Chapter

GIS Applications in Agriculture

Parmita Ghosh and Siva P. Kumpatla

Abstract

Technological innovations during the recent centuries have enabled us to significantly boost agricultural production to feed the rapidly increasing global population. While advances in digital technologies triggered the onset of the fourth revolution in agriculture, we also have several challenges such as limited cropland, diminishing water resources, and climate change, underscoring the need for unprecedented measures to achieve agricultural resilience to support the world population. Geographic information system (GIS), along with other partner technologies such as remote sensing, global positioning system, artificial intelligence, computational systems, and data analytics, has been playing a pivotal role in monitoring crops and in implementing optimal and targeted management practices towards improving crop productivity. Here we have reviewed the diverse applications of GIS in agriculture that cover the entire pipeline from land-use planning to crop-soil-yield monitoring to post-harvest operations. GIS, in combination with digital technologies and through new and emerging areas of applications, is enabling the realization of precision farming and sustainable food production goals.

Keywords: Geographic Information system (GIS), precision agriculture, remote sensing, Global Positioning System (GPS), resource management

1. Introduction

As the world population is projected to grow close to 10 billion by 2050, we need to produce about 50% more food compared to 2013 production to meet the global demand [1]. This goal needs to be met while facing the challenges of climate change, the limited scope of arable land expansion, and dwindling water resources. In addition, anticipated food production also needs to incorporate practices for sustainable management of croplands to preserve soil health, conserve water resources, and encompass biodiversity [2]. Considering these challenges and constraints in achieving our food production targets there is an unprecedented need for monitoring of crop growth and health and timely interventions to maintain or improve crop productivity while reducing wastage of inputs and resources. Advances in sensors, communication technologies, computational systems, and powerful data analytics are enabling us to accomplish these tasks. Technologies that can enable efficient use of agricultural inputs and reduce environmental losses while contributing to increased and sustainable production are of great value for achieving food security. Several existing and emerging tools and technologies such as geographic information system (GIS), remote sensing (RS), Global Positioning System (GPS), Artificial Intelligence (AI), Big Data

Analytics, and Internet of Things (IoT) are instrumental in achieving this goal through efficient monitoring of crops and soils, and, combined with other pieces of information, are providing data-driven insights for targeted or site-specific management of crops ensuring increased productivity [3]. Geographic Information System (GIS), a key foundational technology, is defined as a powerful system comprising tools for the collection, storage, and retrieval of data at will, as well as analyzing, transforming, and displaying the spatial data for a specific purpose [4–7]. It plays a critical role as it provides the spatial context and information on several features each of which is available as a data layer. In addition, it provides the tools to manipulate spatial and non-spatial data and presents them through intuitive and illustrative map formats [8]. GIS has been making an impact in diverse domains that include geography, environmental sciences, natural resources, forestry, agriculture, food, manufacturing, banking, and health services [8]. Recent decades have seen a significant increase in the application of GIS tools for diverse applications in agriculture at local, regional, national, or global scales. These applications most often involve the use of GIS along with partner technologies such as remote sensing, GPS, and data analytics towards an in-depth understanding of a given farm or a region and facilitating intervention or corrective measures for the crops and/or the soils. Since the GIS data are linked to a common referencing system, another advantage GIS offers is that the same data can be used for different applications or goals and we can also bring in other data and, combining that with existing data, we can perform a joint analysis for deriving novel insights. Many studies have reported the use of GIS for diverse applications in different crops [9–11]. To further enable the readers to develop a strong appreciation for the role of this powerful technology in agriculture, here we have reviewed the most widely used and emerging applications of GIS, either by itself or in combination with other partner technologies, and how it has been making major impacts on agricultural productivity and supply chains.

2. Key partner technologies of GIS

The power and impactful contributions of GIS in diverse domains can be attributed to the combined use of GIS and two other key geospatial technologies: GPS and Remote Sensing. Each of these three partner technologies plays a crucial role in realizing the goals of applications (Section 3), and, therefore, are briefly described below.

2.1 Geographic information system (GIS)

Based on its role in supporting the collection, storage, retrieval, and analysis of data on features and location, and its utility for data-driven solutions, especially in site-specific management, GIS is considered the brain of Precision Agriculture [12]. Digital GIS maps differ from conventional maps in that they harbor several layers of information each layer providing information or a map about a given attribute such as soil survey, precipitation, nutrient status, pest infestation, yield, etc. In addition, GIS provides the analytical capability by using statistical tools and geospatial analytics enabling extraction of inter-relationships between attributes, and the insights, thus derived, are valuable for decision making with respect to management practices.

2.2 Global positioning system (GPS)

This positioning/navigation system based on a satellite network enables the determination of positional information by providing the latitude, longitude, and elevation of a location. The location information collected by GPS receivers enables farmers and researchers to the reliable identification of fields, mapping of field boundaries, water bodies, infested or problematic areas in the field, and for understanding the relation to several other attributes within and outside the boundaries of a given field. Such a high-fidelity field mapping permits site-specific application of nutrients, pesticides, herbicides, and water, thereby improving productivity and reducing input costs—the essence of precision agriculture.

2.3 Remote sensing (RS)

Remote sensing, with its diverse methods and applications in agriculture, has revolutionized crop monitoring and interventions for improving farm productivity [13, 14]. RS, in combination with GPS, GIS, and other tools is critical for implementing the goals of precision agriculture. This combination is crucial for enabling several applications that provide the basis for site-specific management of fields and include soil mapping, crop growth monitoring, estimation of soil moisture and fertility, detection of biotic (pests and diseases) and abiotic (drought and flood) stresses, and yield estimation.

3. GIS applications

The onset of digital agriculture, considered the fourth revolution in agriculture, has totally transformed the way farming is done, thanks to advances in geospatial technologies, sensors, artificial intelligence, robotics, and other tools and technologies. The ability to precisely identify the problem areas in cropland and monitoring and management of all steps in the entire agriculture value chain requires image and non-image data along with spatial context. GIS, with its component tools and analytic modules, and the data gathered by its partner technologies like remote sensing and GPS provides intuitive and lucid visualization of information for data-driven decision making for improving crop productivity. While GIS has been used for agricultural applications for quite some time, the number of applications has been growing rapidly in recent years due to technological advances. Several most common and emerging applications are presented and discussed below.

3.1 Land suitability assessment and land use planning

We are in an era where we are facing the challenge of feeding billions of people while the fertile land is shrinking, therefore, we need to optimize the use of natural resources to maximize the benefits. GIS provides an excellent platform for assessing the quality of land for suitable applications. Multi-criteria decision-making (MCDM) approach based on GIS is the most popular choice among researchers for land use planning. Researchers use different features offered by GIS such as soil type distribution, soil texture map, buried deep underground water level distribution, soil fertility distribution, soil pollution distribution, hydraulic conductivity of soil (Ks), slope (S), soil texture (ST), depth to water-table (DTW), and electrical conductivity of groundwater (ECw), climate conditions, topography, and satellite data, and identify the variety of interactions, dependencies, and the impact of these interacting factors on sustainable land use.

Chen et al. [15] evaluated weight sensitivity of MCDM model for land suitability assessment for irrigated agriculture. They aimed to examine the sensitivity of changing weights of the input features on the model output. The results suggested a strong influence of sensitivity and, therefore, they have recommended giving special emphasis on this criterion. Zolekar and Bhagat [16] have used GIS-based MCDM model with IRS P6 LISS-IV images as input for the evaluation of agricultural practices in hilly regions. The rank of influential criteria was determined by correlation analysis and recommendations from scientific literature. The combined use of remote sensing and GIS turned out to be beneficial for land suitability evaluation. Pan and Pan [17] applied three scales, two-step analytic hierarchy processes (AHP) for GIS-based crop suitability assessment. They have emphasized the importance of selecting appropriate evaluation factors and suggested the consideration of features with a significant difference and controlling the land use and avoiding causality. Following this approach of feature selection, the AHP output was spatially distinct. The authors have recommended appropriate land use based on land suitability maps. In another study, [18] selected the features based on growth requirements for examining the land suitability for the wheat crop. Analytic Network Process (ANP) model was deployed for assessing the interdependence of strategic input features for site suitability evaluation of citrus crops [19]. The ANP coupled with GIS–MCDM identified critical factors for maximizing yield and minimizing production loss. AHP integrated with geo-statistics had proven its merit for maize cultivation land suitability mapping in calcareous and saline-sodic soils [20]. These powerful GIS tools enable land reclamation planning with suitable conservation practices.

Integrated fuzzy membership and GIS model were used to analyze arable land suitable for farming. Topography and eight soil parameters were utilized for fuzzy membership classification and the important crop productivity-related soil features were accommodated accordingly. Fuzzy membership allowed the consideration of partial memberships which is unlikely in classical approaches for classification. This self-adaptive approach revealed that the land was better suitable for groundnut cultivation contrary to the current practice of Finger millet cultivation. Results of this experiment proved that the GIS-based decision system can surpass the traditional knowledge and, if deployed accurately, can improve the productivity of land [21]. This is the need of the hour technology as land and natural resources are declining, and the demand for food production is increasing rapidly. The fuzzy set model, AHP, and GIS were combined to generate a land suitability map for tobacco production [22]. This study has once again demonstrated the advantage of using Fuzzy membership functions for land suitability analysis. AHP has the power of accurately assigning weights to the input factors in a logical way. The maps were generated by ArcMap. The integrated application of fuzzy, AHP, and GIS helped to circumvent the problems resulting from the uncertainties, subjectivities, and hierarchy characteristics of the traditional land suitability assessment process. GIS is a powerful tool to delineate the study area, manipulate geographic data, process maps, and present results in land suitability assessment. Integration of Fuzzy set and AHP methods with GIS provides a precise and powerful combination in applying for land suitability analysis. Researchers advocate that Fuzzy logic coupled with other decision-making methods is one of the best approaches for land suitability analysis [21–23]. Scientists are also exploring artificial intelligence along with GIS for efficient land use planning [23].

3.2 Water resource management

Abundance of water supply is a primary requirement for meeting the demand for food production by the ever-increasing global population. As indicated earlier, farmers have the responsibility of feeding about 10 billion people in 2050 which demands a 50% increment in food production compared to 2013 level [24, 25]. The availability of clean water is decreasing and dependence solely on rainfall is not a viable option for the farmers [26, 27]. In this challenging scenario, water resource management is the key to success. Irrigation is the best solution for meeting the water requirement in agriculture. GIS technology backed by remote sensing has already proved its merit for the management of water resources [28–31]. Researchers strongly suggested that remote sensing can supplement the traditional geophysical models for groundwater potential assessment and recharge experiments [32, 33]. Many researchers supported the potential of GIS for groundwater management [34, 35]. Tripathi et al. [36] integrated the MODFLOW groundwater model with the GIS for watershed prioritization. Singh et al. [37–39] combined GIS and remote sensing for delineating groundwater potential zones. Lineament and hydro- geomorphological maps were prepared from remote sensing images. The delineated groundwater potential zones have been found to show synergy with the well-yield data. When sub-watershed level runoff and sediment yield were assessed using the combination of GIS and remote sensing data it reduced the time of the input data process and produced good results compared to actual runoff and sediment yield [40]. Determining the suitability of irrigation for a given geography is one of the most popular applications of GIS. A study conducted in UAE accounted for non-renewable sources like desalination and treated sewage effluent (TSE) to assess irrigation suitability [41]. This type of water-scarce region needs optimization of water resources management. Land management, topography, climate conditions, soil capabilities, and water potential were used in the analytical hierarchical process (AHP) GIS model to assess crop suitability. The results showed that the land was unsuitable for cereals and vegetables but the cultivation of sorghum, jojoba, fruits, date palm, and forage was recommended. This study unleashed the power of GIS technology for using every acre of fertile land in a geography with a high level of water scarcity. Reduction in clean water resources is motivating researchers and policymakers to identify suitable alternatives for irrigation water. Zolfaghary et al. [42] evaluated the scope of using urban treated wastewater as an alternate source of irrigation. They have utilized the MCDM method which was executed in the GIS software environment and the Analytic hierarchy process (AHP) was used. This analysis revealed that the suitability of treated wastewater is subject to suitability for crop cultivation, nitrate contamination burden, and aquifer vulnerability. ISAREG irrigation scheduling model was integrated with GIS with the aim of generating efficient irrigation scheduling advice and identification of practices to account for water savings and salinity control [43]. These results advocated the successful outcome of the model for irrigation scheduling and choosing water saving measures during both wet and dry years. Though the intensification of irrigation is beneficial for food production, it was pointed out that soil salinization and waterlogging are the major drawbacks of irrigated agriculture intensification, and that strong emphasis should be put on leveraging GIS and remote sensing technology for monitoring the problem areas followed by planning conservation and preventive measures [44].

3.3 Soil health and fertility management

Soil fertility is directly proportional to productivity. It controls the availability of nutrients and water to the crop. The soil fertility has been degrading due to various factors like pollution, sealing, overgrazing, waterlogging, excessive use of agricultural chemicals, and erosion. It is crucial to determine soil health and fertility status for planning effective practices for site-specific management or precision farming [45–47]. Soil macronutrients (N, P, and K), micronutrients (Zn, Mn, and Fe), pH, soil organic carbon (SOC), water holding capacity, erosion status, and moisture content are extensively used features for soil fertility status assessment [48–51]. Spatial interpolation, Multi-Criteria Decision Analysis (MCDA) [52–55], and Ordered Weighted Averaging (OWA) [56–59] are the most popular geospatial analysis techniques which provide spatiotemporal variability of soil health and fertility status to the decision-makers.

Soil erosion status is an essential parameter for soil quality assessment and spatial variation in erosion gives a clear picture for agricultural planning [60]. It was demonstrated that geospatial maps of soil erodibility generated by Inverse Distance Weighted (IDW) method is a great tool for assisting in sub-watershed level land use planning. AbdelRahman et al. [61] combined the remote sensing and GIS technology to assess the soil fertility status. They have used the LISS III and IV images for land use classification and the RUSLE method for soil erosion estimation, collected the soil nutrient field data, and applied a geostatistical model to identify the spatial variation of soil erosion and nutrient availability. In another study, [62] used the IDW model for derived soil nutrient maps and applied the OWA method to make the maps homogenized and used those as the input for the fuzzy inference system for soil fertility mapping. Fuzzy mathematics developed with soil organic matter (SOC), total N, total P, total K, available N, available P, available K, pH value, and cation exchange capacity as indicators in ArcGIS showed that the soil fertility of mid- and low- yielding fields were low and are directly correlated with soil profile configuration [63]. The association of crop productivity with the soil fertility is evident and GIS-based soil maps and fertility status give prior information about the field-specific crop suitability.

Leena et al. [64] proposed GIS-enabled cloud technology for soil fertility management decision support system. This system has the capability to make fertilizer recommendation based on soil test and crop response. This recommendation system helps farmers optimize their fertilizer usage and maximize yield. This system generated spatial nutrient variation works as fantastic e-governance system for the government agencies. GPS- and GIS-based soil fertility maps are great tools for thorough monitoring of the soil health and, based on such maps, [65] recommended application of paper mill sludge to reduce acidity in the soil and cultivate pulses and groundnut to make the best use of the acidic soil. These geospatial soil maps have proven to be an effective decision support system in the context of food production challenges due to soil degradation. Tunçay [66] applied soil fertility index (SFI) based on the variables of sand, silt, clay, pH, EC, OM, CaCO3, Ntotal, Pavb, Kexc, Caexc, Naexc, Mgexc, and available micronutrients (Feavb, Cuavb, Znavb, Mnavb) and proved the strength of SFI. This study demonstrated the potential of combining Sentinel 2 image-derived crop yield for validation of soil fertility model. Advances in the observatory systems such as remotely sensed data of fine-to-coarse spatiotemporal resolutions, and in the process-based and data-driven modeling techniques have facilitated the collection, storage, analysis, visualization, and interpretation of non-spatial data for soil fertility index (SFI) [67–72].

Li et al. [72] applied weighted space fuzzy clustering coupled with the soil nutrient space mutation distribution for soil fertility characterization. This information aids in optimizing the fertilizer recommendation system. Agricultural practices such as crop residue management, nutrient management, soil tillage, and pest management affect ecosystem goods and services and soil quality and fertility [73–75]. The best management practices, compatible land use/cover changes, and land suitability analysis are required to prevent the degradation and loss of prime farmlands [73, 76, 77]. Soil erosion management, soil biodiversity improvement, and rehabilitative farming systems are some of the best management practices used to improve soil quality and crop yields [78–80].

A study that leveraged GIS and fuzzy evaluation method to evaluate the soil fertility status used total nitrogen, total phosphorus, total potassium, available nitrogen, available phosphorus, available potassium, soil organic matter, cation exchange capacity, and pH as indicators for the generation of fertility indices [63]. This fertility index revealed that total nitrogen and soil organic matter are higher for paddy fields. These fertility maps also give an insight into the suitable soil qualities under different types of land use and climatic conditions. Sub-watershed level nutrient mapping revealed that available N, P, S, Zn, and Fe are controlling agents of soil fertility [81]. Thus, fertility maps and their relationship with soil properties and crop yields serve as an information system for precision agriculture.

3.4 Biotic and abiotic damage assessment and intervention

Studies have reported that biotic crop damage, caused by insects, fungi, and other pests, can cause 15–70% yield loss [82–84]. This scenario impacts the demand and supply chain and also affects the economy of farmers. The changing pattern of weather makes the crops susceptible to pests and diseases. The availability of crop protection methods is quite beneficial for tackling crop health, but the lack of timely information about the pests and diseases makes the damage irrepressible. GIS technology holds immense potential for site-specific pest and disease management. Remote sensing and GIS-based forewarning systems are boon to farmers to arrest the yield and economic loss. Ranjan and Vinayak [85] advocated that pest and disease forecasting systems allow farmers to apply the control measures in time to reduce the cost of production. Apart from the forewarning system, the pest population density map also plays a crucial role in identifying the hotspots and extending advisory to farmers. According to [86], information about the geospatial density of oriental fruit moth, *Grapholita molesta*, had the scope of reducing the crop injury and pest population by applying geographically suitable management measures. The difference in current and predicted geospatial distribution of two polyphagous and invasive Icerya species clearly indicated the impact of climate change in modifying the pest attack patterns [87]. Such pest distribution maps enable farmers, agricultural experts, and policymakers to prepare management strategies to combat pest attack in the future. Tracking the migratory patterns of pests is of utmost importance given the instances of a sudden outbreaks of cutworm, *Agrotis ipsilon*, and fall armyworm, *Spodoptera frugiperda*, in different continents than their usual geographical locations [88–90]. Remote sensing and GIS are important tools for monitoring habitats of pest species such as western tarnished plant bug, *Lygus hesperus*, and Migratory and Australian Plague locusts [91, 92]. Remote sensing and GIS are rapid and cost-effective technology for assessing the extent of crop damage by pests and diseases [93]. Researchers had demonstrated the feasibility of pest and disease type detection and severity mapping from remote sensing images [94–96]. These damage assessment maps hold key spatial information about the damaged crop acreage and its trend across multiple years over different geographical units. These maps have the potential to act as an aid for insurance settlement for the farmers and for those seeking government subsidies and benefits.

Natural calamities cause irreversible damage to agriculture. Rapid mapping and quantification of damage aid in economic loss recovery and act as a decision support system. A geo-spatial model is used in a case study to assess the impacts of extreme flood events on agricultural production in the Quang Nam province of Vietnam. Chau et al. [97] generated the water surface by interpolating flood depth marks by the inverse distance weighting (IDW) and employed a digital elevation model (DEM) to generate the flood inundation map. This map overlaid with the land use map gave an effective estimate of the damaged agricultural area [98–100]. Drought is another constraint to agricultural productivity and understanding the hotspot and climatology is crucial to strategically minimize the impact. MODIS satellite Normalized Difference Vegetation Index (NDVI) derived drought risk classes were prepared to access the spatial pattern [101]. GIS-based characterization of climate variability and drought zones provides scope for strategic measures adoption to maximize productivity [102, 103].

3.5 Crop monitoring and yield prediction

Monitoring of crop growth, health, and accurate or near accurate prediction of yield is crucial not only for estimating economic return but also for assessing the food production thereby helping in the management of food security. Many studies showed that traditional methods of crop yield estimation could lead to poor assessment and inaccurate crop area appraisal [104, 105]. Moreover, these methods require time-consuming, labor-intensive, and expensive crop and yield data collection. This is where technologies like remote sensing (RS), GPS, and GIS provide a huge advantage as they can be used to assess temporal and spatial variability of crop dynamics and yield output [106]. The use of two key partner technologies, RS and GIS, with required input from others can provide an efficient solution for monitoring crop health and developing models for predicting crop yields across diverse spatial scales. While remotely sensed images and associated analytics permit the tracking of crop health and predicting the yield, GIS technology enables the collection, storage, retrieval, and visualization of data that were linked geographically. Remotely sensed geospatial data acquired by satellites, aircrafts, or unmanned aerial vehicles (UAVs) can be used to gather information on several features of the crops and the characteristics of the soils supporting their growth thereby enabling the assessment of crop health. The images gathered can be used for assessing general vigor, disease or pest infestations, or deviations from expected growth due to drought or other abiotic stresses. Geospatial data collected in a spatiotemporal manner and the associated analysis techniques help in assessing the changes in the health of crops thereby permitting management interventions while providing predictions on anticipated yields based on the growth and health of the crops. A commonly used method for assessing crop health is based on the determination of vegetation indices that are calculated based on surface reflectance from crop canopies at two or more wavelengths. Many vegetation indices are available for evaluating the extent and vigor of vegetation, crop growth dynamics, stress due to biotic or abiotic factors, and other useful assessments

[107]. Adhav et al. [108] used multiple vegetation indices that included Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Chlorophyll Vegetation Index (CVI), and Difference Vegetation Index (DVI) to determine crop health as well as variations in health conditions. To further improve the efficiency of health assessment, they have combined all vegetation indices using ArcMap 10.5 software and reclassified the merged indices which were then used for categorical representation of health scenarios. Such a representation helps farmers to identify areas that need immediate management intervention [108]. Determination of crop health is particularly critical in smallholder farms as the subsistence and livelihood of these farmers depend on the productivity of their crops. As per a recent study, small farms were found to account for 84% of all farms worldwide but they operate only on around 12% of all agricultural land and produce about 35% of world's food [109]. Use of UAVs for gathering and leveraging data for assessing crop growth and dynamics has proven to be crucial for farmers to take timely and appropriate corrective measures to maintain or increase productivity. A recent study in South Africa [110] evaluated the utility of multispectral UAV imagery and random forest machine learning (ML) algorithm to estimate maize chlorophyll content at various growth stages and created a chlorophyll variation map capturing the spatial heterogeneity of chlorophyll in the field thereby helping the farmers to take management actions. Considering the strategic role of sustainable intensification towards the food production goals of Sub-Saharan Africa [111], such RS- and GIS-based diagnostics and interventions are critical for smallholder farmers. Another study assessed crop health using different chlorophyll indices in addition to modified vegetation index by leveraging data from two different satellites and ArcMap (of ArcGIS) for geospatial analytics [112] resulting in insights that could be used for managing nutrient applications towards improving crop productivity. Two essential prerequisites to implement location-specific management practices and interventions are the availability of an accurate acreage map of crop of interest and the cropping systems of a given area and technologies for predicting yield before the reproductive phase or harvesting of the crop. The use of RS and GIS technologies can help achieve both goals. NDVI, a commonly used vegetation index, serves the dual purpose of assessing crop health and predicting crop yield while GIS tools can provide the spatial context. Several studies abound that leveraged NDVI and GIS for yield predictions and a few examples are discussed here. In a study that measured NDVI values at different growth stages of rice, several linear regression-based yield prediction models were developed using NDVI values and narrowed down to a model that had the highest prediction potential and was also able to predict yield well ahead of harvesting time [113]. Such a model can help the farmers to implement changes to the fertilization, water, pest, and disease management practices towards realizing improved productivity. Using time-series data of SPOT vegetation and two key spectro-agrometeorological variables, rainfall estimate (RFE) and NDVIactual (NDVIa), that are highly correlated to maize yield, [114] have developed an operational model with high predictive ability for yield forecasting in Ethiopia. By leveraging both RS and GIS, this model enabled yield forecast at flowering season which is more than two months earlier than the forecast by conventional method thus providing an advantage of early intervention towards crop productivity and crucial data for the authorities for crop production estimates [113]. In a field study aimed at developing an efficient model for predicting potato tuber yield using RS and GIS techniques two vegetation indices, NDVI and soil adjusted vegetation index (SAVI), generated from images acquired by Landsat-8 and Sentinel-2 satellites were found to be highly effective in yield prediction [115]. In

addition, the indices enabled them to create maps of the study area that has clearly shown zones differing in productivity. This is very useful information for both farmers for implementing necessary management practices and for authorities in arriving at accurate production estimates. While manly researchers have used RS-based vegetation indices and GIS for predicting crop yields, several researchers have combined GIS with crop simulation or physiological models and demonstrated their strong performance in yield prediction [116–119]. Crop simulation models came into prominence due to their utility in designing management practices, assessing the role of climate variations on crop performance, and predicting yields [120, 121]. Similarly, physiological crop models have evolved from their original applications in farm management to measuring the impact of climatic changes on crop productivity. The ability to incorporate spatial variability of the inputs that go into physiological or simulation models makes them even more powerful for determining the interactions between climatic variation and crop productivity while highlighting the spatial heterogeneity. In a study that integrated RS data, crop growth model, and GIS, it was found that yield estimates from RS images were more precise compared to another approach where GIS climate layers and soil attributes were integrated into Oryza 2000 rice crop model highlighting the superiority of combining RS, GIS, and crop model for estimating crop yields [118]. To capture the spatial variability of input variables and their influence on yield estimates, [116] have linked RS and GIS with a growth model of soybean. The results demonstrated spatial variability in simulated yield estimates and the variability was primarily attributed to soil characteristics and rainfall. The availability of such spatial patterns from the simulated yield estimates is very helpful in productivity estimates in areas prone to abiotic stresses, for example, droughts, as well as providing insights into factors contributing to yield. Efforts also exist that have created web-based decision support systems based on a combination of simulation model and GIS towards making agronomic decisions [119]. In yet another approach, the Erosion Productivity Impact Calculator (EPIC), a model for the analysis of the relationship between soil erosion and crop yield at field level, was integrated with GIS and an Inference Engine (IE) towards global estimation of crop productivity [122]. While the integration of GIS expands the application of EPIC to regional or global level, the availability of IE helps in determining potential crop combinations for given growing conditions. This study not only demonstrated the ability of GIS-based EPIC for crop productivity simulations at global level but also delivered predictions for future yields and how they are adversely affected by global climate change underscoring the importance of the development of climate-resilient varieties of crops. Since traditional crop productivity simulations are based on site-specific crop models, [123] developed an operational crop model that can be utilized at the regional level, North China, by integrating USDA EPIC model with NASA MODIS LAI product from Earth Resources Observation System (EROS), ancillary ground data, and GIS [123]. Applications also exist where a combination of GIS and RS was used for assessing damage in some high-value crops. Cranberry is one such crop that exhibits extreme crop yield variations due to soil characteristics which in turn influence water and nutrient availability. Using GIS, GPS, and RS, [124] have created a spatial variation map for the crop enabling the analysis of crop losses within zones in a field or at the whole field level.

3.6 Precision farming

Precision Farming, also called Precision Agriculture (PA) or site-specific crop management (SSCM), is the application of technologies and principles to manage spatial and temporal variability associated with all aspects of agricultural production [125]. Earl et al. [126] defined it as a system that integrates information with crop production that is designed to increase long-term, site-specific as well as whole farm production efficiency, productivity, and profitability while minimizing unintended impacts on wildlife and the environment [126]. The operational goals of precision farming include better management of inputs such as seeds, fertilizers, pesticides, herbicides, and water using right amounts of inputs at the right place, and at the right time. Several crucial tools and systems such as GPS, GIS, and RS are required for the collection of timely geospatial information on soil-plant-animal requirements towards mining insights followed by leveraging those insights for prescribing and applying site-specific treatments towards improving agricultural productivity while contributing to sustainability and protecting the environment [127–129]. The role of different tools and technologies as well as the applications of precision farming are described in several review articles and references therein [9, 128, 130]. While GPS, GIS, and RS are vital for obtaining and analyzing the data for deriving insights, a key technology that implements the precision applications by leveraging the input of these three tools is variable rate technology (VRT). VRT systems take all the required information about a field such as soil maps, yield, infestation of pests, diseases, and weeds, and they determine the quantities of fertilizers, pesticides, herbicides, and other inputs and ensure their application at the right place and at the right time saving the input costs. The integration of GIS, GPS, and VRT technologies thus provides farmers an unprecedented ability to view field maps and apply input where and when needed towards ensuring crop productivity. Precision farming can be broadly divided into three steps or stages depending on data collection or site-directed or specific activities happening during, before, and after the crop growth period [131]. These are Preparatory or Pre-planting stage, Crop growth stage, and Harvesting stage. Role of GIS in each of these stages is discussed below.

Preparatory stage: This is essentially a planning stage that encompasses the data collection prior to planting and includes, among other things, gathering data on soil nutrient status, groundwater, previous crops and their residual influence on the next crops, and data on pests, diseases, and problematic weeds in that area that could affect yields of the crop to be planted. Data gathered on all these aspects are stored in a GIS system. Historical crop data from GIS also helps in 'variable planting' decisions that determine where to plant what crop/variety and to what extent so that the variable planting plan can be carried out in the field automatically by seeding machines [131]. A major activity in the preparatory stage is soil mapping and accurate prediction of soil properties is critical for precision farming interventions and for sustainable agriculture. The approach used for traditional soil mapping relies on a representative soil property from a location of focus and, therefore, has the limitation of not capturing the variability of soil properties in the maps generated. Moreover, soil sample collection, analysis, interpretation, and map generation are all monotonous, time-consuming, and costly. These methods have been improved greatly with the developments in spatial science and the geospatial modules in ArcGIS and other tools are being used extensively for their ability in spatial interpolation [132–134].

Crop growth stage: In this stage, the insights and the data gathered in the preparatory stage are retrieved through GIS and used for formulating and implementing management practices addressing irrigation, soil fertility, and protection from biotic and abiotic stresses. The availability of diverse types of imaging sensors, satellite and proximal sensing capabilities, GPS and GIS systems have enabled the assessment of plant characteristics, growth, health, and also in gathering information on the soils and infestation of pests and diseases, all with precise geospatial information. By using RGB, hyper- or multi- spectral remote sensing options for measuring the reflectance, fluorescence, or other useful emissions, it became possible to assess the disease status of the crops and take precise management measures for controlling the diseases at precise locations based on GPS and GIS information, thus improving crop health, and helping to improve productivity [135]. The use of advanced geoinformatics tools and data-driven recommendations are also being used for monitoring and managing pesticides and other plant protection inputs with a particular focus on sustainable practices towards improving productivity while reducing impact on the environment. Geoinformatics-based tools are also being leveraged for accelerating the crop germplasm that is suited for a given location or region towards realizing increased productivity as well as the germplasm that has tolerance to biotic or abiotic resistance needed for a given geographic location [136]. Spectral reflectance and vegetation indices of the crops being monitored combined with GIS are also playing a crucial role in managing nutrients and water stress in precision farming programs. Use of remote sensing and GIS in detecting nutrient stress of the crops enables site-specific correction management of nutrients thereby promoting plant growth while reducing the cost of cultivation due to targeted use of nutrients [137]. Similar site-specific management can also be implemented for addressing water stress and such an approach is especially attractive for croplands with limited water resources. The role of data analytics used in remote sensing, GIS, and other tools for achieving the goals of precision agriculture needs special mention. Early and accurate detection of biotic (pests and diseases) and abiotic (water deficiency) stresses is a prerequisite for taking appropriate management measures. Recent years have seen the use of several machine learning methods for developing models that are enabling both early and accurate detection of biotic stress agents such as diseases and weeds thereby helping precision crop protection [138].

Harvesting stage: This final stage serves the dual purpose of knowing the final output (yield) resulting from the season-long precision practices on the crop and leveraging this yield data to formulate a strategy for the next crop season [131]. The data collected at the harvesting stage is loaded into GIS for analysis towards generation of maps and insights for future use emphasizing the central role of GIS in precision farming. Yield monitoring and mapping is an important component of precision farming. The purpose of a yield monitor is to provide the farmer or a researcher with an accurate assessment of yield variability in the field and when combined with GPS, it can provide the data for creating yield maps [130]. Information on yield measurements and the geospatial context is critical for precision farming as it helps in formulating necessary tweaks to the management decisions for the next crop season.

3.7 Biomass assessment

Renewable sources of energy are crucial to achieving climate change and sustainability goals. Agricultural residues are a promising source of biomass-based energy the demand for which is rapidly increasing around the globe. One challenge with agricultural residues for efficiently channeling them for energy production is the fact that their availability is seasonal and is geographically widely distributed. A solution that can address this spatio-temporal variability, seasonal fluctuations in biomass supply levels, and identification and transport of residues to power plants is a critical prerequisite for biomass-based energy generation. GIS, in combination with remote sensing, can be a great tool for precise identification and assessment of the crop residues and

DOI: http://dx.doi.org/10.5772/intechopen.104786

for planning a given region's feedstock material for renewable energy and its economical transportation to power plants. GIS-based estimation of bioenergy potential enables a technologically advanced solution for leveraging the residues from existing cropping practices that promise even more benefits as the farmers shift from conventional to smart farming [139]. Some of the efforts in leveraging GIS and its partner technologies to this end are discussed below. Methods that can predict biomass potentials of a given region containing weather and crop production variations are of high value for enabling an efficient supply chain from biomass to power plants. By using BioSTAR, a carbon-based crop model, [140] have calculated biomass potentials for maize, triticale, and cup plant, and linked them with a GIS map of the soil dataset of Hannover region in Germany and demonstrated the utility of this method for predicting agricultural potentials under diverse environmental and crop management practices and conditions [140]. In a study that mapped rice cropland in a rural area in India, images from WorldView-2 satellite were used and the resulting map along with agricultural production statistics was analyzed in GIS for assessing the availability of rice straw as a feedstock for generating bioenergy [141]. In addition, the study also estimated the annual rice straw availability and the electrical power it could generate, thus providing valuable information for energy developers and policymakers for planning. Since the success and sustainability of a biomass-based energy generation project depend on several factors that include the feedstock resource, logistics, and environmental considerations, the role and value of GIS and key associated tools and technologies need to be understood prior to establishing the supply chain and the power plants. Two tools can help to address this task: GIS and life cycle assessment (LCA). While GIS is critical for assessing the resources dispersed in small or large areas, LCA is useful in evaluating the environmental impacts of bioenergy production projects. A comprehensive review on the application of LCA, especially spatial LCA, in understanding the impact of biomass-based energy generation on different ecosystem services and the value of integrating LCA and GIS to conduct a holistic assessment of environmental benefits in connection with bioenergy production recommended the inclusion of LCA as an essential component in planning bioenergy projects [142]. To assess the spatial and temporal availability of crop residues and to pinpoint locations for ideal power plants along with cost considerations, an integrated GIS-based biomass, site optimization, and logistics cost model was developed by using soil erosion, soil conditioning index (SCI), and crop residue yield indicators [143]. To estimate crop residues, prediction models based on artificial neural networks (ANNs) were developed for each of these indicators and were implemented on a GIS platform. The utility of this model was also demonstrated using a sustainable assessment of cotton stalks (CS) that are used to produce fuel pellets. An advantage of this model is that its use can be extended to assessment of multiple types of crop residues [143]. Models based on GIS and multi-criteria inclusion-exclusion analysis and facility location-allocation were also developed for the identification of sustainable crop biomass at larger spatial and longer temporal scales and to suggest ideal biogas plants along with cost considerations for biomass delivery [144].

3.8 Supply chain management

GIS technology has proved to be of great value in understanding and optimizing agricultural supply chains and its use is being extended to diverse crops and locations. For ease of understanding its impact on supply chains can be discussed using the following three categories.

3.8.1 Improving supply chain management process

GIS technology has the potential to assist the successful transition of traditional agriculture systems to smart systems. While there are many studies that have thoroughly investigated the role of big data analytics in supply chains of diverse industries, such studies are lacking in the application of big GIS analytics (BGA) in agriculture. To this end, a systematic review of recent literature examined the role of BGA in agricultural applications and has proposed a framework for supply chains where BGA can play even a bigger role in improving the quality of GIS applications in agriculture [145]. The proposed framework serves as a useful reference for scientists and authorities for the successful management of big GIS data and leveraging it for improving productivity. The utility of Geographical Information Technologies (GITs) for improving the complex supply chain management process in the cotton crop was explored and was found to be of great value since the GITs framework enables visualization of current states as well as alternative options and what-if analyses for all steps that require decision making [146]. Another important application for which GIS was used is the analysis of supply chain patterns and description of spatial components of safe crop product (SCP) in China [147]. By using the spatial functions provided by GIS such as representation, location, analysis, traceability coding, and other techniques, tracing and retracing of the quality of safe crop product (SCP) was achieved. This system was also successfully demonstrated in a real supply chain for (re)tracing of SCP. By developing a GIS-based constrained linear programming model for minimizing transportation and storage costs for soybean and its byproducts, and further optimizing this model using General Algebraic Modeling System (GAMS), [148] have identified the lowest cost supply chains. The origin to destination cost matrices and geographic data maps required for the model development and optimization was developed by ArcGIS Network Analyst and ArcMap, respectively. This study demonstrated the combinatorial utility of ArcGIS, ArcMap, and GAMS for developing optimal supply chains that are of value to the players in the process [148].

3.8.2 Decision support systems

Production of biofuels from renewable sources such as agricultural residues can reduce the usage of fossil fuels thereby helping in the reduction of greenhouse gases. Identification of ideal locations for establishing biofuel facilities and designing a cost-effective supply chain for transferring biomass to the facility is highly desirable. To this end, in one approach a decision support system (DSS) has been developed by integrating a GIS-based method and two modeling methods, simulation, and optimization [149]. While GIS-based method was used for selecting facility sites, the selected sites were run through simulation and optimization modeling, and together these three methods provided an integrated DSS for assessing the cost, energy use, and emissions for the facility candidates as well as minimizing supply chain costs. In another approach, an intelligent spatial decision support system (ISDSS) was proposed to overcome the drawbacks of GIS in enabling creation of a knowledge base that supports decision making. The ISDSS combines GIS and intelligent systems and has spatial data mining capability through IoT devices [150].

3.8.3 Locating power plants and developing supply chains

The sustainability of a biomass-based power plant depends on, among other things, a consistent supply of the feedstock, an economical supply chain, and an optimal location of the facility. The GIS-based analysis enables the identification of an ideal location for the plant and in making valid decisions related to the supply chain development. Using open-source GIS software, Latterini et al. [151], have simulated the identification of suitable locations for a small size power plant in Lazio region of Italy that can use olive prunings as the feedstock. This user-friendly and low-cost procedure, which can also be extended to other feedstocks, also provided supply chain costs for the evaluation of different sites and can serve as a useful tool for stakeholders in the development of economical biomass-based end-to-end supply chains [151]. In another study, an integrated approach combining GIS-based analysis with optimization modeling was developed resulting in a support system for decision-makers in comparing facility candidates and in minimizing supply chain costs [152]. The system developed could also be used for similar supply chains such as low capital biodiesel plants.

4. Conclusions

The use of GIS in agriculture has increased at a rapid pace during the recent decades and the number of applications and the prominence of GIS has further amplified in the recent years due to advances in digital technologies that have been leveraging GIS as an essential partner technology for assessing crops, soils, and their environments. As discussed in this chapter, GIS is being used at all stages of agricultural value chain. In addition to the historical, current, and popular uses of GIS in land suitability/use planning and management of water, soil, and biotic and abiotic stresses, the advent of digital agricultural tools and technologies has increasingly leveraged the capabilities of GIS in new and emerging applications in high fidelity crop monitoring, yield prediction, precision farming, and supply chain management for both primary produce and biomass utilization towards energy production. The multitude of capabilities and insights provided by GIS, including the recent enhancements to collect and analyze data in real time, has further elevated its importance in providing location/spatial intelligence needed for improving the productivity and profitability of farms through precision practices. With the current and emerging applications, in combination with existing and newer partner technologies, GIS has a pivotal role in achieving sustainable agricultural productivity.

Acknowledgements

We would like to thank Anu Swatantran for the support and helpful discussions, Chris Seifert, Andrea Arias, and Brian Lutz for support and funding, and Jochen Scheel, Steve Callistein, Janae Lehman Bell, and Nicole Janovick for rapid review and approval of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

Author details

Parmita Ghosh[1*†] and Siva P. Kumpatla[2†]

1 Department of Digital Solutions Data Science, Corteva Agriscience™, Telangana, India

2 Department of Data Science and Bioinformatics, Corteva Agriscience™, Johnston, United States

*Address all correspondence to: parmita.ghosh@corteva.com

† These authors contributed equally.

References

[1] FAO. The Future of Food and Agriculture—Trends and Challenges. Rome: FAO; 2017

[2] Gomiero T. Soil degradation, land scarcity and food security: Reviewing a complex challenge. Sustainability. 2016; **8**(3):281

[3] Delgado JA, Short NM Jr, Roberts DP, Vandenberg B. Big data analysis for sustainable agriculture on a geospatial cloud framework. Frontiers in Sustainable Food Systems. 2019;**3**:54

[4] Burrough PA, McDonnell RA. Principles of Geographical Information Systems. Oxford: Oxford University Press; 1998

[5] Gomiero T. Alternative land management strategies and their impact on soil conservation. Agriculture. 2013; **3**(3):464-483

[6] Delgado JA, Vandenberg B, Neer D, D'Adamo R. Emerging nutrient management databases and networks of networks will have broad applicability in future machine learning and artificial intelligence applications in soil and water conservation. Journal of Soil and Water Conservation. 2019;**74**(6):113A-118A

[7] Burrough PA. Principles of Geographical: Information Systems for Land Resource Assessment. Oxford: Clarendon Press; 1986

[8] Soomro TR. GIS enabling smart agriculture. Smart Agriculture: An Approach towards Better Agriculture Management. 2015;**8**:1-6

[9] Gebeyehu MN. Remote sensing and GIS application in agriculture and natural resource management. International Journal of Environmental Sciences & Natural Resources. 2019; **19**(2):45-49

[10] Kingra PK, Majumder D, Singh SP. Application of remote sensing and GIS in agriculture and natural resource management under changing climatic conditions. Agricultural Research Journal. 2016;**53**(3):295-302

[11] Kazemi H, Akinci H. A land use suitability model for rainfed farming by Multi-criteria Decision-making Analysis (MCDA) and Geographic Information System (GIS). Ecological Engineering. 2018;**116**:1-6

[12] Kumar S, Karaliya SK, Chaudhary S. Precision farming technologies towards enhancing productivity and sustainability of rice-wheat cropping system. International Journal of Current Microbiology and Applied Sciences. 2017;**6**(3):142-151

[13] Sishodia RP, Ray RL, Singh SK. Applications of remote sensing in precision agriculture: A review. Remote Sensing. 2020;**12**(19):3136

[14] Weiss M, Jacob F, Duveiller G. Remote sensing for agricultural applications: A meta-review. Remote Sensing of Environment. 2020;**263**: 111402

[15] Chen Y, Yu J, Khan S. Spatial sensitivity analysis of multi-criteria weights in GIS-based land suitability evaluation. Environmental Modelling and Software. 2010;**25**(12):1582-1591

[16] Zolekar RB, Bhagat VS. Multi-criteria land suitability analysis for agriculture in hilly zone: Remote sensing and GIS approach. Computers and Electronics in Agriculture. 2015;**118**: 300-321

[17] Pan G, Pan J. Research in crop land suitability analysis based on GIS. In: International Conference on Computer and Computing Technologies in Agriculture. Berlin, Heidelberg: Springer; 2011. pp. 314-325

[18] El Baroudy AA. Mapping and evaluating land suitability using a GIS-based model. Catena. 2016;**140**:96-104

[19] Zabihi H, Ahmad A, Vogeler I, Said MN, Golmohammadi M, Golein B, et al. Land suitability procedure for sustainable citrus planning using the application of the analytical network process approach and GIS. Computers and Electronics in Agriculture. 2015;**117**: 114-126

[20] Tashayo B, Honarbakhsh A, Akbari M, Eftekhari M. Land suitability assessment for maize farming using a GIS-AHP method for a semi-arid region. Iran. Journal of the Saudi Society of Agricultural Sciences. 2020;**19**(5): 332-338

[21] Mendas A, Delali A. Integration of MultiCriteria Decision Analysis in GIS to develop land suitability for agriculture: Application to durum wheat cultivation in the region of Mleta in Algeria. Computers and Electronics in Agriculture. 2012;**83**:117-126

[22] Zhang J, Su Y, Wu J, Liang H. GIS based land suitability assessment for tobacco production using AHP and fuzzy set in Shandong province of China. Computers and Electronics in Agriculture. 2015;**114**:202-211

[23] Singha C, Swain KC. Land suitability evaluation criteria for agricultural crop selection: A review. Agricultural Reviews. 2016;**37**:2

[24] Yearbook FS. World Food and Agriculture. Rome: Food and Agriculture Organization of the United Nations; 2013. p. 15

[25] Unies N. World Population Prospects. The 2015 Revision, New York, United Nations. Population Division. 2015

[26] Consoli S, Vanella D. Mapping crop evapotranspiration by integrating vegetation indices into a soil water balance model. Agricultural Water Management. 2014;**143**:71-81

[27] Peragón JM, Delgado A, Pérez-Latorre FJ. A GIS-based quality assessment model for olive tree irrigation water in southern Spain. Agricultural Water Management. 2015; **148**:232-240

[28] Teeuw RM. Groundwater exploration using remote sensing and a low-cost geographical information system. Hydrogeology Journal. 1995; **3**(3):21-30

[29] Brahmabhatt VS, Dalwadi GB, Chhabra SB, Ray SS, Dadhwal VK. Land use/land cover change mapping in Mahi canal command area, Gujarat, using multi-temporal satellite data. Journal of the Indian Society of Remote Sensing. 2000;**28**(4):221-232

[30] Quan RS, Liu M, Lu M, Zhang LJ, Wang JJ, Xu SY. Waterlogging risk assessment based on land use/cover change: A case study in Pudong New Area, Shanghai. Environmental Earth Sciences. 2010;**61**(6):1113-1121

[31] Elhag M. Evaluation of different soil salinity mapping using remote sensing techniques in arid ecosystems, Saudi Arabia. Journal of Sensors. 2016;**1**:2016

[32] Engman ET, Gurney RJ. Remote Sensing in Hydrology. London: Chapman and Hall; 1991. p. 225

[33] Meijerink AMJ. Groundwater. In: Schultz GA, Engman ET, editors. RemoteSensing in Hydrology and Water Management. Berlin: Springer; 2000. pp. 305-325

[34] Pinder GF. Groundwater Modeling using Geographical Information Systems. John Wiley & Sons; 2002 Nov 6

[35] Chenini I, Mammou AB. Groundwater recharge study in arid region: An approach using GIS techniques and numerical modeling. Computational Geosciences. 2010;**36**(6): 801-817

[36] Tripathi MP, Panda RK, Raghuwanshi NS. Identification and prioritisation of critical sub-watersheds for soil conservation management using the SWAT model. Biosystems Engineering. 2003 Jul 1;**85**(3):365-379

[37] Singh, A.K., Prakash S.R., 2002. An integrated approach of remote sensing, geophysics and GIS to evaluation of groundwater potentiality of Ojhalasubwatershed, Mirzapur district, U.P., India

[38] Sikdar PK, Chakraborty S, Adhya E, Paul PK. Land use/land coverchanges and groundwater potential zoning in and around Raniganj coal miningarea, Bardhaman District, West Bengal: A GIS and remote sensing approach. Journal of Spatial Hydrology. 2004;**4**(2):1-24

[39] Singh AK, Raviprakash S, Mishra D, Singh S. Groundwater potential modeling in Chandraprabha subwatershed, UP using remote sensing, geoelectrical and GIS. Map India 2002, GIS Development. 2002:1-6

[40] Bhuyan SJ, Marzen LJ, Koelliker JK, Harrington JA Jr, Barnes PL. Assessment of runoff and sediment yield using remote sensing, GIS, andAGNPS. Journal of Soil and Water Conservation. 2001; **57**(6):35-41

[41] Aldababseh A, Temimi M, Maghelal P, Branch O, Wulfmeyer V. Multi-criteria evaluation of irrigated agriculture suitability to achieve food security in an arid environment. Sustainability. 2018;**10**(3):803

[42] Zolfaghary P, Zakerinia M, Kazemi H. A model for the use of urban treated wastewater in agriculture using multiple criteria decision making (MCDM) and geographic information system (GIS). Agricultural Water Management. 2021 Jan 1;**243**:106490

[43] Fortes PS, Platonov AE, Pereira LS. GISAREG—A GIS based irrigation scheduling simulation model to support improved water use. Agricultural Water Management. 2005;**77**(1–3):159-179

[44] Singh A. Managing the water resources problems of irrigated agriculture through geospatial techniques: An overview. Agricultural Water Management. 2016;**174**:2-10

[45] Parnes R. Soil Fertility. A Guide to Organic and Inorganic Soil Amendments. 2013

[46] Marschner H. Mineral Nutrition of Higher Plants. London-UK: Academic Press; 2008. p. 889

[47] Velayutham M, Bhattacharyya T. Soil resource management. In natural resource management for agricultural production in India'. Special publication during International Conference on Management of Natural Resources for Sustainable Agricultural Production in the 21st Century. 2000 Feb 14. pp. 14-18

[48] Wang G, Cao F. Integrated evaluation of soil fertility in Ginkgo (Ginkgo biloba L.) agroforestry systems

in Jiangsu, China. Agroforestry systems. 2011 Sep;**83**(1):89-100

[49] Viscarra Rossel RA, Webster R. Predicting soil properties from the Australian soil visible-near infrared spectroscopic database. European Journal of Soil Science. 2012;**63**: 848-860

[50] Shen W, Ni Y, Gao N, Bian B, Zheng S, Lin X, et al. Bacterial community composition is shaped by soil secondary salinization and acidification brought on by high nitrogen fertilization rates. Applied Soil Ecology. 2016;**108**:76-83

[51] Yang MH, Mouazen AM, Zhao XM, Guo X. Assessment of a soil fertility index using visible and near-infrared spectroscopy in the rice paddy region of southern China. European Journal of Soil Science. 2019

[52] Malczewski J. GIS and Multicriteria Decision Analysis. New York: John Wiley & Sons Inc.; 1999

[53] Shumilov OI, Kasatkina EA, Mielikainen K, Timonen M, Kanatjev AG. Palaeovolcanos, solar activity and pine tree-rings from the Kola Peninsula (northwestern Russia) over the last 560 years. International Journal of Environmental Research. 2011;**5**(4):855-864

[54] Salehi E, Zebardast L, Yavri AR. Detecting forest fragmentation with morphological image processing in golestan national park in northeast of Iran. International Journal of Environmental Research. 2012;**6**(2): 531-536

[55] Feng XY, Luo GP, Li CF, Dai L, Lu L. Dynamics of ecosystem service value caused by land use changes in ManasRiver of Xinjiang, China. International Journal of Environmental Research. 2012;**6**(2):499-508

[56] Asproth V, Holmberg SC, Håkansson A. Decision support for spatial planning and management of human settlements. In: Lasker GE, editor. Advances in Support Systems Research. Vol. 5. Ontario, Canada: Windsor; 1999. pp. 30-39

[57] Jiang H, Eastman JR. Application of fuzzy measures in multi-criteria evaluation in GIS. International Journal of Geographical Information System. 2000;**14**:173-184

[58] Malczewski J, Chapman T, Flegel C, Walters D, Shrubsole D, Healy MA. GIS-multicriteria evaluation with ordered weighted averaging (OWA): Case study of developing watershed management strategies. Environment & Planning A. 2003;**35**(10):1769-1784

[59] Malczewski J, Rinner C. Exploring multicriteria decision strategies in GIS with linguistic quantifiers: A case study of residential quality evaluation. Journal of Geography System. 2005;**7**(2):249-268

[60] Kusre BC, Ghosh P, Nath K. Prioritization of soil conservation measures using erodibility indices as criteria in Sikkim (India). Journal of Earth System Science. 2018;**127**(6):1-3

[61] AbdelRahman MA, Natarajan A, Srinivasamurthy CA, Hegde R. Estimating soil fertility status in physically degraded land using GIS and remote sensing techniques in Chamarajanagar district, Karnataka, India. The Egyptian Journal of Remote Sensing and Space Science. 2016;**19**(1): 95-108

[62] Mokarram M, Hojati M. Using ordered weight averaging (OWA) aggregation for multi-criteria soil

fertility evaluation by GIS (case study: Southeast Iran). Computers and Electronics in Agriculture. 2017;**132**:1-3

[63] Li M, Zhang XL. GIS-based evaluation of farmland soil fertility and its relationships with soil profile configuration pattern. Ying Yong Sheng tai xue bao= The. Journal of Applied Ecology. 2011;**22**(1):129-136

[64] Leena HU, Premasudha BG, Basavaraja PK. Sensible approach for soil fertility management using GIS cloud. In: 2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI). IEEE; 2016 Sep 21. pp. 2776-2781

[65] Mishra A, Pattnaik T, Das D, Das M. Soil fertility maps preparation using GPS and GIS in Dhenkanal District, Odisha, India. International Journal of Plant Soil Science. 2014;**3**(8):986-994

[66] Tunçay T, Kılıç Ş, Dedeoğlu M, Dengiz O, Başkan O, Bayramin İ. Assessing soil fertility index based on remote sensing and gis techniques with field validation in a semiarid agricultural ecosystem. Journal of Arid Environments. 2021;**190**:104525

[67] Liu HH, Zhao YM, Wang XY, Feng YJ, Yang W. Discussion of evaluation methods on soil fertility. Journal of Yangtze River Scientific Research Institute. 2008;**25**(3):62-66

[68] Nie Y, Yu J, Wu Y, Yu L, Jing Y, Zhou Y. A comprehensive evaluation of soil fertility of cultivated land: A GIS-based soil basic Niche- Fitness Model. Communications in Soil Science and Plant Analysis. 2016;**47**(5):670-678

[69] Ren Y, Chen J, Chen L, Zhang H, Zhang K. Research and implementation of a universal workflow model to evaluate the soil fertility based on OGC Web Service. Geo Spatial Information Science. 2018;**21**(4):346-357

[70] Williams H, Colombi T, Keller T. The influence of soil management on soil health: An on-farm study in southern Sweden. Geoderma. 2020;**360**:114010

[71] Li ZW, Huang JQ, Li YY, Guo W, Zhu JF. Assessment on soil fertility of Dongting Lake wetland area (China) based on GIS and fuzzy evaluation. Journal of Central South University. 2011;**18**(5):1465-1472

[72] Li C, Chen G, Zeng G, Ye J. The study of soil fertility spatial variation feature based on GIS and data mining. In: International Conference on Computer and Computing Technologies in Agriculture. Berlin, Heidelberg: Springer; 2012. pp. 211-220

[73] Lal R. Restoring soil quality to mitigate soil degradation. Sustainability. 2015;**7**:5875-5895

[74] Hunter MC, Smith RG, Schipanski ME, Atwood LW, Mortensen DA. Agriculture in 2050: Recalibrating targets for Sustainable intensification. Bioscience. 2017;**67**: 386-391

[75] El-Naggar A, Lee SS, Rinklebe J, Farooq M, Song H, Sarmah AK, et al. Biochar application to low fertility soils: A review of current status, and future prospects. Geoderma. 2019;**337**:536-554

[76] Schipanski M, Snapp S, Jackson LE. Ecologically based nutrient management. In: Snapp SS, Pound CB, editors. Agricultural Systems. second ed. Academic Press; 2017. pp. 203-257

[77] Bagherzadeh A, Gholizadeh A. Assessment of soil fertility for sugar beet production using fuzzy AHP approach

and GIS in the Northeastern region of Iran. Agricultural Research (Kurashiki). 2018;**7**(1):61-71

[78] Govers G, Merckx R, Van Wesemael B, Van Oost K. Soil conservation in the 21st Century: Why we need smart agricultural intensification. The Soil. 2017;**3**:45-59

[79] Kome GK, Enang RK, Palmer B, Yerima BPK. Knowledge and management of soil fertility by farmers in Western Cameroon. Geoderma Regional. 2018;**13**:43-51

[80] Yageta Y, Osbahr H, Morimoto Y, Clark J. Comparing farmers' qualitative evaluation of soil fertility with quantitative sol fertility indicators I Kitui Count, Kenya. Geoderma. 2019;**344**: 153-163

[81] Patil PL, Kuligod VB, Gundlur SS, Katti J, Nagaral IN, Shikrashetti P, et al. Soil fertility mapping in Dindur sub-watershed of Karnataka for site specific recommendations. Journal of the Indian Society of Soil Science. 2016;**64**(4):381-390

[82] Jackai LE, Daoust RA. Insect pests of cowpeas. Annual Review of Entomology. 1986;**31**(1):95-119

[83] Haile FJ, Higley LG, Specht JE. Soybean cultivars and insect defoliation: Yield loss and economic injury levels. Agronomy Journal. 1998;**90**(3): 344-352

[84] Cerda R, Avelino J, Gary C, Tixier P, Lechevallier E, Allinne C. Primary and secondary yield losses caused by pests and diseases: Assessment and modeling in coffee. PloS One. 2017 Jan 3;**12**(1): e0169133

[85] Ranjan R, Vinayak S. Application of remote sensing and GIS in plant disease management. TTPP. 2020;**509**

[86] Duarte F, Calvo MV, Borges A, Scatoni IB. Geostatistics applied to the study of the spatial distribution of insects and its use in integrated pest management. Revista Agronómica del Noroeste Argentino. 2015;**35**(2): 9-20

[87] Liu Y, Shi J. Predicting the potential global geographical distribution of two Icerya species under climate change. Forests. 2020;**11**(6):684

[88] Bale J, Walters KF. Overwintering biology as a guide to the establishment potential of non-native arthropods in the UK. In: Atkinson DA, Thorndyke M. Temperature and Development. 2001 Jan 1

[89] Pretty J, Benton TG, Bharucha ZP, Dicks LV, Flora CB, Godfray HC, et al. Global assessment of agricultural system redesign for sustainable intensification. Nature Sustainability. 2018;**1**(8):441-446

[90] Zeng J, Liu Y, Zhang H, Liu J, Jiang Y, Wyckhuys KA, et al. Global warming modifies long-distance migration of an agricultural insect pest. Journal of Pesticide Science. 2020;**93**(2): 569-581

[91] Carrière Y, Ellsworth PC, Dutilleul P, Ellers-Kirk C, Barkley V, Antilla L. A GIS-based approach for areawide pest management: The scales of Lygus hesperus movements to cotton from alfalfa, weeds, and cotton. Entomologia Experimentalis et Applicata. 2006;**118**(3):203-210

[92] Latchininsky AV, Sivanpillai R. Locust habitat monitoring and risk assessment using remote sensing and GIS technologies. In: Integrated Management of Arthropod Pests and Insect Borne Diseases. Dordrecht: Springer; 2010. pp. 163-188

[93] Mahlein AK. Plant disease detection by imaging sensors–parallels and specific demands for precision agriculture and plant phenotyping. Plant Disease. 2016; **100**(2):241-251

[94] Franke J, Menz G. Multi-temporal wheat disease detection by multi-spectral remote sensing. Precision Agriculture. 2007;**8**(3):161-172

[95] Mahlein AK, Rumpf T, Welke P, Dehne HW, Plümer L, Steiner U, et al. Development of spectral indices for detecting and identifying plant diseases. Remote Sensing of Environment. 2013; **128**:21-30

[96] Zhang J, Huang Y, Yuan L, Yang G, Chen L, Zhao C. Using satellite multispectral imagery for damage mapping of armyworm (Spodoptera frugiperda) in maize at a regional scale. Pest Management Science. 2016;**72**(2): 335-348

[97] Chau VN, Holland J, Cassells S, Tuohy M. Using GIS to map impacts upon agriculture from extreme floods in Vietnam. Applied Geography. 2013;**41**: 65-74

[98] Consuegra D, Joerin F, Vitalini F. Flood delineation and impact assessment in agricultural land using GIS technology. In: Geographical Information Systems in Assessing Natural Hazards. Dordrecht: Springer; 1995. pp. 177-198

[99] Yamada Y. Detection of flood-inundated area and relation between the area and micro-geomorphology using SAR and GIS. In: IGARSS 2001. Scanning the Present and Resolving the Future. Proceedings. IEEE 2001 International Geoscience and Remote Sensing Symposium (Cat. No. 01CH37217) IEEE. 2001 Jul 9;**7**:3282-3284

[100] Pistrika A. Flood damage estimation based on flood simulation scenarios and a GIS platform. European Water. 2010;**30**:3-11

[101] Murad H, Islam AK. Drought assessment using remote sensing and GIS in north-west region of Bangladesh. In: Proceedings of the 3rd international conference on water & flood management. 2011 Jan 8. pp. 797-804

[102] Suryabhagavan KV. GIS-based climate variability and drought characterization in Ethiopia over three decades. Weather and Climate Extremes. 2017;**15**:11-23

[103] Saha A, Patil M, Goyal VC, Rathore DS. Assessment and impact of soil moisture index in agricultural drought estimation using remote sensing and GIS techniques. In Multidisciplinary digital publishing institute proceedings 2018;**7** (1):2

[104] Reynolds CA, Yitayew M, Slack DC, Hutchinson CF, Huete A, Petersen MS. Estimating crop yields and production by integrating the FAO Crop Specific Water Balance model with real-time satellite data and ground-based ancillary data. International Journal of Remote Sensing. 2000;**21**(18):3487-3508

[105] Dadhwal VK, Ray SS. Crop assessment using remote sensing-Part II: Crop condition and yield assessment. Indian Journal of Agricultural Economics. 2000;**55**:55-67

[106] Taylor JC, Wood GA, Thomas G. Mapping yield potential with remote sensing. Precision Agriculture. 1997;**1**: 713-720

[107] Xue J, Su B. Significant remote sensing vegetation indices: A review of developments and applications. Journal of sensors. 2017;**23**

[108] Adhav V, Das S, Patkar V. Crop health monitoring using geospatial technologies for nashik district, Maharashtra. International Journal of Modern Agriculture. 2021;**10**(2): 1395-1409

[109] Lowder SK, Sánchez MV, Bertini R. Which farms feed the world and has farmland become more concentrated? World Development. 2021;**142**:105455

[110] Brewer K, Clulow A, Sibanda M, Gokool S, Naiken V, Mabhaudhi T. Predicting the chlorophyll content of maize over phenotyping as a proxy for crop health in smallholder farming systems. Remote Sensing. 2022;**14**(3):518

[111] Vanlauwe B, Coyne D, Gockowski J, Hauser S, Huising J, Masso C, et al. Sustainable intensification and the African smallholder farmer. Current Opinion in Environment Sustainability. 2014;**8**:15-22

[112] Singhal G, Bansod B, Mathew L. Real time Crop health monitoring using Remote Sensing and ancillary information using GIS. In: 19th Esri India User Conference. India; 2018

[113] Maloom JM, Saludes RB, Dorado MA, Cruz PC. Development of a GIS-based model for predicting rice yield. Philiphines Journal of Crop Science. 2014;**39**:8-19

[114] Zinna AW, Suryabhagavan KV. Remote sensing and GIS based spectro-agrometeorological maize yield forecast model for South Tigray Zone, Ethiopia. Journal of Geographic Information System. 2016;**8**(2):282-292

[115] Al-Gaadi KA, Hassaballa AA, Tola E, Kayad AG, Madugundu R, Alblewi B, et al. Prediction of potato crop yield using precision agriculture techniques. PLoS One. 2016;**11**(9): e0162219

[116] Carbone GJ, Narurnalani S, King M. Application of remote sensing and technologies with physiological crop models. Photogrammetric Engineering and Remote Sensing. 1996;**62**(2):171-179

[117] Hartkamp AD, White JW, Hoogenboom G. Interfacing geographic information systems with agronomic modeling: A review. Agronomy Journal. 1999;**91**:761-772

[118] Sailaja B, Voleti SR, Subrahmanyam D, Nathawat MS, Rao NH. Regional rice yield estimation by integration of spatial technologies and crop model. Journal of Remote Sensing & GIS. 2013;**4**(2):56-66

[119] Kadiyala MD, Nedumaran S, Singh P, Chukka S, Irshad MA, Bantilan MC. An integrated crop model and GIS decision support system for assisting agronomic decision making under climate change. The Science of the Total Environment. 2015;**521**:123-134

[120] Bouman BAM, Van Keulen H, Van Laar HH, et al. The 'School of de Wit' Crop Growth Simulation Models: Pedigree and Historical Overview. Agricultural Systems. 1996;**52**:171-198

[121] Jones JW, Hoogenboom G, Porter CH, et al. The DSSAT Cropping System Model. European Journal of Agronomy. 2003;**18**:235-265

[122] Tan G, Shibasaki R. Global estimation of crop productivity and the impacts of global warming by GIS and EPIC integration. Ecological Modelling. 2003;**168**(3):357-370

[123] Yang P, Tan GX, Zha Y, Shibasaki R. Integrating remotely sensed data with an ecosystem model to estimate crop

yield in north China. In: Proceedings of XXth ISPRS Congress Proceedings Commission VII, WG VII/2, Istanbul, Turkey; 2004 Jul. pp. 150-156

[124] Oudemans PV, Pozdnyakova L, Hughes MG, Rahman F. GIS and remote sensing for detecting yield loss in cranberry culture. Journal of Nematology. 2002;**34**(3):207

[125] Pierce FJ, Nowak P. Aspects of precision agriculture. Advances in Agronomy. 1999 Jan 1;**67**:1-85

[126] Earl R, Wheeler PN, Blackmore BS, Godwin RJ. Precision farming: The management of variability. The Journal of the Institution of Agricultural Engineers. 1996;**51**:18-23

[127] Strickland RM, Ess DR, Parsons SD. Precision farming and precision pest management: The power of new crop production technologies. Journal of Nematology. 1998;**30**(4):431

[128] Goswami SB, Matin S, Saxena A, Bairagi GD. A review: The application of Remote Sensing, GIS and GPS in Precision Agriculture. International Journal of Advanced Technology & Engineering Research. 2012;**2**(1):50-54

[129] Balafoutis A, Beck B, Fountas S, Vangeyte J, Wal TV, Soto I, et al. Precision agriculture technologies positively contributing to GHG emissions mitigation, farm productivity and economics. Sustainability. 2017;**9**(8):1339

[130] Banu S. Precision agriculture: Tomorrow's technology for today's farmer. Journal of Food Processing & Technology. 2015;**6**(8):1

[131] Pfister B. What is Precision Agriculture?. 1998. Available from: http://www.directionsmag.com/articles/what-is-precision-agriculture/124210

[132] Fasina AS, Omolayo FO, Ajayi OS, Falodun AA. Influence of land use on soil properties of three mapping units in Southwestern Nigeria-Implications for sustainable soil management. Research Journal of Applied Sciences. 2007;**2**(8): 879-883

[133] Pravat KS, Gouri B, Ramkrishna M. Spatial analysis of soil properties using GIS based geostatistics models. Earth System and Environment. 2016;**2**:107. DOI: 10.1007/s40808-016-0160-4

[134] Kingsley J, Lawani SO, Esther AO, Ndiye KM, Sunday OJ, Penížek V. Predictive mapping of soil properties for precision agriculture using geographic information system (GIS) based geostatistics models. Modern Applied Science. 2019;**13**(10)

[135] Oerke EC. Remote sensing of diseases. Annual Review of Phytopathology. 2020;**58**:225-252

[136] Roberts DP, Short NM, Sill J, Lakshman DK, Hu X, Buser M. Precision agriculture and geospatial techniques for sustainable disease control. Indian Phytopathology. 2021;**74**(2):287-305

[137] Shanmugapriya P, Rathika S, Ramesh T, Janaki P. Applications of remote sensing in agriculture-A Review. International Journal of Current Microbiology and Applied Sciences. 2019;**8**(1):2270-2283

[138] Behmann J, Mahlein AK, Rumpf T, Römer C, Plümer L. A review of advanced machine learning methods for the detection of biotic stress in precision crop protection. Precision Agriculture. 2015;**16**(3):239-260

[139] Bharti A, Paritosh K, Mandla VR, Chawade A, Vivekanand V. GIS application for the estimation of bioenergy potential from agriculture

residues: An overview. Energies. 2021; **14**(4):898

[140] Bauböck R, Karpenstein-Machan M, Kappas M. Computing the biomass potentials for maize and two alternative energy crops, triticale and cup plant (*Silphium perfoliatum* L.), with the crop model BioSTAR in the region of Hannover (Germany). Environmental Sciences Europe. 2014;**26**(1):1-2

[141] Hiloidhari M, Baruah DC. GIS mapping of rice straw residue for bioenergy purpose in a rural area of Assam, India. Biomass and Bioenergy. 2014;**71**:125-133

[142] Hiloidhari M, Baruah DC, Singh A, Kataki S, Medhi K, Kumari S, et al. Emerging role of Geographical Information System (GIS), Life Cycle Assessment (LCA) and spatial LCA (GIS-LCA) in sustainable bioenergy planning. Bioresource Technology. 2017; **242**:218-226

[143] Sahoo K, Hawkins GL, Yao XA, Samples K, Mani S. GIS-based biomass assessment and supply logistics system for a sustainable biorefinery: A case study with cotton stalks in the Southeastern US. Applied Energy. 2016; **182**:260-273

[144] Sahoo K, Mani S, Das L, Bettinger P. GIS-based assessment of sustainable crop residues for optimal siting of biogas plants. Biomass and Bioenergy. 2018;**110**:63-74

[145] Sharma R, Kamble SS, Gunasekaran A. Big GIS analytics framework for agriculture supply chains: A literature review identifying the current trends and future perspectives. Computers and Electronics in Agriculture. 2018;**155**:103-120

[146] Perveen S, Arsalan MH. A review of potential use of geo-information technologies for cotton supply chain management. International Journal of Biodiversity and Conservation. 2014; **6**(10):724-734

[147] Qu XH, Zhuang DF, Qiu DS. Studies on GIS based tracing and traceability of safe crop product in China. Agricultural Sciences in China. 2007;**6**(6):724-731

[148] Nardi MG, Sperry SE, Davis TD. Grain supply chain management optimization using ARCGIS in Argentina. In: 2007 ESRI User Conference Proceedings. Redlands, CA; 2007. pp. 1-23

[149] Zhang F, Johnson D, Johnson M, Watkins D, Froese R, Wang J. Decision support system integrating GIS with simulation and optimisation for a biofuel supply chain. Renewable Energy. 2016; **85**:740-748

[150] Yusianto R, Hardjomidjojo H. Intelligent spatial decision support system concept in the potato agro-industry supply chain. In: 2020 International Conference on Computer Science and Its Application in Agriculture (ICOSICA). Bogor, Indonesia: IEEE; 2020. pp. 1-7

[151] Latterini F, Stefanoni W, Suardi A, Alfano V, Bergonzoli S, Palmieri N, et al. A GIS approach to locate a small size biomass plant powered by olive pruning and to estimate supply chain costs. Energies. 2020;**13**(13):3385

[152] Zhang F, Wang J, Liu S, Zhang S, Sutherland JW. Integrating GIS with optimization method for a biofuel feedstock supply chain. Biomass and Bioenergy. 2017;**98**:194-205