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Review

Machine Learning-Driven Remote Sensing Applications for Agriculture in India—A Systematic Review

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Abstract: In India, agriculture serves as the backbone of the economy, and is a primary source of employment. Despite the setbacks caused by the COVID-19 pandemic, the agriculture and allied sectors in India exhibited resilience, registered a growth of 3.4% during 2020–2121, even as the overall economic growth declined by 7.2% during the same period. The improvement of the agriculture sector holds paramount importance in sustaining the increasing population and safeguarding food security. Consequently, researchers worldwide have been concentrating on digitally transforming agriculture by leveraging advanced technologies to establish smart, sustainable, and lucrative farming systems. The advancement in remote sensing (RS) and machine learning (ML) has proven beneficial for farmers and policymakers in minimizing crop losses and optimizing resource utilization through valuable crop insights. In this paper, we present a comprehensive review of studies dedicated to the application of RS and ML in addressing agriculture-related challenges in India. We conducted a systematic literature review following the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines and evaluated research articles published from 2015 to 2022. The objective of this study is to shed light on the application of both RS and ML technique across key agricultural domains, encompassing "crop management", "soil management", and "water management, ultimately leading to their improvement. This study primarily focuses on assessing the current status of using intelligent geospatial data analytics in Indian agriculture. Majority of the studies were carried out in the crop management category, where the deployment of various RS sensors led yielded substantial improvements in agricultural monitoring. The integration of remote sensing technology and machine learning techniques can enable an intelligent approach to agricultural monitoring, thereby providing valuable recommendations and insights for effective agricultural management.

Keywords: remote sensing; machine learning; India; agriculture; crop management; soil management; water management

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1. Introduction

The United Nations Food and Agricultural Organization (FAO) has projected that the world's population will reach 9 billion by 2050, boosting agricultural demand by 50 percent compared with 2013 [1]. Moreover, the situation is aggravated by the negative impact of climate change, which contributes to an increase in extreme weather events causing disastrous impact on worldwide agriculture and more commonly to food security of developing nations [2,3]. In addition, the COVID-19 pandemic in 2019 created more uncertainties in the agricultural system and risks to global food security. Therefore, food production systems shall be governed by sustainable management of agricultural lands in order to reduce or end the negative impacts of climate change on agriculture, land degradation, water and energy resources, and biodiversity [4].

Agriculture, along with its allied sectors, is the largest source of livelihood in India. Approximately 80% of the population depend on agriculture or its by-products as the primary means of employment. Considering the rapid growth of the population, it is imperative for government policymakers to promote smart farming to make agriculture sustainable and profitable. Thus, it is essential to accelerate the integration innovative technologies to enhance the agricultural sector, especially in developing countries like India [5].

Traditionally in India, crop estimation and health status was monitored through crop cutting and manual observations. Based on this, farmers apply pesticides, herbicides, fertilizer, and irrigation to their farms for enhancing crop production. However, this process is both time consuming and resource intensive, leading to an increased input costs in agriculture. In light of overcoming this pressing issue, there is an urgent need for real-time crop growth monitoring across diverse locations and under varying environmental conditions. Real-time crop monitoring not only saves time and improves management techniques, but it also enables managers to effectively respond to extreme climatic events and minimize their impact on the global food system [6].

Remote sensing (RS) is an essential tool for meeting the aforementioned needs, as it offers a non-destructive method for acquiring information across local to global scales. It has proven to be a powerful tool to obtain significant volumes of crop data in a short time and generating valuable information for crop managers [7]. RS allows for the characterization of spatiotemporal variability within a given area. In recent times, our capacity to obtain remote sensing data has undergone remarkable advancements, ushering into an era that characterized by the proliferation of large datasets—commonly referred to as "big data". Big data not only encompasses the voluminous data but also challenges arising from its rapid generation, diversity, reliability and inherent value, often encapsulated as 5Vs. The conventional processing techniques are incapable of meeting the constantly growing demands in the era of smart agriculture. To that end, the machine learning (ML) has emerged as a powerful technique for efficiently extracting information from diverse information sources.

Numerous comprehensive reviews focus on the use of ML algorithms for agriculture management at the global level [8–11]. Chlingaryan et al. (2018) reviewed the use of ML algorithms for crop yield and nitrogen status prediction [8]. Liakos et al. included a few contributions from RS tools at the global level [9]. Furthermore, Jha et al. analyzed the automation techniques applied to agriculture systems [10]. The work of Diaz-Gonzalez et al. (2022) included both ML and RS techniques but only to review the studies focused on soil quality assessment at the global level. All the above-mentioned reviews were focused on research studies executed at the global level [11].

Therefore, this review aims to discuss RS and ML applications in solving problems related to agriculture in India. Usage of advanced technology in Indian agriculture also gain momentum at the policy level. The Committee on Doubling Farmer's Income (DFI) formulated the National e-Governance Plan in Agriculture (NeGPA), which is focused on agriculture management through advanced technology viz. remote sensing, machine learning, artificial intelligence, robotics, drones, the Internet of Things (IoT), sensors, data analytics, cloud computing, and blockchain (https://pib.gov.in/PressReleasePage.aspx?PRID=1697526 (18 July 2023). In the present study, we want to highlight the RS satellites and ML techniques used in the agricultural domain. We also summarize the challenges and future scope of linking ML technology to RS data for Indian agriculture based on the searched articles. Consequently, this study can serve as an extensive foundation for future research. In this regard, we conducted a systematic literature review (SLR) by applying a Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) protocol. We selected 54 articles that dealt with the use of ML and RS data in agriculture in India. The structure of the paper is as follows: Section 1 is the introduction; Section 2 deals with the theoretical background of AI/ML techniques/algorithms, RS applications in agriculture, and leveraging ML techniques on RS data for agricultural applications; Section 3 contains

the methodology used to collect the relevant papers for the study; Section 4 explains the findings obtained from the analysis of the selected research articles; and Section 5 discusses and concludes the implications of the study.

2. Background

In this section, we explain the basic concepts of ML and RS. Furthermore, we explain the role of ML and RS in solving agricultural problems in separate sections.

2.1. Machine Learning

Machine learning (ML) is a sub-branch of AI and part of data science that principally focuses on learning systems and algorithm theory, performance, and properties. It is an an intelligent tool which has strong bearing on AI, statistics, engineering, mathematics, information theory, cognitive science, and many other scientific and technological disciplines [12]. In general, the goal of ML is to optimize the performance of a task using past experiences. ML can establish efficient relationships between data inputs based on the past experiences and can effectively analyze large volume of data [13]. It involves the process of creating mathematical models on sample data sets called "training datasets" to make decisions and predictions [14]. The algorithm or model first trained and then classified/predicted with a ML technique. The validity of the ML model is general tested using the "testing dataset", which is further used to improve the model and perform accurate classification/prediction (Figure 1).

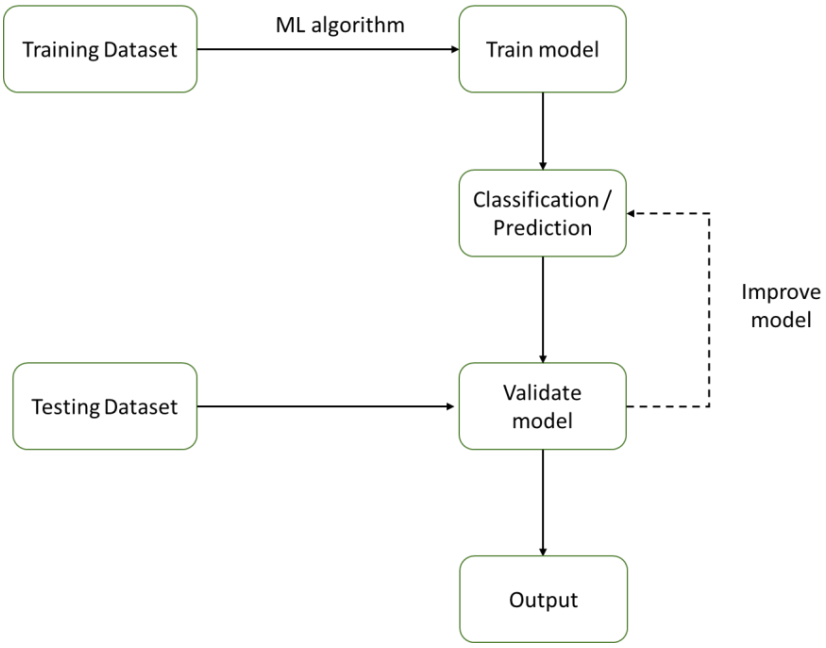

Figure 1. General architecture of the ML model.

The ML algorithm is classified into three main techniques depending on the nature of the feedback available for a learning system, which are unsupervised learning (UL), supervised learning (SL), and reinforced learning (RL) [9] (Table 1).

Table 1. Different ML techniques.

Techniques	Unsupervised Learning	Supervised Learning	Reinforcement Learning
Used for	Clustering Dimensionality reduction	Classification Regression Estimation	Real-time decision-making

Table 1. *Cont.*

Techniques	Unsupervised Learning	Supervised Learning	Reinforcement Learning
Algorithms	k-means X-means Anomaly detection Principal component analysis Independent component analysis Gaussian mixture models	Bayesian networks Support vector machine Random forest Decision tree Neural networks Hidden Markov model Naïve Bayes	Q-learning Markov decision process

UL and SL are mainly focused on data analysis, whereas RL is mainly focused on solving the decision-making problems. Table 2 presents a comparison between different ML techniques according to the definitions provided by Liakos et al. [9]. Due to the numerous abbreviations used in the relative scientific works, Table 3 list the abbreviations referenced in this study.

Table 2. Types of ML models used in this review.

ML Models	Description	Types Used in This Review
Regression	A supervised learning model that aims to predict an output variable according to the known input variables.	PLSR
Instance-based models	Memory-based models that learn by comparing new examples with instances in the training database.	k-NN
Bayesian models	These models belong to the supervised learning category and can be used to solve both regression and classification problems.	NB
Decision tree	This is the type of supervised learning category used to categorize or make predictions based on how a previous set of questions was answered.	DT, CART
Ensemble learning	Ensemble learning (EL) models aim at improving the predictive performance of a given statistical learning or model fitting technique by constructing a linear combination of simpler base learners.	RF, GBR, XGB
Support vector machines (SVM)	SVM is a supervised learning method that looks at data and sorts them into one of two categories. An SVM outputs a map of the sorted data with the margins between the two as far apart as possible.	SVM, SVR, O-SVM, SVM-RBF, KPA-based SVM
Neural networks	A neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates.	ANN, CNN, RNN-LSTM, RNN-GRU, DFNN, FFBPNN

Table 3. List of ML-based abbreviations used in the study along with their full forms.

Abbreviation	Full Form
k-NN	k-nearest neighborhood classifier
LDA	Linear discriminant analysis
SVM	Support vector machine
MLC	Maximum likelihood classifier

Table 3. *Cont.*

Abbreviation	Full Form
ANN	Artificial neural network
OB	Object based
SAM	Spectral angle mapper
RF/RFR	Random forest/random forest regressor
CNN	Convolution neural network
RNN	Recurrent neural network
LSTM	Long short-term memory
GRU	Graded recurrent unit
O-SVM	Optimized SVM
CART	Classification and regression trees
DT	Decision tree
SC	Supervised classification
USC	Unsupervised classification
HCSC	High-confidence sugarcane classification
RR	Ridge regression
FFBPNN	Feed-forward back-propagating neural network
NB	Naïve Bayes
GBR	Gradient-boosting regression
SGB	Stochastic gradient boosting
XGB	Extreme gradient boosting
sDFNN	Deep feed-forward network
DRF	Distributed random forest
PLSR	Partial least square regressions
MLR	Multiple linear regression
SMLR	Sparse multinomial logistic regression
SVR-RBF	Support vector regression—radial basis function
KPA	Kernel principal component analysis
GBM/GBR	Gradient-boosting machine/gradient-boosting regressor

To evaluate the performance of ML algorithms, statistical metrics are utilized [13].

2.2. Performance Metrics Commonly Used in Reviewed Studies

In this section, we provide a brief description of the performance metrics commonly used in the reviewed papers. These metrics are crucial in evaluating ML algorithms, as they offer a standardized way to measure their performance. The performance metrics used in the reviewed studies for regression problems are root mean square error (RMSE), coefficient of determination (R^2), mean absolute percentage error (MAPE), and mean squared error (MSE). The equation of the abovementioned metrics are as follows [13,15,16]:

$$R^2 = [n \sum (Y_A \times Y_P) - \sum (Y_A) \sum (Y_P)]/[(n \sum {Y_A}^2 - (\sum Y_A)^2) (n \sum {Y_P}^2 - (\sum Y_P)^2)]^{0.5}$$

$$RMSE = (1/n \sum (Y_A - Y_P)^2)^{0.5}$$

$$MAPE = 1/n \sum | (Y_A - Y_P)/Y_A |$$

$$MSE = 1/n \sum (Y_A - Y_P)2$$

where n is the sample size, Y_A is the actual/observed value, and Y_P is the predicted value.

In classification problems, to evaluate the model error, a confusion matrix is the most commonly used measure. Let us consider a binary crop classification example where we want to classify crops as "maize" and "wheat" (Table 4).

Table 4. Representative illustration of a binary confusion matrix.

		Actual	
		Maize	**Wheat**
Predicted	**Maize**	TN	FP
	Wheat	FN	TP

True positive (TP): wheat correctly predicted as wheat, true negative (TN): maize correctly predicted as maize, false positive (FP): maize incorrectly predicted as wheat, and false negative (FN): wheat incorrectly predicted as maize. The aforementioned values derived from Table 5 can be implemented to estimate the performance metrics typically observed in classification problems [17].

Table 5. Summary of the performance metrics used in the reviewed studies, typically for classification problems.

Metrics	**Formula**	**Focus**
Overall accuracy (OA)	(TP + TN)/(TP + TN +FP + FN)	Effectiveness of a classifier technique
Precision (PRC)	TP/(TP + FP)	Measures accuracy of positive predictions made by a model, aiming to minimize false positives
Recall/Sensitivity (REC)	TP/(TP + FN)	Measures effectiveness of a classifier model to identify positive predictions, aiming to minimize false negatives
F1 score	2 × ((REC × PRC)/(REC + PRC))	Combination of sensitivity and precision in a single metric

ML has been used effectively to solve different agriculture problems in crop management comprised of yield monitoring, crop identification, disease detection, and crop protection from animal intrusion; in water management; in soil management; and in drought monitoring [9,13,18].

2.3. Remote Sensing and Its Application in Agriculture

Remote sensing involves acquiring information about an object, area, and phenomenon from a distance using instruments and sensors mounted on a platform such as a satellite, aircraft, or unmanned aerial vehicle (UAV). The sensor measures the electromagnetic radiation emitted or reflected by the object/area under interest. The quality of information retrieved using remote sensing technology depends on the specific features of the sensor/instrument, which define the spatial resolution, spectral resolution, signal-to-noise ratio, and revisit frequency of the platform [19].

The use of RS in agriculture dates back to 1972, when the first successful launch of LandSat Multispectral Scanner System (MSS) satellite occurred. Bauer and Cipra classified Midwestern US agricultural landscapes into corn and soyabean fields using a LandSat MSS dataset [20]. RS is a non-destructive method of data acquisition, making it an inevitable tool to meet multiple goals in agriculture, such as monitoring crop production to feed a growing population, choosing economically viable activities, and reducing negative

environmental impacts such as contributing to climate mitigation and minimizing resource depletion [19]. RS technologies serve as a diagnostic tool that can act as an early warning system, allowing the agricultural community to counter potential problems before they can negatively impact crop productivity.

According to the Index DataBase (IDB), there are a total of 519 indexes used particularly for RS application in agriculture [21]. The most widely used VI is the Normalized Difference Vegetation Index (NDVI), which analyzes a near infrared (NIR) band centered at 850 nm and a red band centered at 680 nm [22]. Table 6 shows the RS-derived variables that are identified in this review.

Table 6. List of the RS-derived variables used in the review.

Abbreviation	Meaning
LISS	Linear imaging self-scanning
NDVI	Normalized Difference Vegetation Index
GNDVI	Green Normalized Difference Vegetation Index
SAVI	Soil Optimized Vegetation Index
DVI	Difference Vegetation Index
RVI	Ratio Vegetation Index
NDMI	Normalized Difference Moisture Index
NDWI	Normalized Difference Water Index
LSWI	Land Surface Water Index
GCI	Green Chlorophyll Index
NG	Normalized green
NN	Normalized near infrared
NR	Normalized red
BI	Brightness Index
SI	Saturation Index
HI	Hue Index
SI	Salinity Index
CI	Coloration Index
DSI	Desertification Soil Index
RI	Redness Index
EDI	Evaporative Drought Index
VCI	Vegetation Condition Index
TCI	Temperature Condition Index
VHI	Vegetation Health Index
SMDI	Soil Moisture Deficit Index
PCI	Precipitation Condition Index
PAI	Precipitation Anomaly Index
SPI	Standardized Precipitation Index
SPEI	Standardized Precipitation Evapotranspiration Index
WBI	Water Band Index
MSI	Moisture Stress Index
hNDVI	Hyperspectral Normalized Difference Vegetation Index
NDII	Normalized Difference Infrared Index

Table 6. *Cont.*

Abbreviation	Meaning
MDWI	Maximum Difference Water Index
RI	Ratio Index
SRWI	Simple Ratio Water Index
SR	Simple Ratio
WI	Water Index
NWI	Normalized Water Index
fWBI	Floating Water Band Index
HH	Horizontal transmit and horizontal receive
VV	Vertical transmit and vertical receive
HV	Horizontal transmit and vertical receive
LST	Land surface temperature
VARI	Visual Atmospheric Resistance Index
ARVI	Atmospherically Resistant Vegetation Index
EVI	Enhanced Vegetation Index
GCVI	Green Chlorophyll Vegetation Index
IPD	Indian pine data

2.4. Leveraging Machine Learning Techniques on Remote Sensing for Agricultural Applications

Agricultural monitoring using RS is a wide area of research that has been thoroughly explored from multiple perspectives, based on RS platforms (satellites, UAV, aircrafts), on specific applications (yield prediction, irrigation, crop stress detection and management, weed detection, irrigation management, etc.), and diverse climatic and location contexts (ranging from field scale to global scale, on wetlands or drylands). India has achieved notable success in utilizing RS technology for agriculture applications in crop acreage estimation, yield prediction, crop identification and mapping, crop stress evaluation, and crop protection with a strong expansion on national expansion. There has been a significant increase in published literature related to RS applications in agriculture in India, indicating that the RS for agriculture has reached a certain level of knowledge in the country. (Figure 2). This also reflects the substantial progress made in RS technology, including high-resolution satellite dataset (e.g., Sentinel) and the deployment of cloud computing and ML technology.

The RS research community is currently facing the era of "big data", where the utilization of ML and deep learning (DL) algorithms is growing for agricultural applications [23] through: (i) establishing complex relationships to retrieve RS variables from RS data [24,25] and (ii) solving complex classification/prediction problems. ML technology has been in routine use for the analysis of RS data for some time. One of the applications is classification with RS data (LANDSAT), often using an RF and an SVM technique. The utilization of ML technology for the effective prediction and classification from RS imagery has been reviewed previously and focused on SVM, NN, DT, RF, and k-NN [26,27]. Advanced ML algorithms such as SVM [26], RF [28], Gaussian processes, and neural networks [29,30] have been widely utilized to retrieve agricultural variables from RS data. These approaches allow the complex relationship between variables to be statistically characterized and permits real-time computations, which is of strong interest for agricultural applications. Most phenotypic studies concerned with multispectral cameras use ML algorithms to develop the relationship between vegetation indices and crop traits such as leaf area index (LAI), nitrogen content, and chlorophyll content [31]. ML techniques are also an efficient way to merge datasets of different natures, such as integrating in-situ data (soil data, farming management practice data from field surveys, weather variables) with datasets from various RS

sources [32]. These technological advancements will definitely allow the long-lasting goals for RS applications in agriculture to be met.

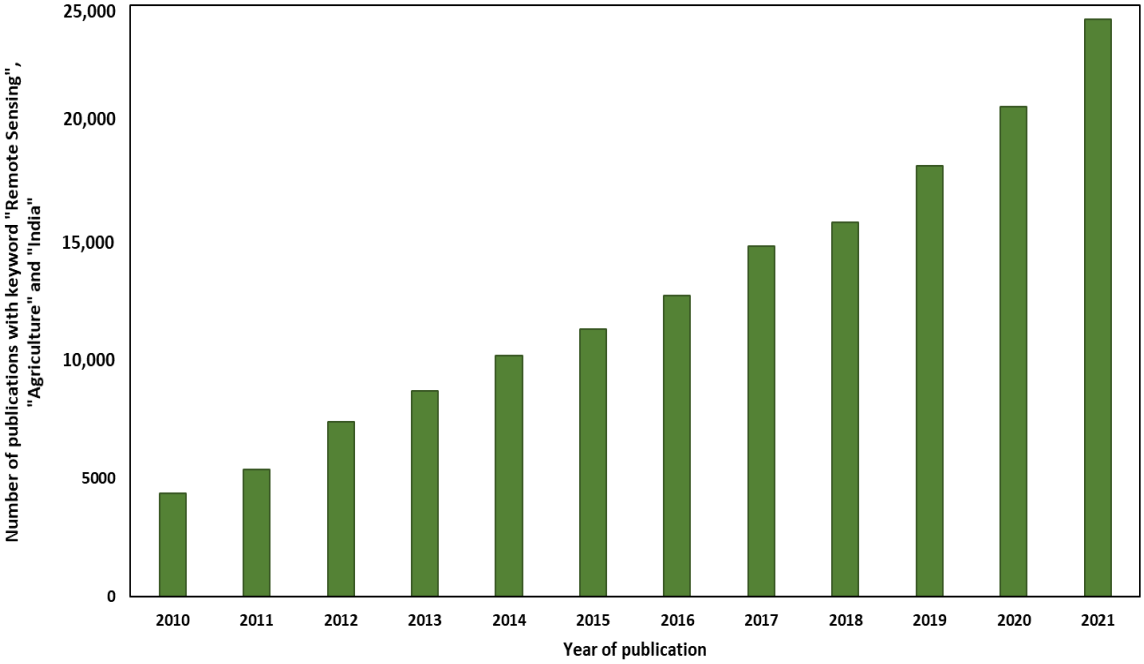

Figure 2. Google Scholar search results. Number of publications, including the keywords: remote sensing, agriculture, and India from 2010 to 2021.

3. Methodology

Systematic Literature Review

In this review article, we conducted a systematic literature review (SLR) using the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) method. Our aim was to identify studies related to the application of ML with remote sensing for agriculture management. The PRISMA method includes 4 stages, namely, identification, screening, eligibility, and inclusion [33]. This review article stems mainly from three research questions: (1) Which agricultural-related issues are solved by linking ML techniques and RS datasets, particularly in India? (2) What are the principal ML algorithms and RS datasets used to analyze the data? (3) What is the progress and future scope of ML and RS to manage agriculture in India? We searched for relevant studies in seven databases, including Web of Science, IEEE, MDPI, Springer, Scopus, and Google Scholar for the literature search, with keywords namely, "machine learning", "remote sensing", and "agriculture", in conjunction with "crop yield estimation", "crop classification", "disease prediction", "water management", "drought monitoring", and "soil management". We looked for these keywords in the article title, abstract, and keywords. Moreover, we considered research articles and conferences in English only from India published from 2015 to 2022. Thus, non-English studies, review articles, preprints, chapters, and master's and doctoral dissertations/theses were excluded. Overall, we identified 54 relevant papers and selected them based on the PRISMA guidelines, as shown through the flowchart in Figure 3. We also considered the exclusive criteria similar to recent review studies such as [13,18] during the selection process.

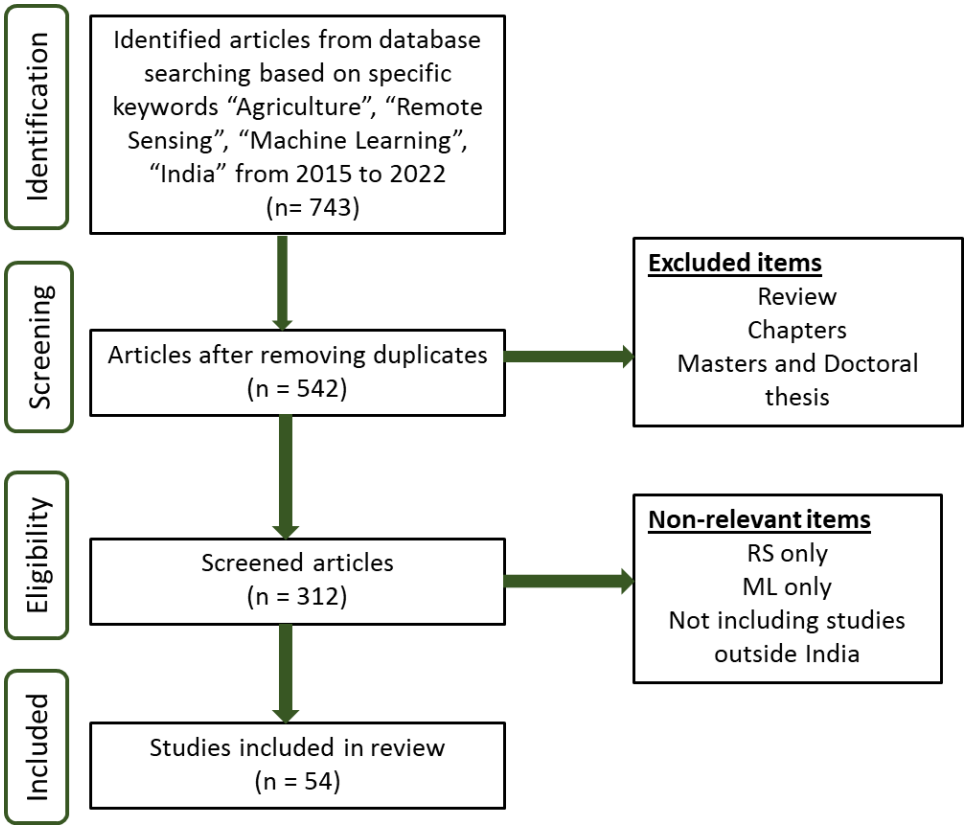

Figure 3. Flowchart of the methodology of the present systematic review based on the PRISMA guidelines.

4. Results

The selected studies were classified into three primary categories, namely, crop management, water management, and soil management. The studies under the crop management category further divided into four sub-categories, namely, crop classification, yield prediction, disease/pest detection, and weed detection. The articles presented here cover the period from 2015 to 2022.

4.1. Crop Management

4.1.1. Crop Classification

Crop classification is one of the most important agricultural applications of RS. The knowledge of the crop type present in the field is important for devising and implementing agricultural policies [34], consequently leading to efficient crop management and ensuring food security [35]. It is worth noting that RS not only enables crop discrimination but also allows for the determination of the crop's development stage. Accurate monitoring of heterogeneous agricultural plots is complex, but it is the foremost step towards monitoring smallholder cultivators' farms. This is even more pertinent in Indian agriculture since small and marginal farmers together cultivate about 86% of all operational landholdings in the country [36], and subsequently improving their economic status can further help to meet the Sustainable Development Goals [37]. RS techniques have improved the effectiveness of crop classification at various scales using optical (Landsat series, Sentinel 2 series, ResourceSat-2 series), microwave (Sentinel 1, RADARSAT), and hyperspectral data (Hyperion) [38,39]. Indian agriculture heavily relies on monsoons, and the *Kharif* (rainy) season, occurring from June to September, is crucial for crops such as rice, maize, cotton, and pulses. During cloudy weather, optical datasets are unavailable. Therefore, microwave data have been instrumental in overcoming the inherent limitation of optical data.

Out of the total studies included in the sub-category of crop classification (Table 7), maximum studies were based on optical dataset [40–50], while six studies [51–56] utilized the capability of both optical and microwave remote sensing to classify crops, particularly during *Kharif* season. Refs. [57–60] used Sentinel 1 and RADARSAT data for crop classification. Ranjan and Parida demonstrated the overall accuracy of LULC classes (forest, paddy, and other) from Sentinel-1A and Sentinel-2B with an overall accuracy of 90 and 91%, respectively. Nevertheless, the optical data were more appropriate for LULC classification using RF, but Sentinel 1 A data were more useful for capturing paddy crops [52]. Only two studies were conducted using hyperspectral remote sensing [61,62]. Hyperspectral remote sensing data offer distinct advantages over multispectral data in identifying and discriminating target features or objects. The narrowband information acquisition in hyperspectral data provides detailed and comprehensive information about any object [63].

Remote sensing (RS) provides vast amounts of information collected globally by various satellite sensors. The availability of open-access datasets and rapid sensor technology advancements has expanded RS-based studies [64,65]. The challenge has shifted from a lack of information to the difficulty of analyzing this large volume of data, often referred to as "big data" [66]. Big data is characterized by its volume, variety, velocity, veracity and value [67]. Machine learning has emerged as a powerful tool to analyze big data and deliver more accurate predictive information. One such tool is Google Earth Engine (GEE), which enables spectral and spatial analyses on batches of imagery. GEE supports advanced image processing and machine learning algorithms through a library of application programming interfaces (APIs) and development environments compatible with JavaScript or Python [68]. Gumma et al., in 2020 and 2022 [49,50], effectively used GEE's computing capabilities along with the random forest (RF) technique to map crop products such as irrigation and rainfed crop maps, cropping intensity maps, and crop type maps for South Asia, including India, Nepal, Bangladesh, Pakistan, and Sri Lanka. The overall accuracy of each product was found to be above 70%.

Table 7. Crop classification using RS and ML techniques in India.

Crop/Season/ Features	Input	Functionality	Algorithm	Result	Reference
Rabi season	Satellite: Sentinel-2	Classify rabi season crop in IARI, New Delhi	RF, SVM and CART	Best model: RF OA: 93.3%	[40]
Paddy, sugarcane, jasmine, turmeric, banana, lemon	Satellite: Sentinel-2	Crop classification using Sentinel-2 in Guntur region of Andhra Pradesh	SVM, RF, CNN, RNN-LSTM, RNN-GRU	Best model: SVM F1 score = 0.99 estimated crop areas have 95.9% agreement with the ground surveyed crop area	[41]
wheat, corn, linseed, lentil, mustard, barley, and other crops	Resourcesat-2: LISS IV sensor data	Crop classification in Varanasi, Uttar Pradesh	SVM, ANN, SAM	Best model: SVM OA = 93.45%	[42]
Cotton, gram	Satellite: IRS P6 RESOURCESAT-2 LISS-IV sensor data	Crop discrimination in Maharashtra	SVM, O-SVM	Only 2% improvement in accuracy was achieved with an optimization of SVM.	[43]

Table 7. *Cont.*

Crop/Season/ Features	Input	Functionality	Algorithm	Result	Reference
Sugarcane	Crowdsourced data: Plantix (point) Satellite data: Sentinel-2 (10 m), SRTM (90 m), MODIS-IGBP (250 m), MODIS-water mask (250 m), Copernicus Global Land Service (100 m), Google Static Map (0.3 m), Airbus (1.5 m) District-level statistics on sugarcane area provided by Indian Government	Sugarcane classification in Maharashtra, Central India	SC: 1DCNN USC: k-means HCSC: SC + USC	Best model: 1DCNN OA: 77% F1 score: 0.77 = 5	[44]
Rice, betelvine, vegetables and others	RS variable: NDVI Satellite: Sentinel-2	Crop type estimation in Tamluk sub-division of West Bengal	k-NN, RF	Best model: RF OA: 97.22%	[45]
Early wheat, mid wheat, late wheat, Desi gram, hybrid gram, garlic, potato, fallow land	RS variable: Band 2—Band 12 Satellite: Sentinel-2	Crop classification in Lakoda Gram Panchayat, Ujjain, Madhya Pradesh	RF, NB	Best model: RF Kappa coefficient: 0.93	[46]
Wheat	RS variable: Band 2, Band 3, Band 4, Band 8 Satellite: Sentinel 2A	Wheat mapping in Maharajganj, Uttar Pradesh, India	RF, SVM	Best model: RF Kappa coefficient: 0.84	[47]
Wheat, sugarcane, fodder	RS variable: NIR, RegEdge-1, RedEdge-2, RedEdge-3 Satellite: Sentinel-2A	Mapping major crop types in Roorkee, Uttarakhand	RF, SVM, SGB, XGB, AdaBoost	Best model: XGB OA: 86.91%	[48]
Cropland and non-cropland	RS variable: Band 2–Band 7, Band 10, NDVI, NDWI, EVI Satellite: Landsat-8	Cropland mapping in South Asia (India, Nepal, Bangladesh, Pakistan, Sri Lanka)	RF	OA: 88.7%	[49]
Crop mapping	RS variable: Band 2–Band 7, Band 10 (Landsat-8), NDVI, EVI, NDWI Satellite: Landsat-8 (for mapping of irrigated and rainfed cropland areas), MODIS (for crop type and cropping intensity mapping)	Mapping of - irrigated and rainfed cropland areas - Crop types Cropping intensity in South Asia	RF	Overall accuracy - Irrigated and rainfed crop map: 79.8% - Cropping Intensity map: 85.3% Crop type map: 63–98%	[50]
Sugarcane	Satellite: Sentinel 1 and Sentinel 2	Classify plant and ratoon sugarcane type in Uttar Pradesh	SVM and RF	Best model: RF OA: 90.75%	[51]

Table 7. *Cont.*

Crop/Season/ Features	Input	Functionality	Algorithm	Result	Reference
Rice	Satellite: Sentinel 1A and Sentinel 2B	Paddy acreage mapping using Sentinel-based optical and SAR data in Jharkhand	RF	OA Sentinel 2B: 91% Sentinel 1A: 90%	[52]
Kharif season (major crop: rice, cotton)	RS variable: VV, VH, ratio, Diff, GCVI Satellite: Sentinel-1, Sentinel-2 Crowdsourced data: Plantix	Crop type mapping in Andhra Pradesh and Telangana	RF, 1D CNN, and 3D CNN	Best model: 1D CNN OA = 74%	[53]
Kharif season (rice, maize, fingermillet)	RS variable: VV, VH, NIR, SWIR Satellite: Sentinel-1, Sentinel-2	Crop classification in Mandar, Ratu and Kanke block of Jharkhand	RF	OA: 83.87%	[54]
Soyabean	RS variable: VH, NDVI Satellite: Sentinel 1, Sentinel 2	Soyabean mapping in Latur district of Maharashtra	Object based (OB): RF, XGB, SVM	Best model: OB-XGB Kappa coefficient: 0.82	[55]
Wheat, mussor, potato, mustard, gram, fallowland	RS variable: Band 2-Band 7, NDVI, VV, VH, Satellite: ALOS DEM, Landsat-8, MODIS NDVI, RISAT, Sentinel-1A	Crop discrimination in Mathura district of Uttar Pradesh	RF, GBM	Best model: RF OA: 93.1%	[56]
Rice, soyabean, maize, pigeonpea	Satellite: Sentinel 1 and RADARSAT-2	Classify *Kharif* crop in Madhya Pradesh	SVM, RF, MLC, SAM	Best model: SVM OA: 79.7%	[57]
Rice, sugarcane, cotton, banana, fallow, mixed fields	Satellite data: HH, VV, HV Satellite: RADARSAT-2	Crop classification in Andhra Pradesh	SVM, KPA-based SVM	Best model: KPA-based SVM OA = 89%	[58]
Pearlmillet	RS variable: Volume scattering, Double Bounce, entropy, alpha angle Satellite: Sentinel-1. RADARSAT-2	Pearlmillet discrimination in Agra, Uttar Pradesh	DT, SVM, RF	Best model: RF OA: 89.1%	[59]
Maize	RS variable: HH, HV, VH, VV, volume scattering, double bounce, entropy, alpha angle Satellite: Sentinel-1, RADARSAT-2	Maize crop mapping in Nashik district, Maharashtra	DT, SVM, RF	Best model: DT OA: 84%	[60]
Tea	ASD FieldSpec 3 Spectroradiometer	Classify tea varieties in Munnar, Kerala	k-NN, LDA, SVM	Six out of nine tea plant varieties could be discriminated with accuracies between 75% and 80%.	[61]

Table 7. *Cont.*

Crop/Season/ Features	Input	Functionality	Algorithm	Result	Reference
Sugarcane, cotton, mulberry	Satellite: IPD-AVIRIS, EO-1 Hyperion	Crop identification in Maharashtra from hyperspectral remote sensing images	CNN	IPD: 97.58% accuracy, EO-1 Hyperion: 79.43% accuracy	[62]

4.1.2. Yield Prediction

Yield prediction is of high importance for yield mapping and crop management to increase the quality and productivity, and subsequently matching crop supply with demand. Further, crop yield prediction plays a crucial role in maintaining food security. It is of utmost importance in a developing country like India, where growing population, heterogeneous agricultural fields, and poor management practices impose a range of uncertainties on the yield prediction and hence on crop management. The studies evaluated under the yield prediction sub-category are tabulated in Table 8.

Table 8. Yield prediction using RS and ML techniques in India.

Crop	Input	Functionality	Algorithm	Scale	Result	Reference
Rice	RS variable: NDVI Satellite: Sentinel 1A and Sentinel 2B	Rice yield prediction in Sahibganj district of Jharkhand	RF	Regional	Rice yield was predicted as 1.60 metric tons/hectare	[52]
Sugarcane	Inputs (a) RS variable: NDVI (b) Meteorological: temperature, dew point temperature, soil temperature, soil moisture, precipitation, relative humidity, sunshine duration, evapotranspiration Satellite: LANDSAT 8	Sugarcane crop yield forecasting in Karnataka	SVR, LR, NB, DT, SVR-RBF	Regional	Best model: SVR-RBF OA = 83.49%	[69]
Rice	RS variable: NDVI Meteorological data: RF, Temperature, SR, RH Satellite: LANDSAT 8	*Kharif* rice production in Purulia and Bankura districts of West Bengal	ANN, RF	Regional	Purulia–Bankura district combined ANN models with Boruta feature selection and random forest variable importance ranged from 0.651 to 0.663.	[70]
Wheat	Inputs (a) RS variable: NDVI, NIRv, NDWI (b) Meteorological variable: Tmin, Tmax, Tmean, RF, VPD, SWdown, day length Satellite: MODIS	Wheat yield prediction in India	CNN, RF, RR	IGP	Best model: CNN with NSE of 0.868	[71]
Sugarcane	RS variable: RVI, NDVI, SAVI, OSAVI, DVI, GCI, EVI, ARVI, VARI, NDMI, NDWI, NN, NG Satellite: LANDSAT-8	Sugarcane yield prediction in Uttarakhand	SVR, CART, k-NN, RF	Regional	Best model: RF with R^2 = 0.94 and RMSE = 1.51 t/ha	[72]
Sugarcane	RS variable: NDVI, WSI, APAR, CWSI (NDVI/Ts) Satellite: LANDSAT 8	Field scale Sugarcane yield estimation in Andhra Pradesh	ANN	Field	Estimated sugarcane yield with 95% accuracy	[73]

Table 8. *Cont.*

Crop	Input	Functionality	Algorithm	Scale	Result	Reference
Cotton	Inputs (a) RS variable: NDVI (b) Meteorological: RF Satellite: MODIS	Cotton yield prediction in Maharashtra	RF	Regional	September month: R^2 = 0.69	[74]
Rice	Inputs (a) RS variable: MODIS-LAI (b) Observed yields from 2003–2017 were obtained from the Directorate of Economics and Statistics (DES), the mandated organization under the Ministry of Agriculture (MoA) for collecting and reporting agricultural production data in India. Satellite: MODIS	Yield estimation in 18 Indian states	GBR	Regional	Validation for the years 2016 and 2017, proved successful with R^2 = 0.84 and R^2 = 0.77	[75]
Sugarcane	RS variable: NDVI, EVI, LAI, FPAR, ET, PET, LE, GPP, RF Satellite: MODIS, CHIRPS	Sugarcane yield forecasting in Uttar Pradesh	RF, SVR, GBR, XGB	Regional	Best model: GBR R^2 = 0.66 RMSE = 7.15 t/ha	[76]

The analysis of the selected articles indicated that the studies differ with scale (ranging from field level to country level), ML algorithm (SVR, ANN, k-NN, GBR), platform (Sentinel, MODIS, LANDSAT), and crop (rice, wheat, sugarcane, arhar/tur). LANDSAT-8 satellite data with 30-meter resolution were effectively utilized for regional yield forecasting [69–73], followed by the images retrieved from MODIS [74–76]. Wolanin et al. conducted wheat yield prediction in the Indo Gangetic Plains. The authors utilized CNN, RF and RR, and ML algorithms to predict wheat yield and found CNN to be the best model for wheat yield prediction, with an NSE of 0.868 [71]. Coarse-to-medium spatial resolution systems like MODIS and Landsat struggle to accurately estimate crop production, as they cannot distinguish small individual fields, resulting in mixed pixels influenced by other landscape components. However, the operational deployment of the Sentinel-2 satellite systems (2A in 2015 and 2B in 2017) offers key spectral wavelengths at 10–20 m resolution, a short revisit period, and open-access data, enabling more frequent high-resolution observations of agricultural fields. This advancement opens new possibilities for satellite-based crop production estimation in Indian smallholder systems. High resolution optical (Sentinel 2) and microwave (Sentinel 1) dataset was effectively utilized for rice yield prediction in Jharkhand [52]. Kurupavathi et al. estimated field-scale yield using medium resolution Landsat 8 satellite data with 95% accuracy [73].

4.1.3. Disease and Pest Detection

Plant diseases and pests pose significant threats to global vegetation [77]. Precisely locating and assessing the extent and severity of these occurrences is crucial for guiding plant protection measures. Remote sensing serves as a "radiodiagnosis" approach, offering non-contact and continuous monitoring of diseases and pests efficiently [78]. The early studies and applications of this technique date back to the 1980s, and Nilsson [79] demonstrated various applications of remote sensing and image analysis in plant pathology. As computer science and sensing technology rapidly advance, a wide spectrum of remote sensing data is now employed for detecting diseases and pests.

In the work of Patil et al. [80], the authors utilized SVM, RF, and ANN algorithms for detection of blight in potato. Selvaraj et al. [81] presented a method for identifying five major banana diseases, such as Xanthomonas wilt of banana (BXW), Fusarium wilt of banana (FWB), black sigatoka (BS), yellow sigatoka (YS), and banana bunchy top disease (BBTV), along with the banana corm weevil (BCW) pest class using CNN architecture. The two studies in Table 9 [82,83] are dedicated to the detection and classification of diseased and healthy rice crops. Ramesh and Vydeki used KNN and ANN algorithms to discriminate crops affected by rice blast from the healthy rice crop [82]. Shrivastava and

Pradhan aimed at the accurate detection of a range rice plant diseases, such as bacterial leaf blight, rice blast, and seath blight from the healthy rice crop based on digital imagery and SVM algorithm [83]. In the literature by Chauhan et al. [84], maize diseases were detected based on digital imagery and SVM, DT, NB, KNN, and RF algorithms. Singh et al. utilized the capability of both thermal and visual images to quantify the severity of stripe rust in wheat crop using SVM and ANN techniques. The performance of SVM was found to be better in comparison to ANN [85].

Table 9. Disease prediction using RS and ML techniques in India.

Crop	Input	Functionality	Algorithm	Result	Reference
Potato	892 potato leaf images	Potato blight disease detection, Dharwad, Karnataka	SVM, RF, ANN	Best model: ANN Overall accuracy: 92%	[80]
Banana	18,000 field images of banana, collected by banana experts, from Bioversity International (Africa) and Tamil Nadu Agricultural University (TNAU, Southern India) Images collected from various sources like cellphones, tablets and a standard RGB camera	Identification of 5 major banana diseases such as, Xanthomonas wilt of banana (BXW), Fusarium wilt of banana (FWB), black sigatoka (BS), yellow sigatoka (YS), and banana bunchy top disease (BBTV), along with the banana corm weevil (BCW) pest class	CNN	Accuracy: 70–99%	[81]
Rice	Image captured using digital camera	Rice blast disease detection in Tamil Nadu	k-NN, ANN	Best model: ANN Accuracy: 99%	[82]
Rice	619 images captured using digital camera	Rice plant disease (bacterial leaf blight, rice blast, seath blight) and healthy leaf classification in Raipur, Chattisgarh	SVM	Accuracy: 94.65%	[83]
Maize	3823 photographs and labels for four categories of diseases such as common rust, gray hair, leaf damage to the north, and health with 1192 images, 513 images, 956 images, and 1162 images, respectively.	Detection of maize disease	SVM, DT, NB, k-NN, RF	Best model: RF Accuracy: 80.68%	[84]
Wheat	Images captured using thermal camera	Estimation of stripe rust severity	SVM, ANN	Best model: SVM Accuracy: 98% R^2: 85%	[85]

4.1.4. Weed Detection

Weed detection in crop fields and its management poses another significant issue in agriculture. Weeds are the most significant threat to crop production, as they induce competition for nutrients, water, and sunlight, which are ascertained to the target crop. Weed detection is of high importance to sustainable agriculture, as weeds are difficult to detect and discriminate from the crops. In this regard, RS sensors in conjunction with ML algorithms can lead to the accurate detection of weeds with low cost and without any negative impact on the environment. Shorewala et al. estimated weed density and distribution using a CNN model with an overall accuracy of 82.13% [86] (Table 10).

Table 10. Weed detection using RS and ML techniques in India.

Properties	Observed Attributes	Functionality	ML Algorithm	Result	Reference
Weed density	RGB (red green blue) image	Weed density and distribution estimation	CNN	Accuracy: 82.13% Recall: 0.99	[86]

4.2. Water Management

Water is a prime contributing factor to the amount and quality of the developed yields. Crop water stress hinders the crop physiological processes. Water management plays a significant role in agronomical, hydrological, and climatological balance. It is particularly important in those areas where irrigation is a key component to attaining the desired crop quality and crop yield. Also, for irrigation management and scheduling, one should know the quantity and timings of the water supply, which can be determined with a proper spatial evolution of plant water stress [87].

This section is based on the detection of two water-based properties that can severely affect the growth and development of the crop: (i) drought and (ii) water stress. The first three studies in Table 11 [88–90] deal with drought prediction using satellite-derived variables and different ML algorithms. Dhyani et al. and Singh et al. utilized CNN and ANN models for drought detection in Karnataka and Maharashtra, respectively [88,89]. In the literature by Prodhan et al., a comparison between ML (GBM, RF)- and DL (DFNN)-based models has been made [90]. The aim of the study was to detect drought in South Asia using different satellite-derived variables from different satellite products and ML/DL algorithms. The authors evaluated better performance of DFNN for drought detection over South Asia. The last three studies in Table 9 were based on the evaluation of water stress in rice crop [91,92] and maize crop [93] using hyperspectral remote sensing and UAV based imagery, respectively.

Table 11. Water management using RS and ML techniques in India.

Properties	Observed Attributes	Functionality	ML Algorithm	Result	Reference
Drought	RS variable: NDVI, SMI Satellite: LANDSAT-8	Drought prediction in northern Karnataka	CNN	OA: 96%	[88]
Drought	RS variable: NDVI, LST, SMI, TCI, VCI, RF, soil moisture Satellite: TRMM, AMSR-E, MODIS,	Drought prediction in Sangli, Maharashtra	ANN	OA: 92%	[89]
Drought	RS variable: Predictor variable: NDVI, RF, SPEI, PCI, PAI, EDI, VCI, VHI, THI, Response variable: SMDI Satellite: MODIS, MERIS and SPOT-Vegetation, GLDAS-NOAA, CHIRPS, AVHRR-GIMMS	Drought prediction	DFNN, GBR, DRF	Best model: DFNN SMDI had high correlation coefficient R^2 ranges from 0.57~0.90, 0.52~0.94, and 0.49~0.82 during the start of the season (SOS), length of the season (LOS), and end of the season (EOS), respectively	[90]

Table 11. *Cont.*

Properties	Observed Attributes	Functionality	ML Algorithm	Result	Reference
Water stress	RS variable: WBI, MSI, NDWI, hNDVI, NDII, MDWI, RI, SRWI Platform: ASD Field Spec 3 Spectroradiometer	Water deficit stress monitoring in rice crop in IARI, New Delhi	PLSR-MLR, PLSR-ANN, SVR, RF, PLSR, ANN	Best model: PLSR-MLR R^2 = 0.98 and 0.97 for calibration and validation, respectively	[91]
Water stress	RS variables: SR, NDVI, WI, MDWI, NWI, fWBI, 1650/2220 nm ratio, RSI, NDSI Visible-near infrared spectroscopy	Water deficit stress monitoring in rice in IARI, New Delhi	PLSR, SMLR, GPR, SVR, and RF	Best model: PLSR R^2 = 0.943	[92]
Water stress	UAV-based remote sensing	Water stressed areas in maize crop in Hyderabad, Telangana	CNN	OA: 95% on train data and 93% on test data Precision: 0.9370 F1 score: 0.9403	[93]

4.3. Soil Management

Soil is a heterogeneous natural resource, entailing intricate mechanisms that pose challenges in comprehension. Soil properties plays a pivotal role in deciphering ecosystem dynamics and their impact on agriculture. Thus, accurate estimation of the soil conditions holds the potential for refined soil management and consequently enhanced agricultural practices. Nonetheless, gauging soil properties typically involves a resource-intensive and time-consuming process, prompting the pursuit of a cost-effective and dependable solution. This can be realized by leveraging readily available Remote Sensing (RS) datasets in conjunction with Machine Learning (ML) techniques.

This specific category encompasses the application of RS in tandem with ML algorithms to predict agricultural soil properties, encompassing aspects like soil nutrients, soil salinity, and soil moisture content. The first three studies (referenced as [94–96] in Table 12) delve into estimating soil nutrients such as nitrogen, phosphorus, potassium (NPK), and soil organic carbon (SOC). For instance, Tiwari et al. harnessed hyperspectral remote sensing (Hyperion) in tandem with ANN technique to map soil organic carbon content [94]. In contrast, Kaur et al. integrated optical remote sensing (Sentinel-2, LANDSAT-8), terrain, and climatic data, employing RFR, SVR, and GBR techniques to estimate NPK and SOC in the Pune and Ahmednagar districts of Maharashtra [95]. Kalambakattu et al., on the other hand, leveraged Landsat 8 and CartoDEM datasets to map soil organic carbon and available nitrogen in Himachal Pradesh's hilly terrain [96]. The assessment and mapping of soil moisture play a pivotal role in determining irrigation needs in agriculture [97]. Backscattering measurements of microwaves from Synthetic Aperture Radar (SAR) sensors have demonstrated promise in effectively monitoring moisture content. Given Sentinel-1's (C-band) high temporal sampling and operational setup, it has significantly contributed to soil moisture monitoring. References [98,99] employed Sentinel 1 data in combination with various ML techniques to map soil moisture across diverse regions in India. In contrast, Das et al. exclusively utilized optical remote sensing datasets (Sentinel 2 and Landsat 8), employing a fusion of ensemble models (RF, Cubist, and GBM) to enhance soil moisture mapping accuracy [100]. Rani et al. introduced an innovative technique for estimating salt-affected soils, employing the Random Forest (RF) algorithm with NDVI data from MODIS, reflectance data from LANDSAT-8, and elevation data from ALOS [101]. Similarly, Kalambakattu et al. [102] and Vibhute et al. [103] harnessed the potential of the Hyperion dataset and Support Vector Machine (SVM) algorithm to map soil salinity severity and soil types, respectively. The digital soil maps can help farmers and decision makers in utilizing precision information for farm-scale decision making leading to increased pro-

ductivity through optimal nutrient use and ecosystem sustainability, ultimately securing food supplies. A unique methodology was developed by Kumarapermual et al. [104], to map three soil attributes and three soil taxonomical units using suite of 6 ML algorithms and 39 environmental covariates derived from RS dataset. The contribution of climate and topography was found substantial in digital soil mapping.

Table 12. Soil management using RS and ML techniques in India.

Soil Properties	Observed Attributes	Functionality	ML Algorithm	Result	Reference
Soil nutrient	Satellite: EO1-Hyperion (400–2500 nm) hyperspectral image dataset, field spectroscopy	Soil organic carbon content mapping	ANN	ANN predictive modeling technique with combination of hyperspectral performed well and carried out a good result for all three datasets, images, and field and lab scales, with almost similar values of performance statistics: R^2 0.93, 0.92, and 0.95, respectively	[94]
Soil nutrients	Input: (1) Satellite: Colouration Index, Brightness Index, Hue Index, and Redness Index (2) Terrain: Terrain wetness index, Stream Power Index and slope Satellite used: LANDSAT-8, CartoDEM (30 m)	Digital mapping of soil nutrients (soil organic carbon and available nitrogen) in Mandi district of Himachal Pradesh	ANN	For SOC R^2: 0.83 and MSE: 0.05 For available nitrogen R^2: 0.62 and MSE: 0.0006	[95]
Soil nutrients	Input: (1) Satellite: BI, SI, HI, CI, RI, NDVI (2) Terrain & climatic: elevation, alope, Aspect, RF, flay, radiation, silt, sand, flow direction Satellite used: LANDSAT-8, Sentinel-2 (April to May 2016)	Prediction of soil nutrients (NPK and OC) in 2 districts of Maharashtra	MLR, RFR, SVR, GBR	Best model: RFR with lowest MAPE in range of 0.125–0.362	[96]
Soil moisture	Variables used: VV, VH Satellite: Sentinel-1	Soil moisture retrieval under different crop types (wheat, corn and barley) in Varanasi district of Uttar Pradesh	RFR, SVR, ANN	The soil moisture retrieval performance achieved by RFR and SVR was good in comparison to the ANN	[98]

Table 12. *Cont.*

Soil Properties	Observed Attributes	Functionality	ML Algorithm	Result	Reference
Soil moisture	Variables used: VV, VH Satellite: Sentinel-1 C band SAR data	Estimation of soil moisture content in Midnapore, West Bengal	SVM, k-NN, RF,	Best model: RF R^2 = 0.87 and 0.93 during modeling and validation, respectively; RMSE: ~0.03)	[99]
Soil moisture	Variables used: backscatter coefficient, NIR, SWIR, NDWI, modified NDWI, LST Satellite: Sentinel-1, Landsat-8	Digital soil moisture mapping in agricultural farm of Indian Agricultural Research Institute, Delhi	Cubist, RF, GBM, Stacking (RF + GBM + Cubist)	Best model: Stacking RMSE: 5.03%	[100]
Soil salinity	Satellite data: (a) MODIS NDVI (b) LANDSAT 8: Reflectance data (c) ALOS: DEM	Identification of salt-affected soils in Unnao, Uttar Pradesh	RF	RF identified 41,224.95 hac salt-affected area, which is 99.34% of the legacy data	[101]
Soil salinity	Variables used: DSI, SI, SAVI, NDWI Satellite data: Hyperion	Soil salinity severity mapping in Mathura district of Uttar Pradesh	SVM	Overall accuracy: 78.13%	[102]
Soil type	Hyperion	Soil type classification (brown sandy soil, black sandy soil, black clay soil, red sandy soil, gray clay soil) in Aurangabad district of Maharashtra	SVM	OA: 71.18%	[103]
Soil quality and quantity	Variables used: 39 covariates listed under climate, relief, organisms and parent material Satellite data: Landsat-8, SRTM, WorldClim 2.1	Qualitative and quantitive digital soil mapping in Tamil Nadu Quantitative soil traits: pH, OC, CEC Qualitative soil traits: Order, suborder and great group	MLR, k-NN, RF, SVM, SVR, NB, Cubist	Best model: RF For quantitative traits (RMSE): - pH: 0.75 - OC: 0.26 - CEC: 8.84 For qualitative traits (OA): - Order: 67% - Suborder: 65% - Great group: 65%	[104]

Farmers traditionally base their irrigation decisions on experience. Now, advanced technologies allow them to predict crop water needs based on weather and soil forecasts, leading to more informed choices. The integration of IoT and wireless sensor network technologies for smart agriculture application through remote sensing has provided valuable insights into weather, soil, and crop conditions throughout the growing season. The platforms lacking ML or mathematical based models are less effective. ML proves to be

a powerful tool, emulating human-like capabilities and exhibiting an inherent commitment to enhancing machine intelligence [105,106]. It effectively addresses complex issues in irrigation systems, handling multivariable, non-linear, and time-varying factors [107]. Therefore, by leveraging massive spatial and temporal data stored in cloud or edge-based servers, smart decisions on irrigation management can be made using various ML-based models.

5. Conclusions

A total number of 54 studies were included in this review article. The collection of chosen articles exhibited considerable diversity. Among the 54 studies, 9 were published as conference papers and the remaining in scientific journals. Specifically, the *GeoCarto Journal* featured 7 of the selected research articles, whereas *Journal of Indian Society of Remote Sensing* hosted 6 articles. Journals such as *International Archive of Photogrammetry, Remote Sensing* as well as *Spatial Information Science*, each hosted 5 articles. Journals that featured 3 articles apiece include *Remote Sensing Applications: Society & Environment* and *International Journal of Remote Sensing*" and *Remote Sensing*. Additionally, 2 articles each were contributed to journals *like International Journal of Engineering Research & Technology*, *International Journal for Innovative Engineering & Management Research*, *Remote Sensing of Environment*, and *GIScience & Remote Sensing*. The remaining articles were published across a range of journals, including *Spatial Information Research*, *Arabian Journal of Geoscience*, *Plant Methods*, *Journal of Earth System Science*, *Advances in Remote Sensing*, *Environmental Research Letters*, *Agricultural Water Management*, *Spectrochimica Acta*, *International Journal of Advanced Remote Sensing & GIS*, *Environmental Earth Science*, *Land* and *Catena*. Delving into the content, a notable 38 articles concentrated on the integration of Machine Learning (ML) and Remote Sensing (RS) technology for crop management. In contrast, 6 articles revolved around water management, while 10 articles centered on soil management. This distribution is elucidated further in Figure 4, which visually delineates the selected studies' allocation according to the application of RS and ML technology within distinct agricultural domains.

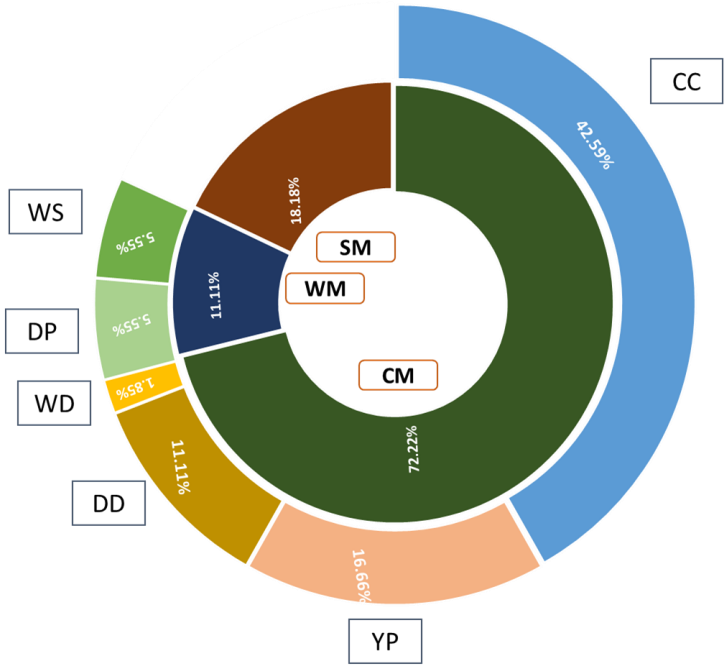

Figure 4. Pie chart showing classification of the reviewed studies in different agriculture domains. The abbreviations in the rectangle form represents the following: CM = crop management, WM = water management, SM = soil management; CC = crop classification, YP = yield prediction, DD = disease detection, WD = weed detection, DP = drought prediction, WS = water stress prediction.

Within the category of crop management, most of the studies were ascribed to crop classification, followed by crop yield prediction, disease detection, and weed identification. Under the soil management category, three studies each were allocated to soil nutrient prediction and soil moisture mapping. Concurrently, two studies centered on delineating soil salinity severity, and a single study focused on classification of soil types. In the water management category, three studies were conducted to predict drought in different regions of India and three studies were carried out to predict the water stress in different crops (rice and maize) using a spectroradiometer and UAV remote sensing technology.

Throughout these studies, remote sensing technology was used in various forms, encompassing optical, microwave, hyperspectral remote sensing, and digital images. Based on the analysis of selected studies, a total of 27 studies exclusively based on optical remote sensing, whereas 6 studies harnessed the combined prowess of both microwave and optical data. On the other hand, 5 studies were exclusively based on microwave datasets. Moreover, among the available research, four studies aligned with hyperspectral and spectroscopy datasets, while digital imagery emerged as the sole avenue in predicting crop diseases. These multifarious remote sensing techniques are visually encapsulated in Figure 5, delineating their application across the diverse categories and sub-categories used in the study.

The investigation revealed the application of seven prominent categories of Machine Learning (ML) models across the selected studies, as detailed in Table 2 and depicted in Figure 6. Notably, variations within ensemble models (EMs)—such as RF, GBR, and XGB—featured prominently, encompassing a total of 31 instances. This prevalence was followed by the utilization of support vector models (SVMs), accounting for 28 occurrences, and neural networks (NNs) with 23 instances. EMs and SVM-based ML techniques were substantially utilized across the domains of crop classification, crop yield prediction, and soil management. On the other hand, NNs demonstrated exceptional effectiveness in identifying and classifying crop diseases, emerging as a prominent tool across all the scrutinized studies. Hence, the analysis underscores the predominant role of EMs in the spheres of crop, soil, and water management.

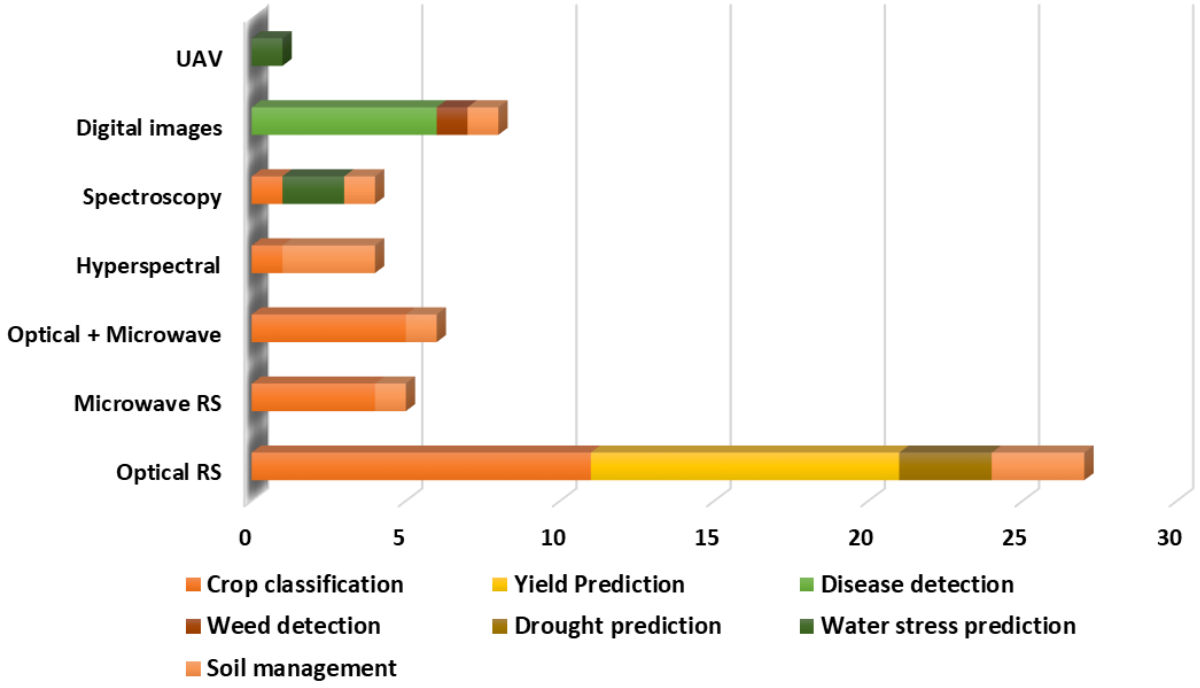

Figure 5. Usage of remote sensing technology within each sub-category.

The preference for EMs like RF over NNs is frequently influenced by practical considerations concerning data availability, computational resources, model complexity, interpretability, and ease of implementation. These factors collectively position the RF model as a versatile and pragmatic selection for diverse applications.

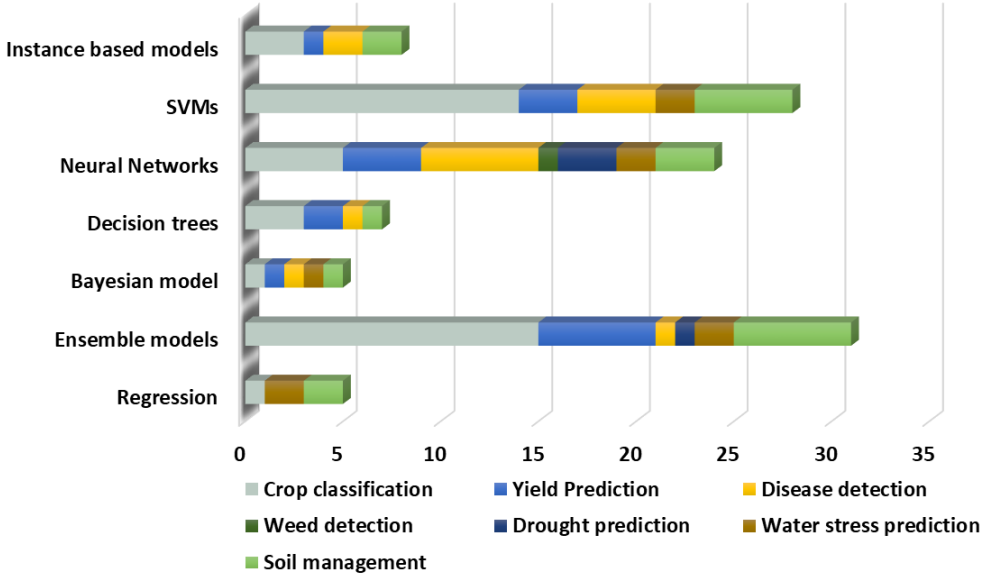

Figure 6. Number of machine learning algorithms used in each category and sub-category.

Leveraging machine learning on remote sensing data has widened the scope of evolving farm management systems into the real artificial intelligence systems. It can further provide a wide arena of smart decision-making with the ultimate aim of improving the quality and production of agriculture. Further, the increasing availability of various RS-based platforms imaging at varied scales along with a range of ML algorithms has the potential to boost even more research and development towards smarter, sustainable farming, preserving natural resources and protecting ecosystems.

5.1. Progress in Synergy of RS and ML Technologies in India

This subsection aims to assess the advancements of RS and ML technology in agricultural management within India. To achieve this, the studies were initially categorized based on the geographical regions where the research was conducted. These research endeavors spanned across diverse regions of India, encompassing approximately 60% of the nation's total land area (as illustrated in Figure 7). A discerning observation of the figure underscores that a majority of studies were undertaken in Uttar Pradesh (10), Maharashtra (9), Andhra Pradesh (4), Karnataka (4), West Bengal (3), Tamil Nadu (2), Jharkhand (2). Furthermore, a single study was conducted in each of the following states: Uttarakhand, Chhattisgarh, Telangana, Haryana, Kerala, Madhya Pradesh, and Himachal Pradesh. Notably, one study [72] estimated rice yield across 18 states in India, while another pair of studies [59,60] harnessed the prowess of cloud computing to classify crops based on irrigation type, crop category, and cultivation intensity across South Asia. Curiously, there is a dearth of studies from northeastern and Himalayan states, with the exceptions of Uttarakhand and Himachal Pradesh. This disparity in study distribution can be attributed to the varying levels of technological advancement in different states, coupled with the availability of suitable agricultural areas for study purposes.

The distribution of selected studies was further assessed on an annual basis, as illustrated in Figure 8. The trajectory of research from India concerning the confluence of RS and ML technologies exhibited substantial variability. As discernible from Figure 8, there was no consistent upsurge in studies spanning the years 2015 to 2019. Conversely, in 2019, there was a marked surge in the number of selected studies, constituting a sub-

stantial increase of 20.37%. The culmination of this trend, reaching its peak at 27.78%, was observed during the year 2022. The increasing number of published studies distinctly highlights the achievement of a particular degree of proficiency and competence in RS and ML technologies within India. The widespread adoption of these advanced methodologies bodes positively for the achievement of long-standing goals connected to sustainable and economically feasible agricultural practices across the nation.

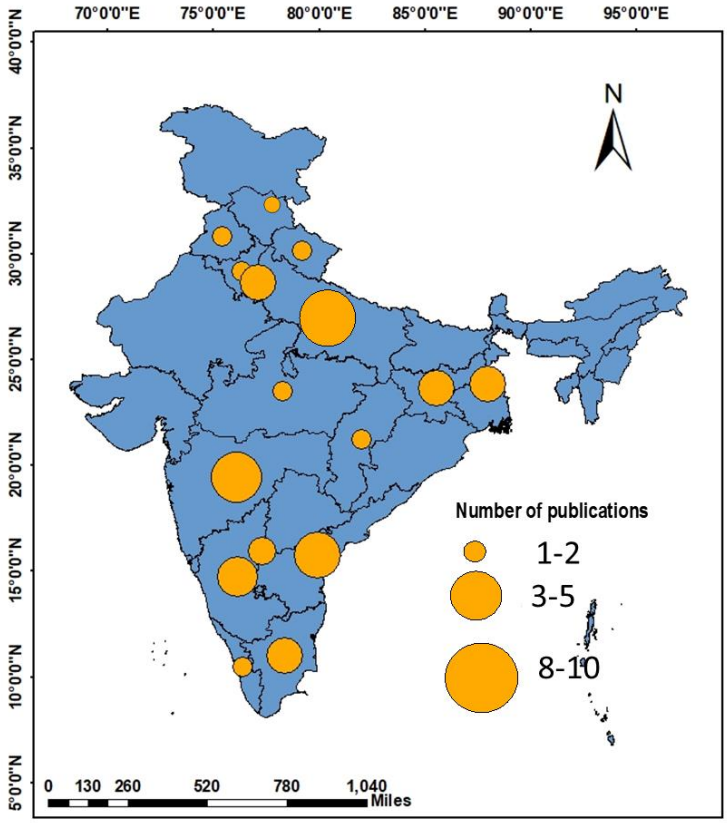

Figure 7. Geographical distribution of the selected articles from each state to the research field, focusing on remote sensing and machine learning applications in agriculture.

Figure 8. Bar chart representing the percentage of the selected articles from the year 2015 to 2022.

5.2. Digital Transformation: Pathway to Prosperity

Remote sensing provides robust, efficient, and reliable monitoring of agriculture. However, limited attention has been paid to how to adapt it for precision agriculture (PA) applications. PA applications require information at a much finer scale; there is a significant challenge to adopting methodologies across different scales. One exciting solution is to leverage high-resolution UAV technology to fine tune the satellite-derived variables in relation to the target crop. Machine learning (ML) technology provides a unique opportunity for the development of accurate and large-scale prediction [108]. ML algorithms with big data can solve extremely complex problems that cannot be solved via simple mathematical models [108]. One can use the crop phenotypic information extracted from the UAV technology to derive accurate satellite-based crop information at larger scales.

Simultaneously, there have been significant advances in crop growth modelling using mechanistic models [109–113]. These models predict the crop evolution from sowing to harvest by utilizing the weather, soil, and crop management information and simulating crop phenology, photosynthesis, dynamics of temperature and soil moisture, gas exchange between the crop canopy and atmosphere, biomass, and crop yield. Crop growth models are difficult to parameterize for large-scale applications, as the variability in terms of varieties, soil types, and crop management practices can vary hugely. In this regard, the assimilation of remotely sensed crop data with a crop simulation model is a promising approach. ML technology has emerged as a promising complimentary tool to the commonly used crop simulation modelling. Although current ML technology is deterministic, crop simulation models are also capable of handling non-experienced scenarios [108]. Machine learning could combine the benefits of remote sensing and crop simulation modelling to make reliable crop-based predictions. Figure 9 demonstrates the integration of remote sensing, machine learning, and crop simulation modelling for agricultural applications.

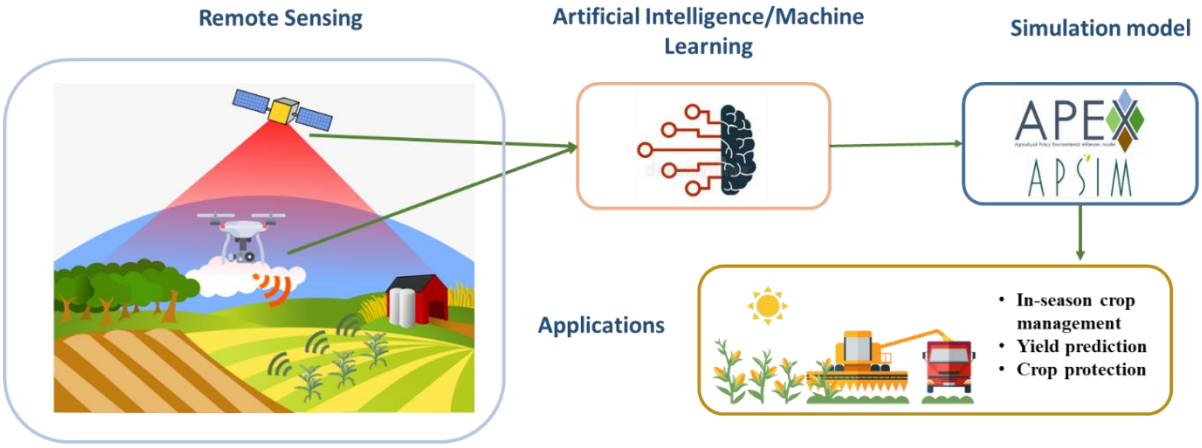

Figure 9. Digital transformation in agriculture representing integration of remotely sensed data, crop simulation, and machine learning. Figure modified from Jung et al. [108].

5.3. Limitations and Way Forward

The agriculture sector in India has yet to fully embrace advanced technologies. However, given the challenges posed by fast-degrading land, water scarcity, and climate change, it has become imperative to adopt modern technologies to ensure rational and efficient agriculture management. Although RS and ML techniques offer many advantages, they also have limitations. For instance, limited availability of RS data on cloudy days, especially the optical data, and the difficulty in real-time monitoring of crops. Additionally, the usage of UAV is not very prominent in India yet.

With regards to the ML technique, the high cost of cognitive solutions in the farming market is a barrier, making it essential to provide more affordable options for wider

adoption. An open-source platform could make these solutions accessible and increase understanding among farmers. To manage today's data accumulation and leverage technological advancements, farms need decision support systems (DSSs) tailored to their specific cultivation systems. DSSs with advanced algorithms can process vast amounts of data and parameters that would be impossible for farmers to handle manually. However, the high infrastructure investment costs frequently prevent farmers from adopting these technologies.

This study highlights the current scenario of remote sensing and machine learning technology in the agriculture domain in India. It is imperative to smartly manage Indian agriculture to sustain a huge percentage of the Indian population. In this regard, leveraging advanced technologies seems to constitute one of our best hopes to meet the emerging challenges. The availability of huge datasets, along with advanced technologies, can in the future lead to smart farming by adopting the decision support systems in relation to diverse cultivation systems in India. The integration of sensors, automatic data recording, ML technology, satellite datasets, UAV datasets, and decision support systems will provide a framework to increase crop production and improve crop quality. ML and RS will definitely provide a holistic framework for establishing sustainable agriculture. In this regard, it is anticipated that the present systematic review will constitute a beneficial guide to governmental policymakers, researchers, developers, and farmers. Consequently, this study adds considerable knowledge to the existing literature in the form of a comprehensive analysis of advances of ML and RS in Indian agriculture, with a holistic overview.

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