



Applications of Hyperspectral Remote Sensing, GIS, and Artificial Intelligence in Agriculture

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ABSTRACT

There is a global need for a new approach that can help in solving the problems of food and water shortage, which are significantly affected by population growth and climatic changes. The conventional methods that are used for evaluating and mentoring different agricultural activities and processes have several challenges. These methods are laborious, destructive, time-consuming, and cost-consuming. Therefore, an integration of different approaches, such as hyperspectral remote sensing (HRS), Geographic Information Systems (GIS), and artificial intelligence (AI) has been found to be a very effective tool for enhancing agricultural productivity as well as sustainability. The main objective of this review is to demonstrate the very advanced applications and achievements of these techniques in the field of agricultural activities, as well as their potentialities in precision agriculture (PA). The HRS sensors acquire detailed spectral data, which can be used in several applications, such as crop monitoring and evaluating soil fertility, as well as providing valuable outputs to help in natural resource management. On the other hand, the GIS technique manages the spatial information, is combined with the attributes of the vegetation cover, water bodies, bare soils, etc., and applies statistical and mathematical spatial models for mapping and modeling purposes in order to enable better decision-making for all agricultural practices. Additionally, AI tools, including machine learning (ML) as well as deep learning (DL), are used for the spatial, spectral, wet chemistry, environmental, and field data processing and modeling to find the best model that can be automatically utilized in management solutions. Furthermore, the article demonstrates the limitations, challenges, and future directions of these approaches. Moreover, emphasizing the critical need for interdisciplinary contribution between the researchers, government, and farmers can optimize agricultural outcomes and address environmental concerns. Therefore, an integration of these approaches is considered as a very effective tool for detecting, characterizing, estimating, and mapping several objects using the mapping tools in the environments of different spatial analysis techniques and software. However, utilizing and privileging these techniques provide crucial and essential benefits in order to achieve better environmental resources management and agricultural sustainability.

Keywords: Agriculture; artificial intelligence; GIS, hyperspectral; remote sensing; machine learning.

1. INTRODUCTION

The agricultural landscape of the globe faces many challenges which threaten food security, especially with dramatic population growth, climatic changes, and water shortage. By 2050, the world population is expected to reach about 10 billion; and the food demand will rise by 70 to 90 percent. Therefore, an urgent need to increase agricultural productivity is required to fill this expected gap [1]. On the other hand, there are several factors that cause these problems, such as land degradation, contentious climate change, and depletion of freshwater resources depletion. Moreover, Climatic changes affect weather patterns, which lead to severe drought conditions, frequent floods, and other factors that disrupt agricultural production as well as other supply chains. For the same purpose, the United Nations reported that about 925 million

population are affected by the climatic changes and very vulnerable livelihoods because of the effects on their income as a result of agriculture depletion [2].

Water shortage and scarcity are considered as a very critical problem the agriculture sector faces. Approximately 70 percent of the globe's consumption of agricultural activities depends only on freshwater. Another parentage is under the demand of urbanization, industrial demands, and climate change mitigation [3]. Moreover, multiple regions are suffering from the absence of freshwater, which directly affects the crop yields and food productivity potentialities. Additionally, over-consumption of groundwater and contamination of its resources need further greater efforts to secure sustainable water resources for irrigation purposes. Thus, the farmers face these challenges and require better

water management practices to achieve better agricultural productivity [4].

The integration between food security and socioeconomic roles can be enhanced to decrease the poverty ratios related to food access. Millions of populations suffer from poverty and unavailability of nutritious food. Furthermore, other factors can affect the food security issue, such as political instability that disrupts agricultural activities as well as migrates the populations searching for aid and to increase their humanitarian need. The pandemic of COVID-19 affected the food systems during the last five years as well as exposing vulnerabilities through the supply chains and wasting available resources [5].

Therefore, there is a critical need for advanced approaches, including sustainable practices, to help in agricultural resilience. These techniques must be invested for the climatic changes using smart systems in order to improve the water resources and enhance land sustainability. Furthermore, the collaboration of government, non-government organizations, and the private sector is mandatory for developing strategies for improving the sectors of food security and ensuring sufficient and nutritional food.

Hyperspectral remote sensing (HRS) is a potential tool for detecting, characterizing and estimating the different agricultural practices. The HRS provides continuous narrow spectral wavelengths within the region of visible-near-infrared and mid-infrared (vis-NIR-MIR) and allows detailed spectral information to be used for different purposes. The applications of the HRS are such as crop health monitoring, soil fertility assessment, irrigation and fertilization requirements estimation, etc. Compared to multispectral remote sensing (MRS), which provides a limited number of spectral broad bands, HRS uses imaging sensors capable of detecting many agricultural factors [6]. Moreover, the HRS is able to characterize several kinds of crop stresses (biotic and abiotic), such as plant diseases and pests, as well as nutrient deficiency symptoms, which can negatively affect crop yields. Many studies demonstrated the HRS potentiality in evaluating the content of the chlorophyll, the levels of nitrogen, and the drought stress. These techniques are used for real-time detection and characterization compared to the conventional methods [7].

The geographic information systems (GIS) play a very vital role in the agricultural sector, with the collaboration of the HRS using the spatial information and visualizing the data. Moreover, the GIS offers integration with different sources of information, such as maps of soils, weather data, and crop and vegetation data, which can be utilized for a full understanding of agricultural landscapes [8]. An integration of the GIS and HRS help the farmers for spatial identification of several activities of the precision agriculture (PA) in a specific field condition. Moreover, this integration provides the possibility of effectively managing the vegetation cover, including irrigation, fertilization, and pesticide applications when only needed in order to reduce waste as well as environmental impact [9].

Artificial intelligence (AI) has been found to be very crucial to be integrated with the HRS and GIS tools for improving the automated analysis of the different kinds of data, and enhancing the processes of decision-making. The AI codes such as machine learning (ML) as well as deep learning (DL) able to process huge amount of the hyperspectral information, recognizing the different patterns and correlations which is very tedious to be done by human. The AI and HRS provide a possibility for developing different prediction models for estimating and forecasting crop performance as well as early detection of stress symptoms, which can be used for achieving optimal management practices. For example, AI tools can be used in analyzing the HRS images in order to detect the specific locations in a single field that require irrigation, fertilization, etc., to help farmers take suitable action [10].

Although these advanced techniques are used for different applications, there are several limitations and challenges, such as the complexity of the hyperspectral information, whereas advanced analyses and experience are required. This challenge is faced by the farmers who are not capable to deal with this technology. Moreover, integration of HRS, GIS, and AI needs multidisciplinary experience, including agronomy, data technician, soil scientist, and RS specialists, to be capable of developing better solutions for agricultural problems. Besides these challenges, the implementation cost is high for the local farmers, highlight the need for flexible solutions that are suitable for all agricultural stakeholders in the near future.

Thus, the objectives of this review article are to demonstrate the potentiality of integrating HRS, GIS, and AI in agriculture, discuss the different applications of using such advanced techniques, and overview the challenges and future directions of these technologies.

2. HYPERSPECTRAL REMOTE SENSING (HRS)

The HRS is a combination of imaging and spectroscopic approaches. It is a technique that combines imaging and spectroscopy and is used to acquire hyper-bands (narrow continuous spectral bands) that include a lot of information. The hyperspectral information can be utilized to provide complete or detailed characterization of several physical and chemical characteristics of different features.

The HRS has many applications in agriculture, such as crop monitoring, crop health management, precision agriculture, crop type identification and mapping, soil parameters mapping, soil fertility evaluation, and pest and disease detection. These applications are briefly

discussed below. Fig. (1) illustrates the applications of using the HRS, GIS, and AI.

2.1 Crop Monitoring and Health Assessment

The HRS-acquired information can be utilized for monitoring crop health and development and early detection of symptoms of pests, diseases, and nutrients deficiency. This application could be achieved by collecting, processing, analyzing, and modelling the spectral signatures of healthy and infected plants in order to prevent stress factors and increase crop yields [11].

2.2 Nutrient Deficiencies and Nitrogen Level

As studied by Fu et al. [12], the HRS collected data are utilized as a rapid, cheap, non-destructive, and non-laborious technique for evaluating the content of the leaf nitrogen as an essential indicator for evaluating crop health. By quantifying the nitrogen status, optimizing the application of nitrogen fertilizers can be managed in order to decrease chemical consumption as well as environmental pollution.

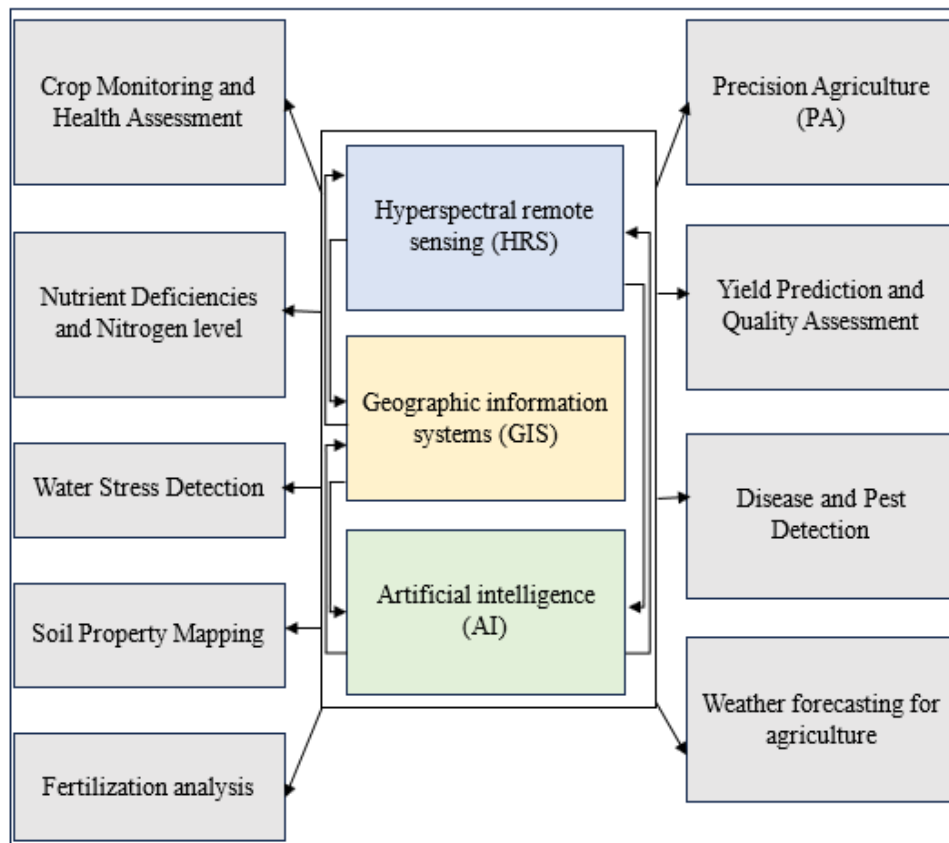


Fig. 1. The applications of RS, GIS, and AI in agricultural activities

2.3 Water Stress Detection

The water, either in soil or in a plant, has a very specific and distinguished spectral characteristic. Water spectral bands have a very strong vibration in the wavelengths of 1400, 1900, and 2200 nm, where the water quantity can be estimated using the suitable ML model. This spectral behavior can be visual interpreted using the hyperspectral curve of the soil or plant spectral signature [13].

2.4 Disease and Pest Detection

The HRS using imaging technique such as unmanned aerial vehicle (UAV) or areophane which combined with a hyperspectral camera (sensor) can capture detailed information of healthy and infected plants [14]. Hyperspectral peak shifts are correlated with diseases or colorimetric symptoms caused by insects or other pests. By using these hyperspectral images, early detection can be delivered to the farmers to take suitable action with the required quantity of pesticides application. Mapping the healthy and infected plants in different geographical scales is crucial for better crop monitoring and management [15].

2.5 Precision Agriculture (PA)

As previously discussed regarding the role of HRS and imaging spectroscopy for detecting, characterizing the water, nutrients and biotic stresses; the agricultural inputs which required for the growing crops can be estimated. By using the hyperspectral imaging or ground-sensors acquired data, the detailed quantities of irrigation water, fertilizers, and pesticides can be provided through the data analysis and the AI modelling [16].

2.6 Yield Prediction and Quality Assessment

Another application of the hyperspectral collected is quantitative and qualitative estimation of crop yield and its parameters such as total sugar, acidity, protein contents, etc. These outputs can be utilized for predicting the harvested crop's time and quality as well as the marketing schedule. Hyperspectral sensors such as UAVs became popularly applied for precision agriculture. Therefore, integrating HRS and advanced data analysis techniques is capable of improving the possibility of comprehensive crop monitoring as well as yield estimating [17].

2.7 Soil property estimation and mapping

For soil properties estimation and prediction, a soil sampling task is required, whereas soil samples and their corresponding geo-coordinates are collected. The samples are analyzed for their physical, chemical, mineralogical, fertility, and biological properties, which this task is called wet chemistry analysis. When the objective is mapping the various soil properties, the hyperspectral images are acquired from the different satellite sensors such as EnMap, Hyperion, PRISMA, etc. The hyperspectral laboratory data must be collected using the analytical spectral device (ASD), which is called a spectroradiometer. These soil spectral signatures are resampled uniformly with the hyperspectral satellite image's spectral range. Afterward, the soil attributes (wet chemistry data) are integrated with the hyperspectral laboratory data to develop prediction models using different algorithms [18]. These algorithms are such as multivariate regression models, support vector regression 'SVR,' multiple adaptive regression splines 'MARS,' partial least square regression 'PLSR'; or such as machine learning algorithms (i.e., Artificial neural networks 'ANN,' Conventional neural networks 'CNNs,' random forests 'RF,' etc.). After developing the prediction models, the better predictor is chosen because of its accuracy using some statistical parameters such as root mean squares error (RMSE), ratio of performance deviation (RPD), coefficient of determination (R^2), or other parameters. The model of the highest coefficient of determination and RPD and the lowest RMSE are selected as the best prediction model. This selection process is being done for each soil parameter accordingly. After that, the significant hyperspectral bands for each soil parameter are selected to be used in developing prediction equations. Moreover, the multiple linear regression model (MLR) is used to develop the prediction equation for mapping the soil properties. Mapping software such as ENVI, ArcGIS, QGIS, etc., is used for mapping the different soil parameters using hyperspectral images and the prediction equation. These outputs (maps and prediction equations or models) are such references for decision makers for achieving better soil management and land suitability evaluation for several crops [19].

2.8 Fertilization Analysis

The HRS can be utilized to determine the components of organic or chemical fertilizer components. The most important factor for

analyzing the different fertilizers that the spectral library of these fertilizers must be created which includes the variation of these materials. This spectral library contains the spectral signatures of a number of fertilizers samples which obtained in laboratory used the ASD spectroradiometer [20]. After developing a calibration model using this library, unknown samples can be entered to the dataset to develop a validation model. Afterwards, prediction equation can be generated for each nutrient parameter in the fertilizer such as (Nitrogen, potassium, phosphorus, etc.).

2.9 Weather Forecasting for Agriculture

For the optimal growing of the crops, suitable temperature, light, relative humidity, and other weather conditions must be available. These weather parameters can be forecasted using several weather sensors fixed on the satellites. These sensors are able to collect thermal data and other information in order to build a database that can be used in further processes. The main process is forecasting the weather conditions, whereas using the database, a prediction model can be developed. These prediction models are equations that include several significant spectral regions (electromagnetic or thermal ranges) related to specific weather parameters. By using these equations, the weather parameters can be estimated and forecasted.

3. HYPERSPECTRAL SATELLITES

There are several types of hyperspectral satellites, such as the Hyperion, PRISMA, EnMap, etc. These satellites capture the data in hyperspectral information in a narrow continuous band between 350 to 2500 nm as a spectral range of the vis-NIR region. Some sensors capture the visible spectral region from 350 to 1100 nm. However, the final product of these satellites is a hyperspectral image that can be used to estimate different ground objects such as soil minerals and soil properties, assess soil fertility, and determine vegetation indices. An integration of HRS, imaging, GIS, and AI tools, so many applications in the agricultural field can be accomplished.

4. AGRICULTURAL DRONES

The drone is a robotic instrument which can be used for different purposes such as agricultural activities monitoring. The drone (UAV) is found in several types like pesticide drones, fertilizer drones, scanning and imaging drones, etc.

Moreover, imaging drones are considered the most common type in agricultural applications. The drone is attached with a GPS, sensor, camera (in different spectral resolutions), antenna, controlling sensor, etc. These components are combined with each other in order to capturing an image of the agricultural field. However, there are many applications of the drones in agricultural activities. Among these activities is monitoring the crop health, vegetation cover, soil status and fertility, and the requirements of irrigation and fertilization for achieving the main objectives of precision agriculture. Therefore, there are some advantages of using these drones in agriculture, such as efficiency in cost, time, effort, and accuracy, and these techniques are eco-friendly and non-destructive.

5. GEOGRAPHIC INFORMATION SYSTEMS (GIS)

The GIS is a technique in which receiving, storing, processing, analyzing, estimating, and exporting different kinds of information (spatial, spectral, spatiotemporal, analytical, etc.) in order to detect, recognize, characterize, estimate, or predict an object or more on the earth surface in a rapid, cost-effective, cheap, non-destructive and eco-friendly approach. There are some components of the GIS like the information, work environment, and the experience of the users. These three components are essential for achieving better outputs from using the GIS in agriculture. However, the GIS is used for different applications in agricultural activities, such as mapping the land use and land cover (LULC) changes of a specific area at different times. These LULC units include vegetation cover, water bodies, soil areas, urban areas, etc. By classifying these LULC units, the stakeholders can easily make a suitable decision regarding their agricultural activities. Moreover, GIS is utilized for land suitability evaluation and modeling as well as land capability, productivity, and quality assessment. There are some common software for using GIS such as QGIS, ArcGIS, Global mapper, etc. The most common software is ArcGIS, which includes different interpolation methods for mapping the spatial variability and different models for predicting and evaluating the spatial variability of any object that has spatial and attributional data. These methods include deterministic methods (i.e. inverse distance weighing 'IDW'), geostatistical methods (kriging 'simple, ordinary, universal, parametric, etc.'), and diffusion kernels (kernel smoothing

and diffusions). In each method, there are several interpolation models that are based on statistical and mathematical calculations used for predicting different soil properties, plant health, and distributions. Semi-variograms are the real application of these spatial models, as in these semi-variograms, all values of the investigated object are distributed around the mean of this dataset to show the accuracy of this geostatistical and spatial model. The final product of these processes is the spatial variability distribution maps, which are considered a guide for achieving better land management and agricultural sustainability.

5.1 Use Cases of Some GIS Applications in Agriculture

Ibrahim et al. [21] pointed out that integrating GIS with the tools of the RS are potential tools to plan sustainable land use. Moreover, Sayed and Khalafalla [22] mentioned that GIS tools such as geostatistical analysis are crucial for the evaluation capability and suitability of agricultural land and social assessing land suitability or capability requires several data layers such as soil, climatic, social, and environmental parameters of specific land use. Land suitability evaluation (LSE) includes questions of (where, why and when) the crops grow [23]. To answer these questions, many different land suitability analysis methods are followed. That meant there was no universal or standard methodology or protocol for this process. The main output of the process of land suitability analysis is to judge the land (Suitable or unsuitable) for specific use. With this data, the possibility to answer questions (when and why) will be there. Using these outputs, land suitability mapping using different spatial variability distributions and geostatistical analysis can be used to answer the question (where) depending on spatial and soil attributes [24]. Because big data is included in the evaluation, a multi-criteria evaluation (MCE) is used. Therefore, Geographical Information Systems (GIS) found to be an effective approach for land evaluation. It is capable of investigating multiple geospatial data. Moreover, the integration of remote sensing, GIS, and machine learning techniques could enhance the accuracy and the predictability of land evaluations' outputs. Decision-makers must have sufficient knowledge about land evaluation techniques, and many factors should be included in the applied criteria. Not only soil attributes are used, but also climate data, as well as socio-economic factors, should be included in the criteria of land evaluation [25].

5.2 Soil Surveying, Sampling and Analysis

For such projects of agricultural land evaluation, a huge number of soil samples should be collected and analyzed. In addition, a lot of effort is given for surveying and data collection. Therefore, a fast and accurate technique should be found to be an alternative to the conventional methods of soil surveying, sampling, and analysis. For that, GIS is a cost-effective tool that savings labor and analysis costs by about 75%. Routine methods are not able to get spatial data for all studied locations, but GIS is helpful for providing this data. GIS products such as mapping of soil properties as well as the land situation and classification of capability and suitability are considered as greatly assist decision-makers. These outputs can be easily shared among different teams, work groups, departments, organizations, and all people. The main importance of GIS is visualizing the outputs on a larger geographic scale without extra cost. Furthermore, the integration of soil attributes, spatial data, machine learning algorithms, GIS and remote sensing is very necessary for getting an accurate situation for un-surveyed locations.

5.3 Soil and Crop Applications

Using GIS tools depends on the spatial data and target attributes. GIS is used in agricultural studies for detecting nutrients, which can help in site-specific nutrient management, reduce the cost of fertilization as well as increase nutrient use efficiency [26]. By application of some useful models such as NDVI integrated with remotely sensed data, Buttar et al. [27] could map the healthy and non-healthy grown plants using GIS tools. Remote sensing and GIS tools of soil and crop can be an attractive alternative to the traditional methods of field scouting because of the capability of covering large areas rapidly and repeatedly providing spatial and temporal information necessary for sustainable soil and crop management [28].

5.4 GIS mapping of Soil

Producing soil maps is absolutely essential. The importance of maps lies in the fact that they are a guide for decision-makers and workers in agricultural lands to ensure good use of these lands. Soil mapping depends on a digital terrain model (DTM) to construct a relation between landform and soil. Fieldwork and laboratory analysis with special reference to soil constraints the main targets to reach land evaluation and

land suitability goals. Land capability and suitability maps are confirmed with the mapping units on the physiographic map for producing the productivity map using several automated models such as microLIES, ALSE, ALES, and others. For example, ALES is used in arid and semi-arid regions to estimate the agriculture land evaluation whereas it is linked directly to its relational database and coupled indirectly with a GIS through the loosely coupled strategy.

5.5 The Land Use Land Cover (LULC) Classification

There is a continuing demand for accurate and up-to-date land use/land cover information for any kind of sustainable development program where land use/land cover serves as one of the major input criteria. As a result, the importance of properly mapping land use/land cover and its change as well as updating it through time has been acknowledged by various research workers for decision-making activities, as for example, the application of a land cover change in an urban environment by Deng et al., [29].

6. ARTIFICIAL INTELLIGENCE (AI)

There are some functions of an AI tools for data analytics which can deal with the different kinds of information (e.g. soil, crop, moisture, minerals, etc.) as well as the hyperspectral signatures in order to create prediction models. The prediction models are developed through initiating calibration and validation datasets for each parameter of the investigated treatment or an objective. There are many AI algorithms such as ML and DL algorithms; for example, the ML models are such as random forest (RF), support vector machine (SVM), artificial neural network (ANN), etc. The multivariate regressions can also be used for modeling the predictability for different agricultural activities which such as partial least square regression (PLSR), support vector regression (SVR), and multiple adaptive regression splines (MARS). However, before apply these models, the spectral and wet chemistry data must be modified using several data transformation techniques. The illustration of the applied methodology is displayed in Fig. (2).

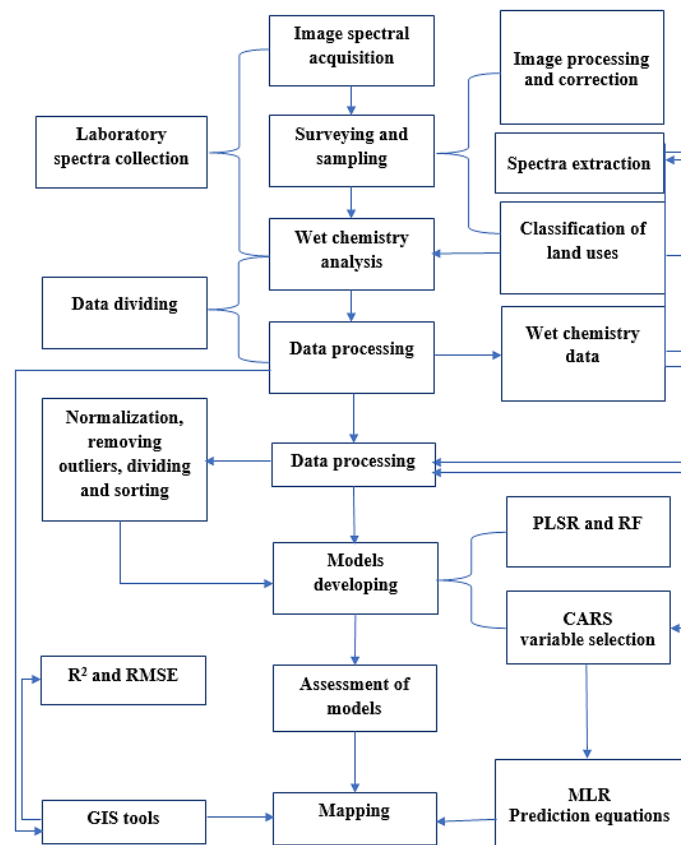


Fig. 2. The illustration of the applied methodology of integrating RS, GIS, and AI in agricultural activities detection

Removing the outliers from the wet chemistry data as well as the vis-NIR datasets is considered as a mandatory step for achieving an accurate estimation of the investigated parameters. Moreover, these outliers can be spectral noises or odd values caused by atmospheric and gaseous effects as well as measuring errors during the wet chemistry analysis. These odd values – either higher or lower – the dataset values can strongly affect the estimation process. Furthermore, this process can enhance the prediction model's accuracy and the parameter's predictability [30]. These values are removed from the dataset because they are unrepresentative to the spectral or wet chemistry database. However, the Box-Cox approach [31] is used as an algorithm of “invBoxCox” in RStudio [32]. The main process of this algorithm is applying the data normalization using Box-Cox transformation as mentioned in equation (1). The normalization process is used to put the values of spectra as well as the investigated object between 0 and 1 values. The role of data normalization is removing outliers and enhancing calibration and validation predictions [33].

$$w_t = \begin{cases} \log(y_t) & \text{if } \lambda = 0; \\ (y_t^\lambda - 1)/\lambda & \text{otherwise.} \end{cases} \quad (1)$$

whereas w = the value of the parameter ‘ y ’ after transformation, ‘ t ’ is the excluded values, and λ is the selected values.

After this process, the whole dataset is divided into two parts: one is for the calibration dataset, which represents 70 percent, and another part for the validation dataset, which represents 30 percent. This process of data division is used in different prediction models such as PLSR, RF, SVR, SVM, and MRS. At the same time, in the case of ANN, 70 percent is kept for calibration, 15 percent for testing, and 15 percent for validation of the prediction model. Here are two examples of the prediction models (PLSR and RF) will be discussed as follows.

The PLSR algorithm in the RStudio environment can be used for a semi-quantitative analysis of different agricultural parameters based on the vis-NIR spectral data. The spectral variables (wavelengths or bands ‘ x ’) are rotated with the wet chemistry data (any parameter values ‘ y ’) and decomposed using the ‘pls’ algorithm, and some of these data are selected to develop the calibration and validation datasets and expressed as ‘ p and q ’. Moreover, some data

residuals are named factor scores ‘ t ’ produce and eliminate noises ‘ e and f ’ as in equations 2. and 3 [34].

$$X = Tp + E \quad (2)$$

$$Y = Tq + f \quad (3)$$

Another prediction model is the random forest ‘RF’ algorithm, which is considered a reasonable tool for predicting objects based on a good calibration database through classifying and regressing different tree predictors, whereas the selection process of this variable is done randomly, as explained by Breiman [35]. The selected variables or vectors can continue the prediction process (forming a node or growing a tree) through the bagging process, which divides the data for training and validating the predictions to 70 and 30 percent, respectively. Moreover, using the ‘rf’ algorithm, it is possible to allow the growth of the trees to occur deepest to produce new training data which can be used for further predictions [36].

For evaluating the performance or accuracy of the prediction models PLSR and RF, some statistical parameters are used, such as root mean squares error (RMSE), the ratio of performance deviation (RPD), and coefficient of determination (R^2) as described in equations 4, 5 and 6. The Y_{pred} is the predicted value, ‘ Y_i ’ is the mean value, ‘ Y_{meas} ’ is the measured value, ‘ n ’ is the number of values (dataset of the investigated parameter), and ‘SD’ is the standard deviation:

$$R^2 = n - \left(\frac{\sum (Y_{pred} - Y_{meas})^2}{\sum (Y_i - Y_{meas})^2} \right) \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n \sum (Y_{pred} - Y_{meas})^2}} \quad (5)$$

$$RPD = \frac{SD}{RMSE} \quad (6)$$

6.1 Selecting the Sensitive Spectral Variables

The competitive adaptive reweighted sampling (CARS) approach selects the most related bands to the investigated parameters. For example, for estimating soil organic carbon (SOC), some hyperspectral bands are significantly correlated with the SOC. These selected spectral bands can be used to develop prediction equations. The CARS approach is based on Darwin's theory of ‘survival of the fittest,’ which can be applied to vis-NIR data to select the most sensitive variables, as described in equation (7):

$$C_j = \left| \frac{\bar{b}_j}{s(b_j)} \right| \quad (7)$$

The CARS includes four steps, as described by Jobson (2012). These steps are (i) the Monte Carlo approach, where 70% of the dataset is randomly selected to represent the calibration dataset; (ii) the exponential decreasing function (EDF) stage, less significant variables' systematic elimination occurs as described in equation (8):

$$r_i = ae^{-ki} \quad (8)$$

whereas the compound $a = \left(\frac{P}{2}\right)^{\frac{1}{(N-1)}}$; $k = \frac{\ln\left(\frac{P}{2}\right)}{N-1}$; P = number of total variables; and N is the number of sampling runs; (iii) Adaptive Reweighted Sampling (ARS) is used to competitively eliminate variables after the initial EDF-based elimination, whereas variables having weights exceed a specified threshold are kept, while others are removed; (iv) quality evaluation of the generated subsets by calculating their respective RMSE values, whereas the lowest subset in RMSE regards is chosen as an optimal.

6.2 Multiple Linear Regression (MLR) Model for Developing Prediction Equations

The general equation of MLR modelling was formulated as equation (9),

$$Y = a + bX_1 + cX_2 + dX_3 + \dots + nX_n \quad (9)$$

whereas 'Y' is considered the lead dependent variable (soil parameter such as SOM, TP, TK, and CEC); $X_1, X_2, \dots, X_n$ are independent variables including the selected spectral bands obtained from CARS. The order of independent variables varies depending on the regression analysis results [37].

6.3 An Integration of the RS and GIS for Mapping Agricultural Activities

The spatial variability of different agricultural activities (soil, vegetation, water, etc.) can be interpolated, estimated, or predicted using the hyperspectral vis-NIR reflectance data as well as interpolation methods such as kriging interpolation and its entire models such as (ordinary kriging 'OK', universal kriging 'UK') in the ArcGIS software environment. The generated

spatial variability distribution maps of these several agricultural activities can provide a comprehensive overview of the distribution of these parameters. Geostatistical analysis was performed using the ArcGIS geostatistical analysis tool, following the guidelines outlined by ESRI [38]. Initially, the analysis involved examining the histogram of the raw data, followed by selecting semi-variogram models to express spatial relationships. These models were then combined with various interpolation approaches. The first step in kriging interpolation is establishing and modeling the semi-variogram of the parameters. The semi-variance expression, as described by Kupfersberger et al. [39-41] in equation (10), was used for this purpose:

$$\gamma(h) = \frac{1}{2N(h)} \times \sum_i^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \quad (10)$$

whereas an empirical semi-variogram weight = $\gamma(h)$; h = lag interval distance; sample pairs number through the lag distance = $N(h)$; the sample values at x_i and $x_i + h$ spatial locations = $Z(x_i)$ and $Z(x_i + h)$, respectively.

In this research, we validated each semi-variogram model using multiple soil property datasets. Additionally, we used a range of criteria to evaluate the effectiveness of the semi-variogram models. These criteria included penta-spherical, tetra-spherical, spherical, stable, J-Bessel, K-Bessel, hole effect, rational quadratic, Gaussian, exponential, and circular models. The kriging procedure was performed by applying equation 11, as described by Webster and Oliver in their work published in 2007:

$$Z^*(x_0) = \sum_{i=1}^N \lambda_i Z(x_i) \quad (11)$$

where $Z^*(x_0)$ is an expected soil parameter's value at any unsampled location x_0 ; x_i are data points in a selected nearness; $Z(x_i)$ is the soil parameter's observed value at the position x_i ; λ_i is the weight of soil parameter's measured value at x_i location; and N is locations number in the nearness detected point.

The all-encompassing kriging model is an important modification of the ordinary kriging technique. It utilized semi-variograms to correct autocorrelation as well as measure errors, as mentioned by Gundogdu and Guney (2007). In this context, the error was described as both auto-correlated and random. The model selection was based on the deterministic function as well as the error value, as presented in Equation 12:

$$Z(s) = \mu(s) + \varepsilon(s) \quad (12)$$

whereas $Z(s)$ = the variable of interest, $\mu(s)$ = deterministic functions, and $\varepsilon(s)$ = the error.

7. CONCLUSION

The integration of hyperspectral remote sensing (HRS), Geographic Information Systems (GIS), and artificial intelligence (AI) presents a transformative opportunity to address the pressing challenges of food and water scarcity exacerbated by population growth and climate change. This review highlights the significant advancements in these technologies and their applications in precision agriculture (PA), demonstrating their potential to enhance agricultural productivity and sustainability.

HRS provides detailed spectral data that can be utilized for various applications, including crop monitoring and soil fertility assessment. GIS complements this by managing spatial information, allowing for effective mapping and modeling of agricultural practices. Furthermore, AI, particularly through machine learning and deep learning, enhances data processing and modeling, enabling the development of automated management solutions.

Despite the promising capabilities of these integrated approaches, the review also addresses the limitations and challenges that remain, emphasizing the need for interdisciplinary collaboration among researchers, policymakers, and agricultural stakeholders. Future directions should focus on overcoming these obstacles to fully realize the potential of these technologies in ensuring food security and sustainable resource management.

In conclusion, the convergence of HRS, GIS, and AI offers a robust framework for tackling the multifaceted issues of food and water shortages. By fostering collaboration and innovation in these fields, we can pave the way for more resilient agricultural systems capable of meeting the demands of a growing global population in the face of environmental challenges.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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