indices from remotely piloted aircraft images, which are applied to Random Forest machine learning methods to calculate the nitrogen content in coffee leaves. The global accuracy and the kappa coefficient are up to 0.91 and 0.86, respectively.

Fertilizer management is essential for land-use efficiency in **Table 3**. In recent years, machine learning and deep learning approaches have been conducted for most fertilizer prediction projects. Agarwal et al. [13] and Caturegli et al. [14] trained the models by analyzing crop images. Abhaya et al. [15] optimize the quantity of nitrogen fertilization considering the cost of labor and resources.

Table 3. Literature Survey for Fertilizer Prediction.

ID	Year	Focused Problem	Approaches	Accuracy	Datasets
[15]	2022	Fertilizer Optimization	Optimization and simulation	28–53% improvement	Nitrogen contents
[13]	2018	Fertilizer Prediction	Random Forest	86%	RGB crop images
[14]	2020	Fertilizer Prediction	convolutional neural network (extraction of features)	83%	RGB crop field images

ID	Year	Focused Problem	Approaches	Accuracy	Datasets
[13]	2018	Fertilizer Prediction	RF and Simple Linear Regression (SLR)	33.2%(RMSE)	hyperspectral camera data and RGB camera data

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