



Review

# Precision Irrigation Management Using Machine Learning and Digital Farming Solutions

Emmanuel Abiodun Abioye <sup>1,\*</sup>, Oliver Hensel <sup>2</sup>, Travis J. Esau <sup>3</sup>, Olakunle Elijah <sup>4</sup>,  
Mohamad Shukri Zainal Abidin <sup>5</sup>, Ajibade Sylvester Ayobami <sup>6</sup>, Omosun Yerima <sup>7</sup> and Abozar Nasirahmadi <sup>2</sup>

- <sup>1</sup> Electrical/Electronic Engineering Department, Akanu Ibiam Federal Polytechnic, Unwana 480854, Ebonyi State, Nigeria
- <sup>2</sup> Department of Agricultural and Biosystems Engineering, University of Kassel, 37213 Witzenhausen, Germany; agrartechnik@uni-kassel.de (O.H.); abozar.nasirahmadi@uni-kassel.de (A.N.)
- <sup>3</sup> Engineering Department, Faculty of Agriculture, Dalhousie University, Truro, NS B2N 5E3, Canada; tesau@dal.ca
- <sup>4</sup> Wireless Communication Center, School of Electrical Engineering, Faculty of Engineering, Universiti Teknologi, Skudai 81310, Malaysia; elij.olak@yahoo.com
- <sup>5</sup> Control and Mechatronics Engineering Division, School of Electrical Engineering, Faculty of Engineering, Universiti Teknologi, Skudai 81310, Malaysia; shukri@utm.my
- <sup>6</sup> Department of Geography and Remote Sensing, Nigerian Defense Academy, Kaduna 800281, Nigeria; ajibadeslyve957@gmail.com
- <sup>7</sup> College of Engineering, Micheal Okpara University of Agriculture, Umudike 7267, Abia State, Nigeria; omosunyerima@gmail.com
- \* Correspondence: abioyeabiodun1@gmail.com



**Citation:** Abioye, E.A.; Hensel, O.; Esau, T.J.; Elijah, O.; Abidin, M.S.Z.; Ayobami, A.S.; Yerima, O.; Nasirahmadi, A. Precision Irrigation Management Using Machine Learning and Digital Farming Solutions. *AgriEngineering* **2022**, *4*, 70–103. <https://doi.org/10.3390/agriengineering4010006>

Academic Editors: Petr Bartos and Lubos Smutny

Received: 6 December 2021

Accepted: 20 January 2022

Published: 1 February 2022

**Publisher's Note:** MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



**Copyright:** © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

**Abstract:** Freshwater is essential for irrigation and the supply of nutrients for plant growth, in order to compensate for the inadequacies of rainfall. Agricultural activities utilize around 70% of the available freshwater. This underscores the importance of responsible management, using smart agricultural water technologies. The focus of this paper is to investigate research regarding the integration of different machine learning models that can provide optimal irrigation decision management. This article reviews the research trend and applicability of machine learning techniques, as well as the deployment of developed machine learning models for use by farmers toward sustainable irrigation management. It further discusses how digital farming solutions, such as mobile and web frameworks, can enable the management of smart irrigation processes, with the aim of reducing the stress faced by farmers and researchers due to the opportunity for remote monitoring and control. The challenges, as well as the future direction of research, are also discussed.

**Keywords:** precision irrigation; water; machine learning; mobile app; web app; smart agriculture; digitalization

## 1. Introduction

Globally, the agricultural sector utilizes about 85% of the available freshwater due to increasing population growth, creating the need for an increase in food production [1]. The conventional method of irrigation management is characterized by challenges such as low water-use efficiency and low productivity. In addition, the dynamics of climate change and global warming often affect the availability of the amount of rainfall needed to supply water for plants [2,3]. Similarly, plant water requirements and physiological processes are seasonal, varying from one plant to another, and are in turn influenced by environmental factors such as weather. The environment can be controlled in a greenhouse, but these factors are not easy to control in an open field-cultivation farm [4]. The varying environmental conditions need to be adaptively managed using precision irrigation systems.

Sustainable precision irrigation is a crucial step toward the attainment of food security, while also achieving water-saving measures to compensate for the uncertainty of rainfall

and the effect of water scarcity as a result of drought in many parts of the world. Precision irrigation scheduling is directed toward efficient water usage for each plant, where and when it is needed, in the right amounts, to compensate for water loss either through evapotranspiration, erosion or deep percolation, while preventing over- and under-irrigation [5–8]. With proper irrigation management through effective monitoring and optimal control, water can be saved, as well as providing a reduction in other indirect costs incurred from energy use in the form of electricity or fossil fuel for pumping, for optimal cost-effectiveness [9,10].

From the rapid successes seen in the integration of the Internet of Things (IoT) to wireless sensor network (WSN) technologies for smart agricultural application through remote sensing, the controlled monitoring of agricultural processes has enabled a better understanding of the changing dynamics of weather, soil, and crop conditions throughout the growing season. Real-time data can be pooled continuously using IoT-enabled sensors or devices, such as sensors from a point source or mounted on unmanned aerial vehicles (UAV)s, satellites, tractors, or movable irrigation platforms like lateral- or center-pivot-moving machines from the targeted field [11]. There are several available commercial platforms that are used to collect soil, plant, and weather data in real time but these may not be effective because there are no machine learning algorithms or data-driven mathematical models integrated with the system, the output of which will be in numbers, to make sense of the raw data [12]. Therefore, by leveraging on massive spatial and temporal variable data that are collected and stored in the various cloud- or edge-based servers, smart decisions can be made using different machine learning models [4,11].

Machine learning is a rapidly evolving technology for precision irrigation systems, due to its ability to mimic human decision-making while also addressing the multivariable, nonlinear, and time-variant issues affecting irrigation management. According to Chlingaryan et al. [13], machine learning serves as a powerful and flexible architecture for data-driven decision making, as well as expert intelligence on the system. Machine learning has emerged together with big data technologies, leveraging edge cloud computing, creating a new opportunity to make sense of and draw inferences from a great deal of data collected from various sensors, due to the system's ability to learn without being programmed [14].

To develop a sustainable precision irrigation system, the integration of modern technologies, such as computational intelligence and agro-hydroinformatics, and information technology plays an important role through the efficient management of sensed data regarding soil, plants, and weather [15,16]. These technologies will aid the translation of the raw data collected into irrigation decisions and actions on the farm or in greenhouses. This will further enable the optimization of the use of water for irrigation and electricity for pumping, as well as a reduction in labor costs and fatigue [17,18]. The main purpose of machine learning is to provide data from previous experiences and statistical data to the machine so that it can perform its assigned task of solving a specific problem [19]. Furthermore, the advancement of weather- and environment-based models in estimating crop water requirements have necessitated that farmers should have access to the easy monitoring and visualization of the various parameters on smartphones or other computer devices, to guide their decisions either manually or intelligently. Studies have also shown via a survey format that 90% of farmers agree that better irrigation management through the use of mobile and web applications can help to improve the yield and productivity of their farms [20].

Some previous review works have investigated the current trend in the area of smart monitoring and control of irrigation [6,8,21–23]. Numerous papers have explored the role of machine learning in enabling smart irrigation [14,24–30]; these are summarized in Table 1. The majority of these existing works have focused on the application of supervised and unsupervised learning for smart irrigation systems. This paper complements these existing works by reviewing and discussing the emerging areas of the application of machine learning and digital farming solutions to irrigation systems.

**Table 1.** Comparison of the proposed work with previous reviews of machine learning for precision irrigation management.

References	Supervised Learning	Unsupervised Learning	Reinforcement Learning	Federated Learning	Digital Farming Applications
[14]	✓	✓	✗	✗	✗
[24]	✓	✓	✗	✗	✗
[25]	✓	✓	✗	✗	✗
[26]	✓	✓	✗	✗	✗
[27]	✗	✓	✗	✗	✓
[28]	✓	✓	✗	✗	✗
[29]	✓	✓	✗	✗	✗
[30]	✓	✗	✗	✗	✗
This paper	✓	✓	✓	✓	✓

Based on the summary in Table 1, this review work has expanded the scope of the literature in this area of research. The contribution of this paper is to extend further the compendium of literature on machine learning for sustainable precision irrigation through the application of federated learning and the integration of digital farming solutions. The discussion in this paper is organized into various sections, which are as follows: Section 2 reviews the state of the art on the use of machine learning models for precision irrigation, while Section 3 focuses on the state of the art on the application of digital solutions, such as a mobile app–web framework for smart irrigation management. Next is Section 4, which examines the challenges and opportunities of applying machine learning to precision irrigation systems. Section 5 looks at future trends, while Section 6 concludes this paper.

## 2. Machine Learning Algorithms for Smart Irrigation

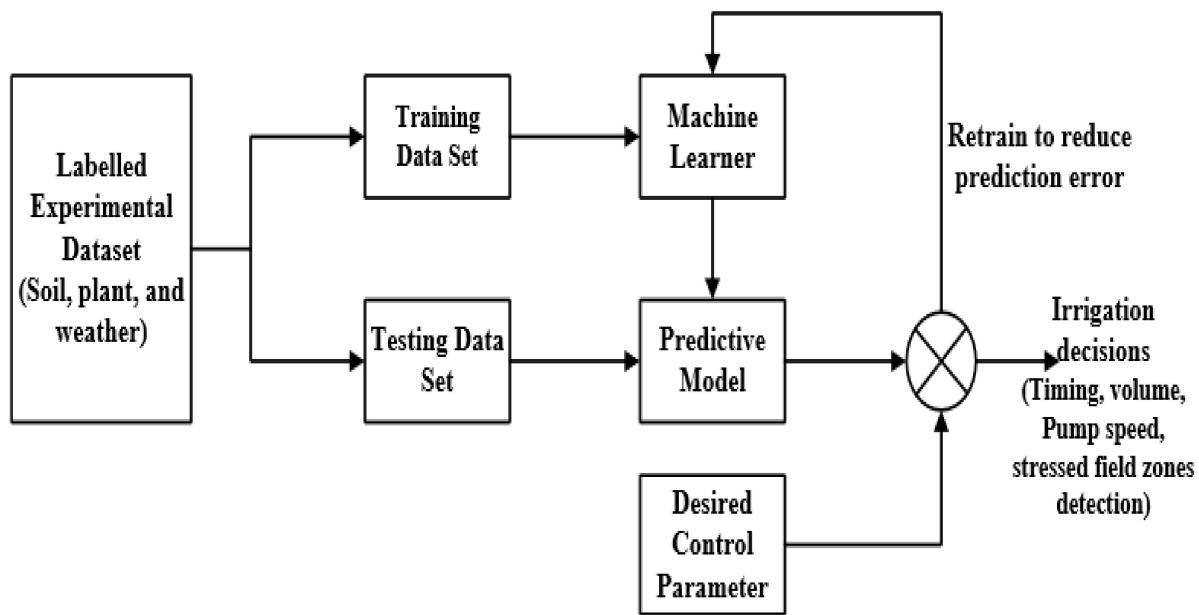
Machine learning is a branch of artificial intelligence that allows computers to learn without being explicitly programmed [31]. Machine learning models have emerged as an effective intelligence-based decision support tool for the rational and sustainable use of freshwater resources in the context of sustainable precision irrigation management. Traditionally, farmers make the decision to irrigate based on their previous experience; however, with advancements in machine learning, irrigation decisions can be better informed using the concept of predicting the water needs of crops based on the forecast of weather and soil conditions. Prediction is a very important feature for irrigation planning, one that involves knowing in advance the water needs, yield, and soil moisture content, to be able to react proactively to ensure better management [32].

Machine learning can learn from experience and perform activities that are similar to those performed by humans, and it is committed to making machines smarter [33,34]. It has the capacity to solve complicated irrigation system issues including multivariable, non-linear, and time-varying factors [35,36]. Machine learning methods can be employed to automatically extract new information in the form of generalized decision rules, in order to accomplish precision irrigation actions using natural resources such as water. In the field of precision irrigation management, the application of machine learning models such as supervised learning, unsupervised learning, reinforcement learning, and federated learning, has become popular for solving challenging issues such as classification and prediction [37].

### 2.1. Application of a Supervised Machine Learning Model toward Smart Irrigation Management

A supervised machine learning method involves the use of a function to map the input with the output, using samples from a labeled experimental dataset, to approximate the mapping function so as to be able to predict the output variables when a new input is received, as illustrated in Figure 1. Supervised learning is a widely used method of developing machine learning models that are used to perform both regression and classification

functions. The regression models and classification models are applied to output variables in the form of real values and categorical values, respectively [29]. Regression models depict the relationship between two variables, while classifications in supervised learning algorithms are preset. These classifications are created in a finite set, defined by humans, which means that a specific segment of data will be labeled with these classifications. The most commonly used types of supervised learning algorithms (K nearest neighbor (KNN), support vector machine (SVM), decision trees (DT), random forest (RF), etc.) are employed to optimize irrigation volume, timing, scheduling, soil moisture prediction, and weather predictions, to guide irrigation decisions [25]. The different types of supervised learning algorithms are discussed in the next subsection.



**Figure 1.** Block diagram of supervised learning for an irrigation system.

### 2.1.1. Linear Regression

Linear regression is a supervised learning model that consists of dependent (target) variables that are predicted from a set of independent (predictor) variables; these provide a prediction of output according to the input variables. The most used regression algorithms to guide irrigation decisions are linear regression and logistic regression. Another type of linear regression is the multilinear regression model, which consists of an equation for prediction and estimation of the difference between the fitted and the reference value, as denoted by Equation (1). The advantage of using regression models for predicting irrigation decisions is that limited data is required, as well as offering low computational complexity while estimating the parameters of the model. However, irrigation system parameters are highly nonlinear, with complex changing dynamics; therefore, linear regression is suitable for parameters with linear relationships between the predictor and target. However, can suffer underperformance for a problem that is nonlinear in nature [38].

$$\hat{y} = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_n x_{in} \quad (1)$$

where  $\hat{y}$  is the outcome of the prediction, which in this case is irrigation need,  $\beta$  represents the regression model parameters,  $x$  is the set of features, and  $i = 1, 2, 3 \dots n$ , which in this case represent soil moisture content and weather variables [39,40].

A regression model was proposed by Kumar et al. [41] to investigate the forecasting of the amount of irrigation volume needed by a farm, while reducing human intervention or energy use through the integration of mobile applications built using Java platforms for remote monitoring and control. Through a laboratory prototype demonstration, the

system comprises an embedded microcontroller interfaced with soil moisture, rain, and temperature sensors, which send further data to the cloud server through an application programming interface (API) key, to update the regression model. A similar implementation using a partial least squares regression (PLSR) model that is trained with weather data, moisture content, and soil characteristics was proposed to predictively generate irrigation reports for crops [42]. The choice of the PLSR model was made to identify the fundamental relationship between output and input parameters. The inputs ( $x$ ) are the weather data and soil moisture content and are known as the predictors or the measured observed variables, defined with matrix  $X = [x_1, x_2 \dots x_n]^T$ , while the output is the response variable, with matrix  $Y = [y_1, y_2 \dots y_n]^T$ .

### 2.1.2. Decision Trees (DT)

A DT is a tree-like architecture model, often formulated as classification or regression models. A decision tree predictive model splits data from observations into conclusions about the data's target value that can be used to visually and explicitly represent decisions [34]. To improve the performance of the DT model regarding irrigation management, a hybrid approach comprising the integration of DT and a genetic algorithm (GA) has been implemented to ensure an optimal decision tree model in predicting irrigation schedule that mimics the farmer's knowledge. The performance of the decision tree predictive model recorded an accuracy of between 99.16% and 100% [43]. The irrigation schedule event is in the form of a binary classification problem, which resulted in the decision to irrigate or not irrigate [43].

Similar work was carried out to compare three different computational intelligence techniques, such as decision trees, simple fuzzy and multi-criteria fuzzy logic for decision support regarding the irrigation of tree crops [44]. Furthermore, to investigate the accuracy versus interpretability of different types of machine learning models, in terms of the performance measures and features needed to adequately predict *E. coli* levels in agricultural water management, using a decision tree has been proposed [45]. A recent study on smart irrigation systems implemented using the DT model was trained using Sklearn libraries with an experimental dataset to predict the irrigation water needs of crops, with a prediction accuracy of 97.86% [46].

### 2.1.3. Support Vector Machine (SVM)

The SVM is a kind of supervised learning model used for classification, regression, and outlier identification. Over numerous high-dimensional planes of data, an SVM seeks to discover the best among all the linear classifiers that may be used between any two classes and create a decision boundary, indicated as a hyperplane close to the extreme points in the dataset [47]. SVM is a binary classifier that classifies data instances by constructing a linear separating hyperplane. The "kernel trick" may significantly improve the classification capabilities of standard SVMs by transforming the original feature space into a higher-dimensional feature space. The model detects any departure from the observed data by a modest amount, using parameter values that minimize the sensitivity to errors in the case of SVM regression.

A study by Vij et al. [48] analyzed the use of support vector regression (SVR) and RF regression to automate irrigation forecasts. This is accomplished by creating a hyperplane per dimension, i.e., a set of hyperplanes in a higher-dimensional space, as in the case of agricultural irrigation demand forecasts. The class labels are chosen, such that the distance between the hyperplanes utilized to identify the best linear classifier is as little as is feasible. Similarly, Goap et al. [17] proposed the utilization of an SVR model to estimate soil moisture content, based on field sensor data and meteorological data, and then gave irrigation choices based on the established amount of soil moisture and projected precipitation to conserve water and energy.

#### 2.1.4. Random Forest (RF)

RF models, also known as ensemble learning models, attempt to improve the prediction performance of decision trees, based on a particular statistical learning or model-fitting approach, by building a linear combination of the simpler base learner [49]. Given that each trained ensemble represents a single hypothesis, these multiple-classifier systems allow for the hybridization of hypotheses not produced by the same base learner, resulting in improved outcomes in cases when single models have high variety. RF models, such as boosting and bagging implementations, have also been suggested for smart irrigation management [50,51]. Decision trees are often employed as the basic learner for RF models.

In a study by Chen et al. [52], an ensemble learning model was used to predict the irrigation volume needed daily by crops, based on the agricultural IoT system. About four models, including linear SVR, support linear regression, Adaboost DT, and RF were trained to benchmark the performance of the intelligent irrigation system. To enable the deployment of the model for real-time irrigation scheduling, an IoT framework was implemented, alongside a website and mobile applications. The relevance of reference evapotranspiration (ET<sub>0</sub>) in the management of water-saving agriculture was reported by Chen et al. [53], its prediction using RF and an artificial neural network (ANN) was reported, with findings showing that the proposed hybrid model can map the nonlinear relationship between the input and output data of wind, solar radiation, air temperature, humidity and ET<sub>0</sub>. Through the integration of prediction concepts in irrigation system management, dynamic changes in environmental parameters can be anticipated through training and adaptation using predictive models. This was investigated in a study where extreme gradient boosting and autoregressive moving-average models were trained, using data stored in a dedicated IoT-enabled database, for the prediction of weather and environmental parameters, in order to guide the farmer's decision as to when to commence or stop irrigation [54].

#### 2.1.5. K-Nearest Neighbor (KNN)

KNN is a common supervised learning technique that is based on the principle of grouping data points that are nearby into each category. KNN is a non-parametric model that is often used to solve classification problems, and it uses the full dataset to train the model. When a new data point has to be categorized, the KNN algorithm searches the whole data set for the K-closest instances that are comparable to it [49]. The Euclidean distance between the linearly separable data points of  $x$  and  $y$  is measurable using Equation (2), while the K-nearest learned data instances vote to identify the class in which the test case belongs, through finding possible values based on the optimal number of K-values [55].

Euclidean Distance:

$$d(x, y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \dots + (x_n - y_n)^2} \quad (2)$$

An intelligent irrigation management approach with remote monitoring was implemented with the KNN model, used to classify the crop that would be likely to grow well, based on the water need and drought sensitivity of each of the regions, while the on-and-off pump motor was triggered using a float sensor. A laboratory prototype was implemented experimentally using an adafruit.io rest server and client android application for remote status monitoring. The authors reported that the proposed method was feasible for estimating the required amount of water to compensate for the water loss [56,57].

In addition, the possibility was investigated of using the concept of ontology and sensing value of various parameters from edge devices and stored on edge servers to decide irrigation schedules on a 50–50% basis. A KNN machine learning algorithm was deployed on an IoT server and updated the model with data stored on an edge server [58]. A similar intelligent irrigation method based on KNN was implemented, using a laboratory prototype demonstration for smart irrigation with the aid of IoT technology. The research findings in both cases show that the KNN algorithm deployed on Arduino by Kavyashree [59], and

Raspberry Pi by Das et al. [60], were able to predict irrigation needs, as well as control the on/off switch of a relay based on the sensed soil and weather data.

### 2.1.6. Naïve Bayes

Naïve Bayes is a machine learning model that is built very rapidly for fast prediction and is often used for classification. The naïve Bayes classifier is a set from a model that uses Bayes' theorem, as described in Equation (3), where each element is independent and equal [61]. The equation is used to calculate the posterior probability, using the prior probability that is to be calculated:

$$P\left(\frac{x}{y}\right) = \frac{P\left(\frac{x}{y}\right)P(x)}{P(y)} \quad (3)$$

where  $P\left(\frac{x}{y}\right)$  is the probability of occurrence of the event  $x$  and  $P(x)$  is the known prior probability.

The findings from our review of supervised learning techniques for irrigation management show that they have been widely explored for predictively managing irrigation, fertigation toward improving yield, and water-saving. Figure 1 shows how supervised machine learning models can be used for the prediction of irrigation volume, timing, yield, and nutrient or fertilizer management, as well as for the classification function of plant images for detecting plant diseases, farm area delineation, and the detection of plant stress due to inadequate irrigation. Table 2 summarizes other studies that have investigated smart irrigation management using a supervised learning approach. It further reveals research efforts on the use of machine learning to guide irrigation decisions.

**Table 2.** Summary of previous work on supervised machine learning models for smart irrigation management.

References	Supervised Model Used	Features	Simulation	Experimental	
				Cloud	Edge
[62]	PCA, K-means Clustering, GMM	The model uses online weather data and human-induced irrigation instinct to decide irrigation rate. The model notifies the operator of the required irrigation volume through short message sending (SMS)	✓	✓	✓
[63]	KNN, GND, SVM, ANN, DT	The machine learning model is used to predict irrigation volume aimed at reducing the usage of water in crop irrigation systems. The top two models are ANN and KNN, which have an accuracy of 90% and 98%, respectively.	✓	✗	✗
[64]	SVM	An SVM-based smart irrigation system that adjusts the irrigation quantity automatically, based on home garden environmental data	✓	✓	✗
[41]	Linear Regression	The model is used to predict the amount of daily irrigation water required, based on the data provided by various sensor devices. The prediction information is made available on the mobile application (app) for remote monitoring	✓	✓	✓
[65]	Principal Component Regression (PCR)	The model integrated with data envelopment analysis (DEA) helps to optimize water usage, management, personnel and water costs, incorporating increasing the irrigated area and the irrigation service coverage	✓	✗	✗

**Table 2.** Cont.

References	Supervised Model Used	Features	Simulation	Experimental	
				Cloud	Edge
[66]	KNN, DT, SVM, Logistic Regression	IoT-enabled machine learning irrigation systems with real-time monitoring of temperature, moisture, nutrients, and rainfall, to forecast the amount of water and fertilizer required by the plants for irrigation	✗	✓	✓
[67]	SVR and Bagging	The ensemble machine learning model is trained with collected real-time weather data to make an optimized decision, with an accuracy of 90%. The predicted soil moisture content is used to control the ON/OFF of the water pump	✓	✗	✓
[30]	DT, Random Forest, ANN, and SVM	Adaptive irrigation management using machine learning to predict the time of the day for irrigation using the air-soil humidity and temperature, the current time of the day, wind speed, and direction data. The data collected is visualized remotely on a mobile app. The app is interfaced with an API through message-queuing telemetry transport (MQTT) for the remote control of actuators.	✓	✗	✓
[68]	DNN, XGBoost, and Random Forest	An intelligent framework for smart irrigation planning, data analysis, feature extraction and irrigation prediction. The hybrid irrigation management approach is based on reference evapotranspiration and volumetric soil moisture content	✓	✗	✗
[69]	Random Forest, ANN, XGBoost, DT, SVM	Machine learning to improve irrigation timing using real-time data. The models classify an ideal hour for irrigation to take place, based on sensor and weather data. The two best-optimized models with high accuracy are XGBoost, with an accuracy of 87%, and RF, which is at 84%	✓	✗	✗
[70]	SVM, KNN Naïve Bayes	Real-time monitoring using sensors and data storage on the “ThingSpeak” cloud. The machine learning models perform classification based on a threshold value. The classification accuracy for the models is, namely, SVM 87.5%, Naïve Bayes 76.4%, and KNN 70.8%	✓	✗	✓
[71]	Gradient Boosting Regression Tree (GBRT)	Sensing and actuation test bed on an edge device, irrigation decision on a cloud. The model was able to learn irrigation decisions for different plants while adapting to the changing dynamics of the environment.	✓	✓	✓
[72]	PCA, LDA, Linear SVM, RBF SVM, DT, RF, ANN, AdaBoost, Naïve Bayes	Both PCA and LDA were used for image processing to reduce the dimensionality to improve classification accuracy, while seven other scikit-learn machine learning algorithms were used for onion irrigation treatment inference	✓	✗	✓
[73]	KNN, SVM	Real-time monitoring of temperature, humidity, and soil moisture content with infection detection on 2000 samples of plants, with a classification accuracy of 96%	✓	✗	✓
[74]	Least-square SVM	Uses soil moisture content and environmental parameters, with feature extraction of irrigation water requirement based on kernel canonical correlation. SVM was further used for the prediction of irrigation requirements with high prediction resulting in improved irrigation efficiency	✓	✗	✗
[75]	MLR, KNN, DT, and RF	Prediction of rainfall using online data from the weather station to guide irrigation decisions. The model performance, in terms of RMSE obtained for MLR, KNN, DT, and RF, is 0.165, 0.103, 0.094, and 0.083, respectively	✓	✗	✓

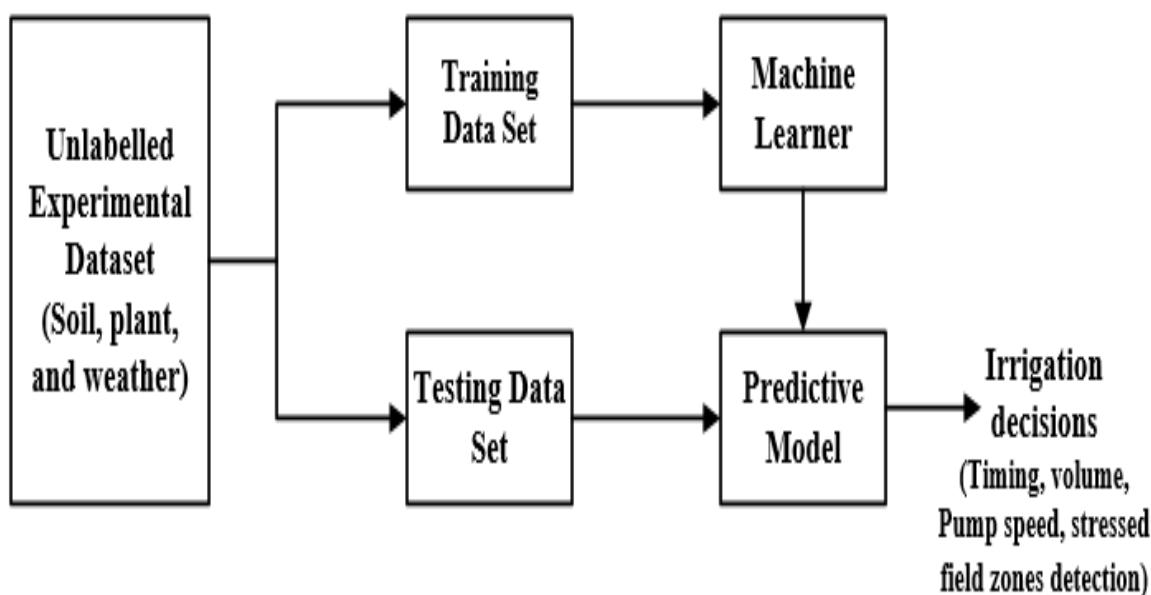
**Table 2.** Cont.

References	Supervised Model Used	Features	Simulation	Experimental	
				Cloud	Edge
[39]	MLR, KNN-Regression	The accuracy of MLR is better than KNN-R; hence, it is integrated with an android application. The android app accurately enables real-time scheduling of the fertigation at the correct time it needed to be applied	✓	✗	✓
[76]	KNN	Agricultural monitoring system and analytics using drone data processed with a KNN algorithm	✓	✗	✓
[77]	ANN	Estimation of ETo using daily data on solar radiation, humidity, temperature and wind speed. The estimation and scheduling algorithm was implemented on a Raspberry Pi interface with a local weather station, using Zigbee	✓	✗	✓
[78]	ANN	Prediction of ETo using weather variable to decide irrigation scheduling	✓	✗	✓
[79]	ANN	Using time series analysis and the predictive model, prediction of rainfall aid determination of which crops is favorable to grow in a particular area	✓	✗	✓

Note: PCA—Principal Component Analysis, GMM—Gaussian mixture model, KNN—K Nearest Neighbor, GND, SVM—Support Vector Machine, ANN—Artificial Neural Network, DT—Decision Tree, Random Forest, LDA—Linear discriminant analysis, RBF—Radial basis function, MLR—Multiple Linear Regression. GND—Generalized N-Dimensional.

## 2.2. Application of Unsupervised Smart Irrigation Management

The fundamental goal of unsupervised learning is to build categorization labels automatically. These algorithms look for similarities between units of data to see whether they can be classed and put together into a group [80,81]. Unsupervised learning techniques are characterized by drawing an inference or underlying pattern from an unlabeled dataset, as described in Figure 2. This method can be implemented to deduce the patterns contained in the collected dataset of soil, plant, and weather parameters for optimal irrigation decisions in different irrigation field zones [82]. Examples of unsupervised learning models are clustering, ANN, dimensionality reduction, hierarchical clustering, etc.

**Figure 2.** Block diagram of unsupervised machine learning for an irrigation system.

### 2.2.1. K-Means Clustering

Clustering is aimed at the identification of a distinct group, based on the similarity of a given dataset, while the arrangement of data into clusters results in low intercluster similarity and high intercluster similarity [83]. Another review explores the feasibility of how clustering with fuzzy time series techniques can be used to manage a network of wireless sensor nodes scattered on an agricultural field. The review concluded that farmers can experience improved energy efficiency of the sensors with real-time monitoring of the farm by using the proposed method [84].

Furthermore, it has been widely reported that farmers experience low yields due to inadequate irrigation and attack from pests. This led to an investigation of the integration of the K-means clustering algorithm for image processing, with smart irrigation enabled by WSN. The captured images were partitioned and segmented into overlapping groups having similar features. The work demonstrated an improvement over other WSN-based irrigation systems, with the clustering model able to detect the presence of pests and affected areas on the plant leaves [85]. Ohana-Levi et al. [86] proposed the integration of a multivariate spatial clustering with fuzzy K-means, using the hierarchical method to determine different fertigation management zones in a citrus orchard field, to determine in-field variability and guide site-specific irrigation management. Six different variables were considered, namely, crop water stress, normalized difference vegetation index (NDVI), digital surface model, aspect, slope, and elevation. The models were able to ascertain that infield spatial variabilities were not constant among the variables and within the orchard.

### 2.2.2. Artificial Neural Network (ANN)

ANNs were inspired by the physiology of the human brain neuron and can be implemented as both an unsupervised and supervised model. The ANN is characterized by its pattern of connections between the neurons, its method of assigning the weights on the connections, and lastly, its activation function [34]. Some nodes have many layers, such as an input layer where data is supplied into the network, one or more hidden layers where learning occurs, and an output layer where the decision with a prediction is made. The weights and biases in each layer are learned throughout the training procedure, in order to minimize the loss function. Backpropagation (BP) with gradient descent is a key ANN approach that aims to speed up the network's convergence to a local and global minimum by updating the many associated weights [87].

ANN has been widely applied explored for optimizing water applications in trickle irrigation [88] and drip irrigation [80]. A study by Murthy [89] used meteorological data acquired from the local weather station to develop a neural network-based model that forecasts the irrigation demand for any set of antecedent circumstances. When the model's forecast was compared to a state-of-the-art irrigation controller, the volume of water wasted by weather-aware runoff prevention irrigation control (WaRPIC) was only 2.6% that of the state-of-the-art. Also, working toward a water-saving irrigation system, a multilayer perceptron neural network was used to train sensor data collected using IoT to predictively control the duration of pumping of water, and was demonstrated using a laboratory prototype [90].

To further improve the performance of ANN for irrigation water management, the integration of fuzzy logic was used to compensate for the performance of the neural network, through the fusing of different parameters from various sensors used for sensing the irrigation environment [91]. A similar method was investigated using ANN and a fuzzy controller for water and fertilizer saving [92]. The monitoring of the volumetric water content of the soil is required for irrigation scheduling and water resource allocation, management and planning. The prediction of the volumetric water content of the soil in a paddy rice field was implemented using limited weather data. The weather data and rainfall data were used to predict the volumetric water content of the soil through the use of a dynamic ANN model [93].

In addition, considering the importance of accurate estimation of evapotranspiration in guiding precision irrigation management, the use of ANN for estimation and modeling the non-linear features of reference evapotranspiration has been proposed [94–99]. This approach was able to effectively estimate the crop water requirement that could be used to guide irrigation decisions using temperature, solar radiation, humidity, and wind speed. Although several studies have proved the applicability of ANN for the prediction of irrigation or weather approaches using a BP algorithm, through minimizing the error squared, or by adjusting the different weights of a network. Improved performance has also been reported by Gu et al. [100], where a GA for the better prediction of yield or corn for different irrigation was used with a subsurface drip irrigation system. GA is an optimization model that mimics the natural biological evolution process by using a global optimization search method [101]. The use of BP neural networks with GA enhances BP learning training, optimizes the network power threshold, promotes speedy convergence, boosts the model's efficiency, and accuracy.

Although the training of neural networks requires a great deal of data for proper learning, Perea [102] proposed a new method that makes use of limited data conditions for the short-term forecasting of daily crop water needs. This was made possible through the integration of GA, ANN, and Bayesian networks, with model performance assessed in terms of the coefficient of determination ( $R^2$ ) and standard prediction error of 96% and 8.7%, respectively. Further investigation of the applicability of ANN for smart irrigation with IoT integration was implemented by Risheh et al. [103], using a transfer learning approach to address the limitations of ANN, such as the high number of dataset requirements and the need for high training of the network, resulting in high processing complexity.

An intelligent hydroponics control system was deployed on an edge device named Raspberry Pi and Arduino, where a deep neural network implemented with a TensorFlow library was used to adaptively control the opening and closing of valves, based on multiple input sensed parameters. The sensed data were collected for several weeks, while the neural network was trained several times to achieve a better accuracy of 88% [104]. In another study, an ANN-based irrigation management strategy was used, where input parameters, such as temperature, air humidity, soil moisture content, wind speed and solar radiation, were fed into an evapotranspiration model to estimate the actual soil moisture. The ANN controller then compared the desired soil moisture content with the actual soil moisture content to determine the error, upon which determination the opening and closing of valves was triggered [105,106].

Dursun and Özden [107] proposed a solar-powered intelligent site-specific irrigation system, where an ANN was used to simulate the moisture distribution in the soil, as determined by training the values obtained from soil moisture sensors placed in the farm area, to reduce pumping energy and water saving. The major limitation of the practical implementation of the ANN model included the issue of over- and under-fitting, the selection of the learning rate and weight, as well as the large size of dataset needed for training requirements. In addition, the performance accuracy of a trained ANN model-based irrigation schedule depends on how carefully the representative data of the physical system and data collection using IoT/WSN devices were taken.

### 2.2.3. Adaptive Neuro-Fuzzy Inference System (ANFIS)

The ANFIS is a hybrid model consisting of an artificial neural network and a fuzzy inference system (FIS). In terms of enhancing the prediction of the irrigation needs of a farm, the ANFIS model has demonstrated better performance, as shown by Atsalakis et al. [108], where a daily forecast of irrigation demand was proposed to optimize pumping effort and reduce cost. In addition, a study by Navarro-Hellín et al. [109] proposed a closed-loop irrigation control scheme, using ANFIS and PLSR as the reasoning and decision engine of the decision support system. A similar approach using ANFIS has been implemented to improve the performance of an irrigation sprinkler, leading to the realization of better

infiltration equilibrium, soil moisture uniformity, and high water redistribution efficiency when tested experimentally [110].

In terms of sustainable water management, an intelligent neuro-fuzzy controller that was based on the ANFIS model was implemented on a Raspberry Pi edge device for the smart control of drip irrigation, with solar-powered pumping facilities. The input of the ANFIS controller was the temperature of the solar panel, rate of water flow, and irradiance, while the output was the irrigation frequency, in terms of a pulse width modulated signal. The model performance showed a fast and stable response, with optimized irrigation efficiency of 95%. Readers are referred to [111–113] for more information about the architecture and prediction ability of ANFIS. Another widely utilized rule-based model for irrigation management, with similar features to that of ANFIS, is a fuzzy logic system. Much success has been recorded in its practical implementation for the intelligent control of irrigation when integrated with WSN and IoT devices [114–128].

Unsupervised learning has been widely utilized for irrigation management, as shown in the summary given in Table 3. The findings show that a large experimental dataset is required in order to train the different models to make accurate predictions using these techniques. Determining the hidden pattern in an unlabeled dataset is the most common feature of this machine learning method. However, most of the review works were realized using a simulation only, as seen in Table 3. Future work in this area should focus more on the realization of the simulation on both edge and fog platforms, as well as on the translation to digital farm solutions such as mobile and web apps for local farmers who, in most cases, could not afford the high cost of sensors and hardware installation on their farms. Readers are referred to the literature [31,83,129–133] for more details about unsupervised learning.

**Table 3.** Summary of previous work on unsupervised machine learning models for smart irrigation management.

References	Unsupervised Learning Model	Summary	Simulation	Experimental Implementation	Cloud	Edge
[134]	K means clustering, Gaussian Mixture, and ISODATA	Investigation of delineation of multiple irrigation zoning scenarios on a large field with a center pivot irrigation system, using data on soil moisture content, electrical conductivity (EC), and hyperspectral images with yield data. A kappa coefficient of 0.79 was recorded for EC, demonstrating a high potential for zoning irrigation	✓	✗	✗	
[135]	Fuzzy Clustering	Delineation of irrigation management zones in a farm using NDVI measured at different growth stages of a grapevine cultivation field. The measure is transformed to a 48-cell grid ( $10 \times 9 \times 20$ m) and maps of two management zones using the MZA software	✓	✗	✗	
[136]	K-means clustering	A K-means clustering algorithm was applied to the spatial clustering of irrigation networks, based on soil and environmental data. The clustering model provided a context for better and easier irrigation decision-making	✓	✗	✗	
[137]	PCA, Fuzzy clustering	Delineation of soil management zones (MZs) for effective irrigation management and evaluation of spatial variability of soil properties	✓	✗	✗	
[138]	Hidden Markov	The system made use of data from soil moisture content, air temperature, and leaf wetness and compares it with predetermined threshold values of various soil and specific crops to guide irrigation decisions. The Markov model detected possible plant disease conditions	✓	✓	✓	

**Table 3.** Cont.

References	Unsupervised Learning Model	Summary	Simulation	Experimental Implementation	Cloud	Edge
[139]	CNN	The system made use of an analytical approach for IoT-based irrigation, to enhance smart farming with integration with plant recognition and wilt detection	✓	✓	✓	✓
[140]	Mask R-CNN, NN	The algorithm automatically detected water from aerial footage of irrigation systems, using UAV-captured images. The smart recognition software helped in the irrigation system inspection, therefore reducing time and costs in system maintenance. This helped to identify malfunctioning irrigation systems, to reduce under- or overwatering	✓	✓	✓	✓
[141]	CNN	Using an unlabeled dataset, an identification was made of center pivot irrigation using a variance-based approach through image processing to allocate irrigation water on the field. A precision and recall of 95.85% and 93.3% was achieved.	✓	✗	✗	✗
[142]	ANFIS	An intelligent neuron-fuzzy controller was implemented on Raspberry Pi for drip irrigation management; 95% water pumping efficiency was achieved	✓	✗	✓	✓
[143]	RNN	An autonomous irrigation system was used to optimize yield and reduce water usage for irrigation	✓	✗	✓	✓
[144]	ARIMA model, LSTM and BLSTM models	A time series forecasting evapotranspiration was used to create a metric of water loss from the crop to the environment, to guide irrigation decision management	✓	✗	✗	✗
[145]	Google Net, PVANET	Lightweight and fast, Google Net reduced the false detections associated with PVANET, to accurately detect the shape of center pivot irrigation systems. In addition, the area of irrigation in the region was estimated	✓	✗	✗	✗
[146]	Artificial Neuro-Genetic Networks	Short-term forecasting of daily irrigation water demand. The prediction model had a standard prediction error of daily water demand of 12.63% and 93% total variance	✓	✗	✗	✗
[147]	ANN	ANN was used to simulate nitrate distribution for a drip irrigation system. The model was able to simulate the nitrate distribution with a 0.83 coefficient of distribution ( $R^2$ )	✓	✗	✗	✗
[148]	ANN, FIS, ANFIS	The models of FIS, ANN, and ANFIS were used to develop a smart model to simulate the adequacy of water delivery in an irrigation canal. The accuracy of the models, in terms of MAPE index, was 57.07% and 56.6% for ANN and ANFIS, respectively	✓	✗	✗	✗
[149]	LSTM	An estimation of irrigation, based on soil matric potential data, was measured from two different soil types. For both soil types, the LSTM model had an excellent prediction performance, with $R^2$ ranging from 0.82 to 0.98 for one hour ahead of prescription, decreasing as the forecast time rose	✓	✗	✗	✗

**Table 3.** *Cont.*

References	Unsupervised Learning Model	Summary	Simulation	Experimental Implementation	Cloud	Edge
[150]	GRU, LSTM, BLSTM, CNN	At a location in Portugal, the model utilized climatic data and soil water content to schedule irrigation and estimate the end-of-season point of tomato and potato harvests. With an MSE of 0.017 to 0.039, the LSTM model captured the nonlinear dynamics between irrigation volume, climatic data, and soil water content to forecast production. With a regression coefficient ( $R^2$ ) score of 0.97 to 0.99, the bidirectional LSTM outperformed the other models	✓	✗	✗	✗

### 2.3. Deep Learning (DL)

DL is an area of machine learning that allows computer models with several processing layers to learn complicated data representations at various levels of abstraction. One of the main advantages of DL is that in certain circumstances, the model performs the feature extraction process. DL models have significantly enhanced the state-of-the-art in a variety of sectors and industries, including agriculture [149–154], where they are often used for image and sound processing. DL models are essentially ANNs with many hidden layers between the input and output layers, with recurrent neural network (RNN), long short-term memory (LSTM), and convolutional neural network (CNN) being examples of supervised and unsupervised learning techniques for irrigation decision optimization.

#### 2.3.1. Recurrent Neural Network (RNN)

The RNN is a DL technique that is often used for the dynamic modeling of data, using the loop in the network in the forward and backward direction. It has a memory retention capability, due to feedback and the fact that the output is a reflection of the current input and previous input. RNNs are also designed to incorporate sequence information inside the hidden layer vector as a context that is often used for time-series prediction, sequence classification, and labeling [151]. The downsides to this model are the fact that it suffers a vanishing gradient during model training, computational feasibility, and the limited availability of hardware (GPUs) powerful enough to train a big model in less time, which is why it was difficult to implement this model experimentally on hardware.

An investigation of irrigation rate and timing prediction was carried out with NARX and RNN models, using weather and soil matric potential data. The simulation result showed a good prediction performance of  $R^2$  of 0.94 and RMSE of less than 1.2 mm, with the possibility of being used as a decision support system for irrigation scheduling [151]. Similar work was implemented using RNN with LSTM, a feedforward neural network, wavelet neural network, and ARIMA for forecasting rainfall, with an RNN-based LSTM having a better forecasting performance when compared with other models [152]. Another work on the use of the RNN model for optimal water allocation of irrigation during droughts, through forecasting annual irrigation inflow based on climate and hydrological data and optimization, scheduled water among the irrigation units by considering the crop coefficient and water stress at different growth stages [153].

#### 2.3.2. Convolutional Neural Network (CNN)

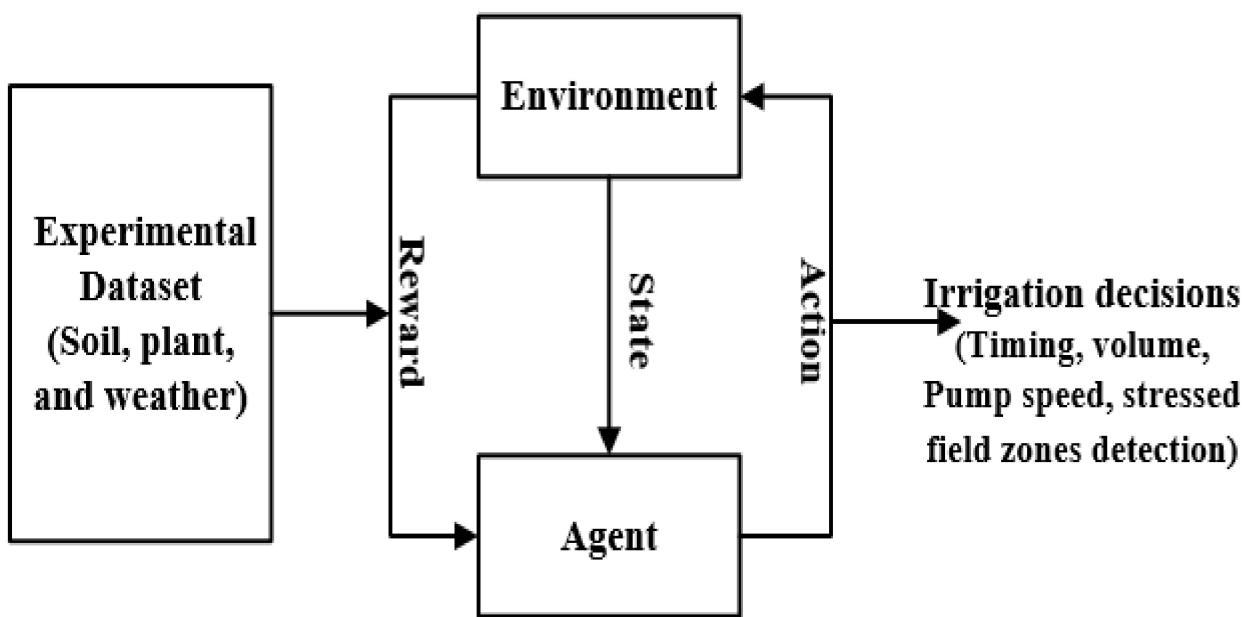
Another DL model often used for processing agricultural image datasets is the CNN, where feature maps are extracted by performing convolutions in the image domain. The idea of using the CNN algorithm to enable irrigation water management through the processing of images captured using IoT sensors and cameras deployed on the field has been proposed. After training the CNN model using the images, an estimation of recognition

was set to determine the precision and yellowing of plant leaves while also being able to detect when soil dampness reached a certain threshold, at which point a signal was sent to the cloud to recalculate the needed irrigation volume [154].

Henry [155] developed a new method for mapping irrigation using an ensemble of convolutional neural networks that only rely on raw Landsat surface reflectance data. As DL models work with supervised, unsupervised machine learning, and reinforcement learning techniques, Tables 2 and 3 detail some studies that have investigated smart irrigation management using DL techniques. Another interesting machine learning implementation technique that requires more research effort is federated learning. Not many studies have been reported using this technique, regarding smart irrigation management, easy scalability and its deployment for farmers' use. Readers are referred to [156–158] for more information about this machine learning method.

#### 2.4. Application of Reinforcement Learning (RL) toward Smart Irrigation Management

Every action has an effect on the environment, and the environment then gives the learning algorithm feedback. RL is based on the concept that the farmer/agent can learn from their environment through actions and feedback, based on reward signals. Each time he observes a situation, he selects an action and gets feedback in the form of reward/punishment, as described in Figure 3. An investigation on the applicability of model-free RL for the control and management of agricultural irrigation through simulation was outlined in [159]. Chouaib [160] proposed an approach based on reinforcement learning, a type of machine learning that uses the trial-and-error principle to learn how best to fit a situation to an action in a highly dynamic, stochastic environment. In this proposed approach, a farmer or agent learns to choose the optimal cropping pattern, defined by the type of crop, area to cultivate, sowing data, and irrigation plan, depending on the water availability at the beginning of the agricultural season. Each agent interacts with the environment, which is composed of environmental and socio-economic modules containing different processes, to provide the farmer or agent with the information he needs to learn.



**Figure 3.** Block diagram of reinforcement learning (RL) for irrigation systems.

The use of reinforcement learning in this complex system has changed the traditional irrigation water management method and brought more intelligence into the system. A reinforcement Q-learning decision-making strategy, based on past irrigation experience and short-term weather forecasting for the irrigation of a rice paddy was proposed, and

benchmarked with conventional irrigation scheduling. The predictive irrigation performance for daily rainfall over 7 days was evaluated [161]. In another study, the optimization of irrigation without negative effects on cultivated maize yield was proposed. The implementation was carried out using a maize crop simulation model on a decision support system for agrotechnology transfer (DSSAT). The system was able to adapt to the changing dynamics of soil, plant, and weather conditions through adaptive Q-learning from past and present experience, leading to a reduction in the water used for irrigation by 40% when validated with a constant irrigation simulation model on DSSAT [162].

A case study on maize irrigation management investigated the comparison of reinforcement learning and dynamic programming using a moderator simulator, in terms of optimal irrigation strategy. The results obtained showed that RL outperformed the DP over a short sampling time [163]. Conventional RL does not accurately capture the dynamics of a practical real-world irrigation environment, due to its small state space; hence, the use of deep RL makes use of a multidimensional dataset to train an ANN model that adaptively learns the environment and approximates the Q function. A deep RL that extracted measured sensor data to construct Q learning features for irrigation scheduling and decision-making in a greenhouse cultivation experiment was implemented [164].

A similar deep RL approach was proposed for irrigation scheduling, with an increased net return achieved under different weather conditions and crop types [165]. Recently, CropGym, an open smart environment, was implemented to learn the fertigation process using a crop growth state-space model and weather data to generate action and reward, optimizing fertilizer usage as well as enhancing the yield [166]. Other areas of applicability of RL are in watershed management [167] and biological environments [168]. Readers are referred to [169,170] for more details about RL principles.

### 3. Digital Farming Solutions for Smart Irrigation Management

Aiming for the achievement of food security with increased water use efficiency requires an improvement in irrigation systems that is driven by digital farming solutions, such as mobile and web applications. In this section, the adoption of digital solutions such as mobile apps and web-based apps is discussed. The application of this digital solution in terms of remote irrigation scheduling, the control of valves and actuators, data analytics visualization, and advisory services for farmers and users is presented.

#### 3.1. Mobile Applications for Smart Irrigation Management

The efficiency of an irrigation system plays a major role in providing significant contributions to food production. Surplus and, therefore, wasted freshwater can only be visually monitored in extreme cases of mismanagement but any overdose results in high water demand and often also in nutrients being washed out from the soil. Irrigation management systems for farmers need to be precisely designed so as to be able to deliver the appropriate amount of water to the crops, where and when it is needed, based on the requested amount calculated for each crop. Consequently, by leveraging on the implementation of IoT and machine learning scenarios, an efficient monitoring and control system through mobile and web applications for agricultural irrigation can be implemented with high accuracy, to achieve great savings in water, energy and manpower. In addition, the role of machine learning for irrigation prediction is needed to complement irrigation decisions based on the farmer's knowledge. Mobile phones have become a widely used device that has become an inseparable electronic gadget from nearly every human's pocket; this has ensured that farmers, too, use software programs in the form of apps, either for information-sharing or for agro-advisory services [171,172].

Sensors used for irrigation management capture a variety of environmental and meteorological data, such as ET<sub>0</sub>, rainfall, air temperature and humidity, from the farm. These data are transferred over the gateway and then loaded into a cloud server database. Farmers may utilize mobile apps to regulate water valves, fans, and other controls remotely, depending on the trends of soil, plant, and weather data visualized [52]. The concept of

using mobile technology to provide agricultural help has taken numerous shapes. Top-down services offer a method of delivering material that is governed by the aims of a designer. SMS push-alerts, for example, are a kind of service that sends out agricultural suggestions and seasonal reminders to users. These programs offer the advantage of giving farmers access to the most up-to-date agricultural research and introducing new themes, but they lack the flexibility to address challenges that are specific to each farmer's circumstances [173].

To analyze the collected data from an experimental setup for sustainable irrigation by Glória et al. [30], a mobile application named "smart farm" has enhanced the possibility of farmers performing a task without being present on the farm. The application has the functionality of displaying the collected data in real-time, connected with the developed API using MQTT to remotely switch on/off actuators such as pumps on the farm. Another interactive system of irrigation management named SMART was implemented by Matukhina et al. [174]. The SMART android application has a window for both landscape and portrait display, with the ability to display the latest weather information, as well as irrigation status and schedules. Furthermore, Zhang et al. [175] proposed a distributed IoT-based environmental monitoring system for air, water temperatures, and dissolved oxygen, using the information perception layer, the information transmission layer, system architecture for hydroponics, and aquaculture management. A long-range communication protocol was utilized to send sensor data, while 4G was employed to collect data and send it to the cloud platform.

### 3.2. Web Framework for Smart Irrigation Management

The adoption of web and mobile applications is becoming increasingly important in the management of irrigation systems. A web framework can be integrated with databases for users to perform data manipulation, visualization, analytics and remote control [176]. These web-based applications may also help farmers to make irrigation-related decisions, such as calculating the total irrigation water used and the cost of the irrigation practice, estimating soil water status (water consumed), and managing remotely controlled irrigation equipment, among other things. Furthermore, the integration of IoT and big data analytics on cloud databases (DB) such as the Amazon web service, Microsoft Azure, the Oracle DB Google cloud platform MongoDB Atlas, etc., has offered an opportunity for the mining of stored experimental data to generate a prediction for farmers, through their mobile and web framework on fertilizers with irrigation requirements, as well as the marketing projection of harvested produce [177].

### 3.3. The Application of the Digital Solutions

#### 3.3.1. Data Analytics and Visualization

Before the advancement of information technology, farmers have had to be on their farms for physical examination of the plants, while also examining the moisture content of the soil [178]. However, with the recent progress in the area of wireless sensor networks, the IoT has made it possible for data to be collected from various sensors, such as soil moisture content, soil and air temperature, humidity, and plant parameters like the vegetation index, and then viewed remotely. This data can be aggregated through a gateway and stored on cloud databases [179]. With the opportunity offered by these cloud platforms and databases, an integrated machine learning model can learn and relearn to reveal the hidden patterns and relationships between the measured data. In terms of sustainable precision irrigation management, the analysis and visualization of sensor data are crucial. This has been demonstrated using ThingSpeak, which is another open-source data visualization tool offered by MATLAB that has been used for prototyping applications in irrigation management. It has been used for managing irrigation for date palm [180] and cucumber cultivation [181].

### 3.3.2. Remote Irrigation Scheduling, Control of Valves and Actuators

Farmers can remotely and conveniently monitor various sensor measurements and control actuators such as relays and variable frequency drives on irrigation fields or greenhouses from anywhere. This will reduce the need to manually monitor the operations on the farm while improving farm management and crop yield. Regarding the improvement of irrigation scheduling using a remote automatic control system, along with WSN, a graphical user interface for data logging, visualization, and remote control of infield parameters was implemented [182,183]. Seven different irrigation scheduling models, based on the soil water budget model, feed-forward and feedback models, were proposed for drip-irrigated apple trees. In another study, a smart irrigation scheduling application named “cotton app” is proposed to estimate root-zone soil water deficit (RZSWD) and rainfall in inches and percentages, using a soil–water balance model that is calibrated and validated using an experimental dataset and is run once a day when the user launches the app. The application notifies the user when the RZSWD drops below a particular threshold, while also estimating the crop water used [184].

To reduce the stress experienced by farmers who are regularly required to manually switch irrigation pumps on or off, Ogidan et al. [185] proposed an Android-based remote control app that has a data-logging capability. The system prototype uses WiFi for internet connectivity between the cloud server to the remote devices, providing flexibility for the user to start irrigation with his mobile device. A similar method, known as a multiplatform application, was used for ET-based irrigation scheduling and was tested on commercial farms where strawberries are grown [186], as well as the cFertigUAL app for managing the supply of fertilizer and water for greenhouse-cultivated vegetables [187].

In the area of liquid pesticide spraying using a wireless control mobile robot, as well as the remote control of an irrigation sprinkler pump, a mobile application was developed to enhance the automation of both processes [188]. The irrigation of large fields requires the use of large machinery-based irrigation systems, such as a center-pivot, variable rate, lateral move system, integrated with a sensor-based decision support system (DSS). A DSS named ARSPivot, ARSmartPivot v.1 containing an embedded supervisory control and data acquisition were used for site-specific variable-rate center-pivot irrigation scheduling based on soil water content and plant stress [189,190]. A similar method was proposed as a web-based application for remote feedback control and data analytics of soil, plants, and weather for center-pivot-based irrigation management [191] with GIS-based DSS [192].

### 3.3.3. Advisory Services for Farmers and Users

Extension and advisory services have long been recognized as valuable instruments for improving agricultural production activities. The service aims to improve the dissemination of information, regarding the best practices in agricultural production, marketing, irrigation strategies, income and well-being, to farmers in poor and remote communities [193]. Agricultural extension services have become more efficient, with advances in the usage of smartphones with mobile applications and web services for the dissemination of agricultural information, to address farmers’ problems in a timely and effective manner [194–196].

One study proposed a flexible and user-friendly smart agricultural kiosk, based on an Android application that can facilitate real-time communication between farmers and experts. Other interesting features of the app included weather forecasting and crop disease management information [197]. Likewise, Vuolo et al. [198] proposed the integration of earth observation data to estimate crop water requirements, while also delivering a satellite-based irrigation advisory service and map to farmers, using a mobile application named WebGis to optimize irrigation management.

A mobile app has been developed for farmers and young people, aimed at information dissemination about the buying and selling of farm produce and fertilizer and pesticide application, as well as crop management, was tested in Mali, Africa. A user-centered and friendly design method was used for the app development, with 89.66% of users agreeing

with the effectiveness of the design prototype [199]. An online-based irrigation advisory service, with a user interface that enables the farmer to adopt irrigation strategies that reduce crop water use, has been proposed [200]. Likewise, an integrative hydrological application that uses real-time data from satellite services, such as weather reports, vegetation index imagery, and GIS capability for cost-effective online irrigation scheduling to maximize the yield of the crop and reduce water usage and plant stress [201]. The use of virtual conversational assistants, such as the machine learning-based Chabot, has helped to automate agro-advisory interaction between farmers, as reported in [202].

Table 4 summarizes other previous work on the application of mobile and web apps for smart irrigation management. A layer of machine learning-based irrigation architecture, with digital farming solutions, is illustrated in Figure 4. The architecture comprises UAV and satellite-captured data (such as plant images and vegetation index), soil information (soil moisture, soil type), and weather information from an onsite weather station, online weather database (reference evapotranspiration, air temperature, solar radiation, air humidity, etc.). The data thus collected can be stored on a cloud server integrated with a machine learning model that can predictively recommend irrigation decisions and scheduling for the irrigation field.

**Table 4.** Summary of previous work on the application of mobile and web apps for smart irrigation management.

References	App Name	Features	Android	iOS	Webpage	Country of Origin
[203]	Agrowetter	Estimation of weather and evaporation to guide irrigation decisions	✓	✓	✓	Germany
[184]	Cotton app	Interactive, easy-to-use app for variable-rate irrigation scheduling. The app notifies the user when the RZSWD exceeds 40% and displays precipitation and other weather variables for users	✓	✓	✗	Georgia and Florida, USA
[185]	Smart irrigation app	Laboratory prototype, user-friendly, real-time on/off remote control of irrigation pumps, as well as data-logging capability	✓	✗	✗	Ondo State Nigeria
[204]	Sprinkler irrigation app	Online weather data source, soil information, irrigation scheduling. An app used for weather forecasting to schedule timer for automatic sprinkler irrigation of turf	✓	✗	✓	Florida USA
[205]	Citrus Smart Irrigation apps	Optimized irrigation scheduling for avocado, citrus, strawberry, urban turf, and vegetables	✓	✓	✗	Florida USA
[206]	iChilli app	Remote monitoring and control app for fertigation management	✓	✗	✗	Malaysia
[207]	Apex mobile application	Water stress detection app. The app can be used at the field or the within-field scale for temporal or spatiotemporal monitoring of vine water status	✓	✓	✗	France
[198]	WebGIS application	Weather forecasting, fertigation, irrigation maps	✓	✓	✓	Austria
[186]	Multiplatform (Irrifresa) app	ETo-based irrigation scheduling for strawberry growing	✓	✗	✓	Spain
[187]	CFertigUAL app	Easy to use, fertigation management app	✓	✗	✗	Spain
[208]	REUTIVAR app	Weather forecasting, irrigation scheduling, soil and water quality analysis	✓	✗	✓	Spain

**Table 4.** Cont.

References	App Name	Features	Android	iOS	Webpage	Country of Origin
[209]	Hygrometry app	Fast and accurate estimation of water consumption	✓	✓	✗	Uzbekistan
[210]	eRAMS App	Sprinkler irrigation scheduler, daily weather updates	✓	✓	✓	Colorado, USA
[211,212]	Hydro-Tech decision support system	Uses the field water balance and dynamic optimizer for fertigation management	✓	✗	✓	Italy
[213,214]	IrrgaSys decision support system	Weather forecasting, soil water balance irrigation scheduling, remote sensing	✓	✗	✓	Portugal
[215]	Web irrigation framework	Estimation of irrigation requirement using the Rawls and Turq model	✗	✗	✓	Algeria
[216]	Mobile app integrated smart irrigator	Remote control of irrigation, plant monitoring	✓	✗	✓	India
[199]	Agro Mali app	Agro-advisory service	✓	✗	✗	Mali, Africa
[217,218]	Smart decision support system	Support illiterate farmers to make irrigation decisions	✓	✗	✓	Pakistan
[219]	Smart Avocado app	Irrigation scheduling uses a one-dimensional soil–water balance model	✓	✗	✗	USA
[220]	Smart-phone irrigation sensor	Uses a smartphone camera to capture the image of the soil, analyze the image to estimate the wetness or dryness of the soil, used for irrigation of a pumpkin crop	✓	✗	✗	Mexico
[221]	WISE online Irrigation manager	Uses soil, plant and weather to estimate daily soil water deficit	✗	✓	✓	Kansas, USA
[222]	SWAMP Farmer app	Uses cloud-based water need model, estimate irrigation requirement, soil moisture monitoring and the remote map	✓	✓	✗	Brazil
[223]	Smart & Green app	Uses weather and water balance with crop register function for smart irrigation management. The framework comprises physical communication services and an application layer	✓	✓	✗	Brazil
[224]	WebGIS app	Displays server-side information, visualization of real-time irrigation performance, GPS to track location	✓	✗	✓	Indonesia

**Table 4.** Cont.

References	App Name	Features	Android	iOS	Webpage	Country of Origin
[225]	Irrigation meter calculator	The provides an interface that estimates soil moisture content based on installed watermark sensors at different soil depths	✗	✓	✗	Kansas State University
[175]	Distributed monitoring system	Real-time monitoring and control to support the actual hydroponics and aquaculture production management	✓	✗	✓	Tongzhou, Beijing
[201,226]	Wise mobile app	The user can access and upload information, view soil moisture deficits and weather reports	✓	✗	✓	Colorado, USA
[227]	AWD app	A Node.js server was used to store the data and produce alerts, and a web client was utilized as a dashboard to show all the AWD parameters, such as water level and pump operating times, using either the smartphone app or the online interface	✓	✓	✓	Bangladesh/Canada
[228]	Blynk app	Smartphone-based mobile application for remote monitoring and control of irrigation	✓	✓	✗	India
[229]	Bluleaf app	App for real-time scheduling of timing and irrigation needs for wheat using soil, plant, and weather data	✓	✗	✗	Lebanon/Italy
[172]	Masa app	Machine learning-driven advisory and marketing app for farmers	✓	✓	✓	Canada

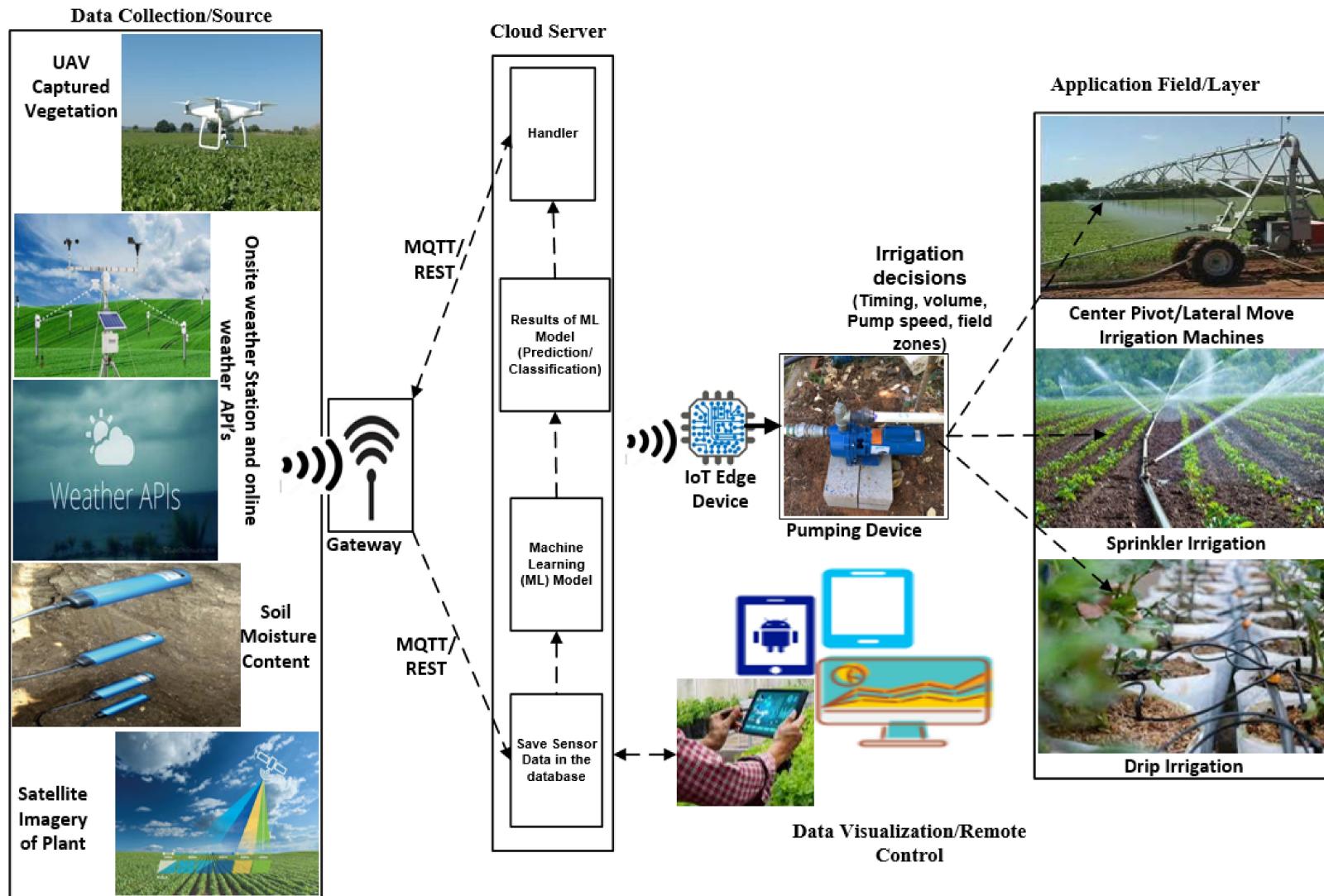


Figure 4. Layers of machine learning-based irrigation architecture with a digital farming solution.

#### 4. Challenges and Opportunities

In this section, the challenges and opportunities of the application of machine learning are discussed. The development of machine learning, as well as digital software solutions for smart irrigation systems for the management of different crops, is faced with several challenges. Issues are the common availability of experimental datasets and the overfitting and under-fitting of machine learning models, as well as accessibility to a cloud and online web infrastructure for the deployment of trained models and software solutions. Furthermore, the development of a robust machine learning model to ensure good prediction or classification performance requires a huge experimental dataset for training. In most cases, the accessibility of a good dataset to train these models may not be feasible due to the huge costs of a data collection infrastructure and subscription to online databases.

Another common challenge encountered when training for machine learning (particularly in classical machine learning techniques) is the underfitting and overfitting of trained models. Underfitting scenarios denote high bias and low variance, inferring that a trained model has not learned the data, while in cases where the model has memorized and performs well with training data but performs poorly with unseen (test) data that was not used to train it, this can be inferred as overfitting. Both issues can be managed through cross-validation, pruning for DT and RF, the use of more training data, an increased number of model parameters, etc. Another challenge is that of how to translate the optimized decisions from machine learning models into the control actions for irrigation system actuation devices [230].

A major concern about the various deployment issues of machine learning algorithms, either on the edge or the cloud, is the accessibility of web infrastructure. Edge-based and cloud-based machine learning represent two up-and-coming ways for the implementation of machine learning models regarding the control of irrigation. These offer a fast response time at the edge and quick-action data privacy [231]. In addition, to deploy machine learning models for real-time irrigation management so that farmers can use them, there is a need to have dedicated servers containing REST APIs that can be used to call various functionalities from the model. The model deployment will require the use of Python Flask, Docker, or other similar web technology. In addition, the user can also deploy applications using Amazon, Azure Web Services, or similar cloud-based platforms that charge the user fees for use [81].

One of the major challenges of the adoption of machine learning and digital software applications in terms of improving sustainable precision irrigation is the initial cost of deployment, particularly for small-scale farmers. This requires the digitization of the farm process, using sensors, actuators and networking of the hardware used for precision agriculture. Although there is an increase in available cloud infrastructures, such as the platform as a service (PaaS), infrastructure as a service (IaaS), and software as a service (SaaS) for irrigation management. The cost of adopting machine learning and digital software applications is reducing, but issues regarding privacy and data security remain a concern for most farmers [232]. Without an affordable cloud-based infrastructure and hardware setup, it will be difficult to implement machine learning for smart and sustainable irrigation.

There are several opportunities for farmers and users that integrate a combination of machine learning prediction with mobile software solutions. The efficiency of water use can be improved in the prediction of irrigation need, timing and volume can be better matched with the water needs of plants, as well as adaptively compensating for water loss due to evapotranspiration. This will result in improved yield, using minimal irrigation, and with the reduced wastage of irrigation water. As a result of the training of the models and eventual deployment, the system becomes intelligent and can have some autonomous features for irrigation decision-making. Therefore, much of the stress and burden of irrigation can be reduced for farmers and users. In some cases, farmers can also remotely visualize and monitor their cultivation environment, to see the performance and state of their plant and soil conditions, as well as control the status of actuators using mobile phones and computers. Most farmers are interested in knowing their return on investment (RoI) in

terms of the adoption of machine learning and software applications for their irrigation process. The use of machine learning techniques can help evaluate and predict the number of resources needed for the irrigation of farms. This makes it possible to determine the ROI and know the value of adopting such technologies. Lack of adequate data makes it difficult to calculate the ROI; hence, it is difficult to convince farmers of the importance of adopting machine learning and smart irrigation techniques.

## 5. Future Trends

### 5.1. Application of Reinforcement Learning

Due to its self-learning and model-free ability to adapt its policy directly to irrigation system dynamics, reinforcement learning offers good potential for the adaptive control of irrigation systems [170]. More work can explore ways to influence the changing dynamics of plants and control weather parameters, as well as the fertigation process [168].

### 5.2. Application of Federated Learning

The deployment of machine learning techniques uses centralized systems where the data and computational analysis are carried out in the cloud. However, due to privacy concerns regarding user-generated data, there is a shift and a growing interest in the adoption of federated learning [156,157]. Federated learning is a procedure that allows devices such as nodes, sensors, and local clients to train and share prediction models collaboratively, but the individual devices retain their data [158]. A global statistical model is developed from data that are stored on local or remote devices. However, there are some challenges associated with the applications of federated learning that have been identified in the literature [233]. This includes communication challenges faced by sending model updates from heterogeneous devices and the use of privacy protection methods that reduce system efficiency and model performance [233]. Nevertheless, the potential benefits of the application of federated learning is expected to attract research interest from both academia and industry.

### 5.3. Deployment in Less-Developed Countries

The adoption of digitization and smart agricultural practices is less common in developing countries, especially in Africa and parts of Asia. Adoption is slow due to the infrastructural challenges faced by most African countries. For instance, a large number of farmers are located in rural areas with less internet coverage and low broadband penetration [234]. Hence, more research in innovative technologies that can be adapted in developing countries for the deployment of machine learning in improving sustainable precision irrigation is needed. These include the deployment of low-power wide-area communication technologies, such as long-range (LoRa) communication technology [235], which combines edge computing and federated learning for rural agricultural practices.

### 5.4. Digital Twin

The adoption of the digital twin concept for smart irrigation is opening up new research opportunities. “Digital twin” simply means a digital or virtual representation of physical assets or products or services. Digital twin technologies are a combination of several technologies, such as IoT, simulation, data analysis and modeling. Some of the applications of the digital twin model in agriculture have been presented in [236–240]. However, there are still limited studies on the deployment of smart irrigation systems that employ digital twins and machine learning. The development of digital twins using machine learning and digital software applications is expected to open up further research opportunities.

### 5.5. Fertigation

The application of machine learning and digital solutions is not just limited to precision farming. Recent developments have shown applications regarding fertigation farming,

where the water is mixed with the nutrients to enable the optimal use of resources [241,242]. This creates several issues, like an increase in the input data to be analyzed and trained via different machine learning techniques. More studies are expected to adopt machine learning techniques for precision fertigation systems.

## 6. Conclusions

A major driver regarding the attainment of sustainable precision irrigation has been the integration of smart technology, such as machine learning, IoT, the web, and the mobile framework. Some of the findings from this study suggest that sustainable precision irrigation management plays an important role in enhancing the attainment of food security and the prevention of water scarcity. Therefore, this paper has expanded further the reviewing of machine learning techniques used for irrigation management, namely, supervised, unsupervised, and reinforcement learning. The findings also show that the choice of a machine learning model to be used for irrigation management depends on the availability of an experimental data set, computational complexity, the nature of implementation, and the type of deployment. Challenges and opportunities in the application of machine learning techniques and digital solutions have been discussed. Furthermore, future trends in the adoption of machine learning and digital farming solutions aimed at improving sustainable precision irrigation were presented. These include the application of reinforcement learning, federated learning, digital-twin models and fertigation in precision irrigation. The findings from this review show that supervised and unsupervised learning have largely been used for precision irrigation with positive outcomes. However, due to the many advantages of federated learning, such as data privacy and security, more research works are expected in this area. In addition, the drive for Industry 4.0 in agriculture is expected to prompt more research work into the adoption of digital-twin technology in smart irrigation systems. The integration of machine learning techniques and the integration of mobile and web solutions are expected to bring many benefits to both farmers and users. This paper will be of benefit to farmers, researchers and generalists who are interested in the digitization of the farming process. Future work will address the environmental concerns associated with the use of digital solutions for irrigation management when applied to mechanized farms.

**Author Contributions:** Conceptualization, E.A.A., O.H. and A.N.; methodology, E.A.A., A.N., O.Y., A.S.A.; software, E.A.A., O.Y., A.S.A.; validation, O.H., T.J.E., O.E., A.N. and M.S.Z.A.; investigation, E.A.A., A.N.; resources, O.H., A.N.; data curation, E.A.A.; writing—original draft preparation, E.A.A., O.E.; writing—review and editing, O.H., A.N., O.E., T.J.E. and M.S.Z.A.; visualization, E.A.A., O.E.; supervision, O.H., T.J.E., O.E., A.N. and M.S.Z.A. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Talaviya, T.; Shah, D.; Patel, N.; Yagnik, H.; Shah, M. Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artif. Intell. Agric.* **2020**, *4*, 58–73. [[CrossRef](#)]
2. Afzaal, H.; Farooque, A.A.; Abbas, F.; Acharya, B.; Esau, T. Precision irrigation strategies for sustainable water budgeting of potato crop in Prince Edward Island. *Sustainability* **2020**, *12*, 2419. [[CrossRef](#)]
3. Pereira, R.M.S.; Lopes, S.; Caldeira, A.; Fonte, V. Optimized planning of different crops in a field using optimal control in Portugal. *Sustainability* **2018**, *10*, 4648. [[CrossRef](#)]
4. Zinkernagel, J.; Maestre-Valero, J.F.; Seresti, S.Y.; Intrigliolo, D.S. New technologies and practical approaches to improve irrigation management of open field vegetable crops. *Agric. Water Manag.* **2020**, *242*, 106404. [[CrossRef](#)]
5. Benyezza, H.; Bouhedda, M.; Djellout, K.; Saidi, A. Smart irrigation system based Thingspeak and Arduino. In Proceedings of the 2018 IEEE International Conference on Applied Smart Systems(ICASS2018), Medea, Algeria, 24–25 November 2018; pp. 1–4. [[CrossRef](#)]
6. Devanand Kumar, G.; Vidheya Raju, B.; Nandan, D. A review on the smart irrigation system. *J. Comput. Theor. Nanosci.* **2020**, *17*, 4239–4243. [[CrossRef](#)]

7. Bigah, Y.; Rousseau, A.N.; Gumiere, S.J. Development of a steady-state model to predict daily water table depth and root zone soil matric potential of a cranberry field with a subirrigation system. *Agric. Water Manag.* **2019**, *213*, 1016–1027. [[CrossRef](#)]
8. Gu, Z.; Qi, Z.; Burghate, R.; Yuan, S.; Jiao, X.; Xu, J. Irrigation scheduling approaches and applications: A review. *J. Irrig. Drain. Eng.* **2020**, *146*, 04020007. [[CrossRef](#)]
9. Tognetti, R.; Kamienski, C.; Dantas, R.; Prati, R.; Toscano, A.; Soininen, J.-P.; Cinotti, T.S. Advancing IoT-based smart irrigation. *IEEE Internet Things Mag.* **2020**, *2*, 20–25. [[CrossRef](#)]
10. Cáceres, G.; Millán, P.; Pereira, M.; Lozano, D. Smart farm irrigation: Model predictive control for economic optimal irrigation in agriculture. *Agronomy* **2021**, *11*, 1810. [[CrossRef](#)]
11. García, I.F.; Lecina, S.; Ruiz-Sánchez, M.C.; Vera, J.; Conejero, W.; Conesa, M.R.; Domínguez, A.; Pardo, J.J.; Léllis, B.C.; Montesinos, P. Trends and challenges in irrigation scheduling in the semi-arid area of Spain. *Water* **2020**, *12*, 785. [[CrossRef](#)]
12. Osroosh, Y. Internet of Plants and Plant-Based Irrigation Scheduling. Available online: <https://www.duruntashlab.com/post/internet-of-plants-and-plant-based-irrigation-scheduling> (accessed on 21 September 2021).
13. Chlingaryan, A.; Sukkarieh, S.; Whelan, B. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Comput. Electron. Agric.* **2018**, *151*, 61–69. [[CrossRef](#)]
14. Liakos, K.G.; Busato, P.; Moshou, D.; Pearson, S.; Bochtis, D. Machine learning in agriculture: A review. *Sensors* **2018**, *18*, 2674. [[CrossRef](#)] [[PubMed](#)]
15. Celicourt, P.; Rousseau, A.N.; Gumiere, S.J.; Camporese, M. Hydro-informatics for sustainable water management in agrosystems. *Front. Water* **2021**, *3*, 119. [[CrossRef](#)]
16. Maduranga, M.W.; Abeysekera, R. Machine learning applications in iot based agriculture and smart farming: A review. *Int. J. Eng. Appl. Sci. Technol.* **2020**, *4*, 24–27. [[CrossRef](#)]
17. Goap, A.; Sharma, D.; Shukla, A.K.; Rama Krishna, C. An IoT based smart irrigation management system using machine learning and open source technologies. *Comput. Electron. Agric.* **2018**, *155*, 41–49. [[CrossRef](#)]
18. Koech, R.; Langat, P. Improving irrigation water use efficiency: A review of advances, challenges and opportunities in the Australian context. *Water* **2018**, *10*, 1771. [[CrossRef](#)]
19. Jha, K.; Doshi, A.; Patel, P. Intelligent irrigation system using artificial intelligence and machine learning: A comprehensive review. *Int. J. Adv. Res.* **2018**, *6*, 1493–1502. [[CrossRef](#)]
20. Jaafar, H.; Kharroubi, S.A. Views, practices and knowledge of farmers regarding smart irrigation apps: A national cross-sectional study in Lebanon. *Agric. Water Manag.* **2021**, *248*, 106759. [[CrossRef](#)]
21. Abioye, E.A.; Abidin, M.S.Z.; Mahmud, M.S.A.; Buyamin, S.; Ishak, M.H.I.; Rahman, M.K.I.A.; Otuozie, A.O.; Onotu, P.; Ramli, M.S.A. A review on monitoring and advanced control strategies for precision irrigation. *Comput. Electron. Agric.* **2020**, *173*, 105441. [[CrossRef](#)]
22. Hassan, S.I.; Alam, M.M.; Illahi, U.; Al Ghamsi, M.A.; Almotiri, S.H.; Su'ud, M.M. A systematic review on monitoring and advanced control strategies in smart agriculture. *IEEE Access* **2021**, *9*, 32517–32548. [[CrossRef](#)]
23. Bwambale, E.; Abagale, F.K.; Anorlu, G.K. Smart irrigation monitoring and control strategies for improving water use efficiency in precision agriculture: A review. *Agric. Water Manag.* **2022**, *260*, 107324. [[CrossRef](#)]
24. Ait Issad, H.; Aoudjit, R.; Rodrigues, J.J.P.C. A comprehensive review of data mining techniques in smart agriculture. *Eng. Agric. Environ. Food* **2019**, *12*, 511–525. [[CrossRef](#)]
25. Çetin, M.; Yıldız, S.; Beyhan, S. Water need models and irrigation decision systems: A survey on machine learning and control theory. *arXiv* **2021**, arXiv:2103.11133.
26. Hans, K.; Jayakumar, A. A review of intelligent practices for irrigation prediction. *arXiv* **2016**, arXiv:1612.02893.
27. Jimenez, A.F.; Cardenas, P.F.; Canales, A.; Jimenez, F.; Portacio, A. A survey on intelligent agents and multi-agents for irrigation scheduling. *Comput. Electron. Agric.* **2020**, *176*, 105474. [[CrossRef](#)]
28. Jha, K.; Doshi, A.; Patel, P.; Shah, M. A comprehensive review on automation in agriculture using artificial intelligence. *Artif. Intell. Agric.* **2019**, *2*, 1–12. [[CrossRef](#)]
29. Balducci, F.; Impedovo, D.; Pirlo, G. Machine learning applications on agricultural datasets for smart farm enhancement. *Machines* **2018**, *6*, 38. [[CrossRef](#)]
30. Glória, A.; Cardoso, J.; Sebastião, P. Sustainable irrigation system for farming supported by machine learning and real-time sensor data. *Sensors* **2021**, *21*, 3079. [[CrossRef](#)]
31. Pathan, M.; Patel, N.; Yagnik, H.; Shah, M. Artificial cognition for applications in smart agriculture: A comprehensive review. *Artif. Intell. Agric.* **2020**, *4*, 81–95. [[CrossRef](#)]
32. Bhat, H.S.; Kumar, N. Quantile regression trees for prediction in irrigation management. In Proceedings of the 4th EFITA Conference in Debrecen, Debrecen, Hungary, 5–9 July 2003; Volume 2, pp. 747–753.
33. Fuentes, B.S.; Tongson, E. Advances and requirements for machine learning and artificial intelligence applications in viticulture. *WINE Vitic. J.* **2018**, *33*, 47–51.
34. Mekonnen, Y.; Namuduri, S.; Burton, L.; Sarwat, A.; Bhansali, S. Review—Machine learning techniques in wireless sensor network based precision agriculture. *J. Electrochem. Soc.* **2020**, *167*, 037522. [[CrossRef](#)]
35. Su, C.; Ma, J. Nonlinear predictive control using fuzzy hammerstein model and its application to CSTR process. *AASRI Procedia* **2012**, *3*, 8–13. [[CrossRef](#)]

36. Singh, S.N.; Jha, R. Optimal design of solar powered fuzzy control irrigation system for cultivation of green vegetable plants in rural India. In Proceedings of the 2012 1st International Conference on Recent Advances in Information Technology (RAIT), Dhanbad, India, 15–17 March 2012. [CrossRef]
37. Sayari, S.; Mahdavi-Meymand, A.; Zounemat-Kermani, M. Irrigation water infiltration modeling using machine learning. *Comput. Electron. Agric.* **2021**, *180*, 105921. [CrossRef]
38. Siddique, T.; Barua, D.; Ferdous, Z.; Chakrabarty, A. Automated farming prediction. In Proceedings of the Intelligent Systems Conference, IntelliSys, London, UK, 7–8 September 2017; pp. 757–763. [CrossRef]
39. Torres-Sánchez, R.; Navarro-Hellín, H.; Guillamón-Frutos, A.; San-Segundo, R.; Ruiz-Abellón, M.C.; Domingo-Miguel, R. A decision support system for irrigation management: Analysis and implementation of different learning techniques. *Water* **2020**, *12*, 548. [CrossRef]
40. Lindholm, A.; Wahlström, N.; Lindsten, F.; Schön, T.B. Supervised Machine Learning. Lecture Notes for the Statistical Machine Learning Course. 2019. Available online: <https://mwns.co/blog/wp-content/uploads/2020/01/Supervised-Machine-Learning.pdf> (accessed on 15 December 2020).
41. Kumar, A.; Surendra, A.; Mohan, H.; Valliappan, K.M.; Kirthika, N. Internet of things based smart irrigation using regression algorithm. In Proceedings of the 2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT) Internet, Kerala, India, 6–7 July 2017; pp. 1652–1657. [CrossRef]
42. Choudhary, S.; Gaurav, V.; Singh, A.; Agarwal, S. Autonomous crop irrigation system using artificial intelligence. *Int. J. Eng. Adv. Technol.* **2019**, *8*, 46–51.
43. González Perea, R.; Camacho Poyato, E.; Montesinos, P.; Rodríguez Díaz, J.A. Prediction of irrigation event occurrence at farm level using optimal decision trees. *Comput. Electron. Agric.* **2019**, *157*, 173–180. [CrossRef]
44. Christias, P.; Daliakopoulos, I.N.; Manios, T.; Mocanu, M. Comparison of three computational approaches for tree crop irrigation decision support. *Mathematics* **2020**, *8*, 717. [CrossRef]
45. Weller, D.L.; Love, T.M.T.; Wiedmann, M. Interpretability versus accuracy: A comparison of machine learning models built using different algorithms, performance measures, and features to predict *E. coli* levels in agricultural water. *Front. Artif. Intell.* **2021**, *4*, 628441. [CrossRef]
46. Blasi, A.H.; Abbadi, M.A.; Al-Huweimel, R. Machine learning approach for an automatic irrigation system in southern Jordan valley. *Eng. Technol. Appl. Sci. Res.* **2021**, *11*, 6609–6613. [CrossRef]
47. Yazici, M.; Basurra, S.; Gaber, M. Edge machine learning: Enabling smart internet of things applications. *Big Data Cogn. Comput.* **2018**, *2*, 26. [CrossRef]
48. Vij, A.; Vijendra, S.; Jain, A.; Bajaj, S.; Bassi, A.; Sharma, A. IoT and machine learning approaches for automation of farm irrigation system. *Procedia Comput. Sci.* **2020**, *167*, 1250–1257. [CrossRef]
49. Singh, A.; Thakur, N.; Sharma, A. A Review of Supervised Machine Learning Algorithms. In Proceedings of the 3rd International Conference on Computing for Sustainable Global Development, New Delhi, India, 16–18 March 2016; pp. 1310–1315.
50. Cai, W.; Wei, R.; Xu, L.; Ding, X. A method for modelling greenhouse temperature using gradient boost decision tree. *Inf. Process. Agric.* **2021**, *in press*. [CrossRef]
51. Mancipe-Castro, L.; Gutiérrez-Carvajal, R.E. Prediction of environment variables in precision agriculture using a sparse model as data fusion strategy. *Inf. Process. Agric.* **2021**, *in press*. [CrossRef]
52. Chen, Y.A.; Hsieh, W.H.; Ko, Y.S.; Huang, N.F. An ensemble learning model for agricultural irrigation prediction. In Proceedings of the 2021 International Conference on Information Networking (ICOIN), Jeju Island, Korea, 13–16 January 2021; Volume 2021, pp. 311–316. [CrossRef]
53. Chen, S.; Chen, L.; Chen, L.; Song, S.; Yang, Z. Application of random forest and back propagation neural network in estimating radiation-based reference evapotranspiration model in Gansu province. In Proceedings of the International Conference on Network and Information Systems for Computers Application, Wuhan, China, 15–17 April 2016; pp. 228–232. [CrossRef]
54. El Mezouari, A.; Najib, M.; El Fazziki, A. *Towards a Smart Irrigation Scheduling System Through Massive Data and Predictive Models*; Springer: Berlin/Heidelberg, Germany, 2019; Volume 1103.
55. Shakoor, T.; Rahman, K.; Sumaiya, N.R. Intelligent Agricultural Information Monitoring Using Data Mining Techniques. Ph.D. Thesis, BRAC University, Dhaka, Bangladesh, 2017.
56. Karthikeya, H.K.; Sudarshan, K.; Shetty, D.S. Prediction of agricultural crops using KNN algorithm. *Int. J. Innov. Sci. Res. Technol.* **2020**, *5*, 1422–1424.
57. Choudhari, P.; Borse, A.; Chauhan, H. Smart irrigation and remote farm monitoring system. *Int. J. Comput. Appl.* **2018**, *180*, 24–26. [CrossRef]
58. Munir, M.S.; Bajwa, I.S.; Ashraf, A.; Anwar, W.; Rashid, R. Intelligent and smart irrigation system using edge computing and IoT. *Complexity* **2021**, *2021*, 6691571. [CrossRef]
59. Kavyashree, T.; Shreedhara, K.S. Intelligent IoT based smart irrigation system. *Int. J. Creat. Res. Thoughts* **2021**, *9*, 2709–2722.
60. Das, A.; Dey, S.K.; Mishra, S.; Sahoo, A. Smart irrigation system, a statistical approach, using Raspberry Pi. *Int. Res. J. Eng. Technol.* **2016**, *3*, 341–345.
61. Mosavi, A.; Sajedi-Hosseini, F.; Choubin, B.; Taromideh, F.; Rahi, G.; Dineva, A.A. Susceptibility mapping of soil water erosion using machine learning models. *Water* **2020**, *12*, 1995. [CrossRef]

62. Gu, W.; Yi, Z. Machine learning on minimizing irrigation water for lawns. *J. Sustain. Dev. Energy Water Environ. Syst.* **2020**, *8*, 701–714. [[CrossRef](#)]
63. Jain, T.; Garg, P.; Tiwari, P.K.; Kuncham, V.K.; Sharma, M.; Verma, V.K. Performance prediction for crop irrigation using different machine learning approaches. In *Examining the Impact of Deep Learning and IoT on Multi-Industry Applications*; IGI Global: Hershey, PA, USA, 2021; pp. 61–79. [[CrossRef](#)]
64. Suzuki, Y.; Ibayashi, H.; Mineno, H. An SVM based irrigation control system for home gardening. In Proceedings of the 2013 IEEE 2nd Global Conference on Consumer Electronics, GCCE 2013, Tokyo, Japan, 1–4 October 2013; pp. 365–366. [[CrossRef](#)]
65. Zema, D.A.; Nicotra, A.; Mateos, L.; Zimbone, S.M. Improvement of the irrigation performance in water users associations integrating data envelopment analysis and multi-regression models. *Agric. Water Manag.* **2018**, *205*, 38–49. [[CrossRef](#)]
66. Arulselvi, G.; Poornima, D. Implementation of precision soil and water conservation agriculture (Pswca) through machine learning, cloud enabled iot integration and wireless sensor network. *Eur. J. Mol. Clin. Med.* **2020**, *7*, 5426–5446.
67. Ramya, S.; Swetha, A.M.; Doraipandian, M. IoT framework for smart irrigation using machine learning technique. *J. Comput. Sci.* **2020**, *16*, 355–363. [[CrossRef](#)]
68. El Mezouari, A.; El Fazziki, A.; Sadgal, M. Toward smart farming through Machine learning based automatic irrigation planning. In *Smart Sensor Networks; Studies in Big Data* 2022, 92; Singh, U., Abraham, A., Kaklauskas, A., Hong, T.P., Eds.; Springer: Cham, Switzerland, 2022. [[CrossRef](#)]
69. Cardoso, J.; Gloria, A.; Sebastiao, P. Improve irrigation timing decision for agriculture using real time data and machine learning. In Proceedings of the 2020 International Conference on Data Analytics for Business and Industry: Way Towards a Sustainable Economy, ICDABI 2020, Sakheer, Bahrain, 26–27 October 2020. [[CrossRef](#)]
70. Bhanu, K.N.; Mahadevaswamy, H.S.; Jasmine, H.J. IoT based smart system for enhanced irrigation in agriculture. In Proceedings of the International Conference on Electronics and Sustainable Communication Systems, ICESC 2020, Coimbatore, India, 2–4 July 2020; pp. 760–765. [[CrossRef](#)]
71. Cagri Serdaroglu, K.; Onel, C.; Baydere, S. IoT based smart plant irrigation system with enhanced learning. In Proceedings of the 2020 IEEE Computing, Communications and IoT Applications (ComComAp), Beijing, China, 20–22 December 2020. [[CrossRef](#)]
72. Niu, H.; Zhao, T.; Wang, D.; Chen, Y. A UAV resolution and waveband aware path planning for onion irrigation treatments inference. In Proceedings of the 2019 International Conference on Unmanned Aircraft Systems (ICUAS), Atlanta, GA, USA, 11–14 June 2019; pp. 808–812. [[CrossRef](#)]
73. Kumar, S.; Mishra, S.; Khanna, P. Precision sugarcane monitoring using SVM classifier. *Procedia Comput. Sci.* **2017**, *122*, 881–887. [[CrossRef](#)]
74. Zhong, B. Research on model of predicting irrigation water requirement based on Kernel method. In Proceedings of the 2nd International Conference on Electronic & Mechanical Engineering and Information Technology, Shenyang, China, 7 September 2012; Volume 2012, pp. 1338–1341. [[CrossRef](#)]
75. Shalini, H.; Aravinda, C.V. *An IoT-Based Predictive Analytics for Estimation of Rainfall for Irrigation*; Springer: Singapore, 2021; Volume 1133. [[CrossRef](#)]
76. Meivel, S.; Maheswari, S. Standard agricultural drone data analytics using KNN algorithm. *Test Eng. Manag.* **2020**, *82*, 206–215.
77. Subathra, M.S.P.; Blessing, C.J.; George, S.T.; Thomas, A.; Raj, A.D.; Edwards, V. Automated intelligent wireless drip irrigation using ANN techniques. In *Advances in Big Data and Cloud Computing*; Springer: Singapore, 2018; pp. 555–568.
78. Nawandar, N.K.; Cheggoju, N.; Satpute, V. ANN-based model to predict reference evapotranspiration for irrigation estimation. In Proceedings of the International Conference on Recent Trends in Machine Learning, IoT, Smart Cities and Applications, Hyderabad, India, 28–29 March 2020; Springer: Singapore, 2020; pp. 671–679.
79. Kondaveti, R.; Reddy, A.; Palabtla, S. Smart Irrigation system using machine learning and IOT. In Proceedings of the International Conference on Vision Towards Emerging Trends in Communication and Networking, ViTECoN 2019, Vellore, India, 30–31 March 2019. [[CrossRef](#)]
80. Dike, H.U.; Zhou, Y.; Deveerasety, K.K.; Wu, Q. Unsupervised learning based on artificial neural network: A review. In Proceedings of the 2018 IEEE International Conference on Cyborg and Bionic Systems, CBS 2018, Shenzhen, China, 25–27 October 2019; pp. 322–327. [[CrossRef](#)]
81. Malik, M.U. *Python Machine Learning for Beginners*; AI Publishing: Assam, India, 2020; Volume 148.
82. Kumar, A.V.S.P.; Bhramaramba, R. Adapting mining into agriculture sector with machine learning techniques. *Int. J. Control Autom.* **2017**, *10*, 13–22. [[CrossRef](#)]
83. Swamynathan, M. *Mastering Machine Learning with Python in Six Steps*; Apress: New York, NY, USA, 2019. [[CrossRef](#)]
84. Prabhu, S.R.B.; Mathew, A.I. A review of efficient information delivery and clustering for drip irrigation management using WSN. *Int. J. Comput. Sci. Bus. Inform.* **2014**, *14*, 1–13.
85. Nisha, G.; Megala, J. Wireless sensor network based automated irrigation and crop field monitoring system. In Proceedings of the 2014 Sixth International Conference on Advanced Computing (ICoAC), Chennai, India, 17–19 December 2014; pp. 8–13.
86. Ohana-Levi, N.; Ben-Gal, A.; Peeters, A.; Termin, D.; Linker, R.; Baram, S.; Raveh, E.; Paz-Kagan, T. A comparison between spatial clustering models for determining N-fertilization management zones in orchards. *Precis. Agric.* **2021**, *22*, 99–123. [[CrossRef](#)]
87. Sherwani, F.; Ibrahim, B.S.K.K.; Asad, M.M. Hybridized classification algorithms for data classification applications: A review. *Egypt. Inform. J.* **2020**, *22*, 185–192. [[CrossRef](#)]

88. Schmitz, G.H.; Schütze, N.; Petersohn, U. New strategy for optimizing water application under trickle irrigation. *J. Irrig. Drain. Eng.* **2002**, *128*, 287–297. [CrossRef]
89. Murthy, A.R.S. An IoT and machine learning approach for site specific irrigation in residential irrigation systems. Masters Thesis, Texas A&M University, College Station, TX, USA, 2019. Available online: <https://hdl.handle.net/1969.1/186512> (accessed on 20 September 2021).
90. Karar, M.E.; Al-Rasheed, M.F.; Al-Rasheed, A.F.; Reyad, O. IoT and neural network-based water pumping control system for smart irrigation. *Inf. Sci. Lett.* **2020**, *9*, 107–112. [CrossRef]
91. Wu, B.; Ye, B.Y.; Wu, C.L.; Zhang, C.Z. Irrigation water compensation control system based on fuzzy neural network. *Adv. Mater. Res.* **2010**, *108*, 1386–1391. [CrossRef]
92. Sun, F.; Ma, W.; Li, H.; Wang, S. Research on water-fertilizer integrated technology based on neural network prediction and fuzzy control. In Proceedings of the IOP Conference Series: Earth and Environmental Science, Ordos, China, 28–29 April 2018; Volume 170, p. 032168. [CrossRef]
93. Arif, C.; Mizoguchi, M.; Setiawan, B.I.; Doi, R. Estimation of soil moisture in paddy field using artificial neural networks. *Int. J. Adv. Res. Artif. Intell.* **2012**, *1*, 17–21. [CrossRef]
94. Antonopoulos, V.Z.; Antonopoulos, A.V. Daily reference evapotranspiration estimates by artificial neural networks technique and empirical equations using limited input climate variables. *Comput. Electron. Agric.* **2017**, *132*, 86–96. [CrossRef]
95. Zanetti, S.S.; Sousa, E.F.; Oliveira, V.P.S.; Almeida, F.T.; Bernardo, S. Estimating evapotranspiration using artificial neural network and minimum climatological data. *J. Irrig. Drain. Eng.* **2007**, *9437*, 83–89. [CrossRef]
96. Sharma, S.; Regulwar, D.G. Prediction of evapotranspiration by artificial neural network and conventional methods. *Int. J. Eng. Res.* **2016**, *5*, 184–187. [CrossRef]
97. Kelley, J.; Pardyjak, E.R. Using neural networks to estimate site-specific crop evapotranspiration with low-cost sensors. *Agronomy* **2019**, *9*, 108. [CrossRef]
98. Pandorfi, H.; Bezerra, A.C.; Atarassi, R.T.; Vieira, F.M.C.; Filho, J.A.D.B.; Guiselini, C. Artificial neural networks employment in the prediction of evapotranspiration of greenhouse-grown sweet pepper. *Rev. Bras. Eng. Agrícola Ambient.* **2016**, *20*, 507–512. [CrossRef]
99. Koutsoyiannis, D. Discussion of “generalized regression neural networks for evapotranspiration modelling”. *Hydrol. Sci. Sci. Hydrol.* **2009**, *52*, 1092–1105. [CrossRef]
100. Gu, J.; Yin, G.; Huang, P.; Guo, J.; Chen, L. An improved back propagation neural network prediction model for subsurface drip irrigation system. *Comput. Electr. Eng.* **2017**, *60*, 58–65. [CrossRef]
101. Sadati, S.K.; Ghahraman, B.; Speelman, S.; Sabouhi, M.; Gitizadeh, M. Optimal irrigation water allocation using a genetic algorithm under various weather conditions. *Water* **2014**, *6*, 3068. [CrossRef]
102. Perea, R.G.; Camacho, E.; Montesinos, P.; Gonz, R.; Rodri, J.A. Optimisation of water demand forecasting by artificial intelligence with short data sets. *Sci. Eng.* **2018**, *7*, 3–10. [CrossRef]
103. Risheh, A.; Jalili, A.; Nazerfard, E. Smart Irrigation IoT solution using transfer learning for neural networks. In Proceedings of the 10th International Conference on Computer and Knowledge Engineering (ICCKE), Mashhad, Iran, 29–30 October 2020.
104. Mehra, M.; Saxena, S.; Sankaranarayanan, S.; Tom, R.J.; Veeramanikandan, M. IoT based hydroponics system using deep neural networks. *Comput. Electron. Agric.* **2018**, *155*, 473–486. [CrossRef]
105. Umair, S.; Muhammad, R.U. Automation of irrigation system using ANN based controller. *Int. J. Electr. Comput. Sci.* **2015**, *10*, 41–47.
106. Widjianto, S.A.; Widodo, A.; Achmad Hidayatno, S. Error analysis of ON-OFF and ANN controllers based on evapotranspiration. *Telkomnika Indones. J. Electr. Eng.* **2014**, *12*, 6771–6779. [CrossRef]
107. Dursun, M.; Özden, S. An efficient improved photovoltaic irrigation system with artificial neural network based modeling of soil moisture distribution—A case study in Turkey. *Comput. Electron. Agric.* **2014**, *102*, 120–126. [CrossRef]
108. Atsalakis, G.; Minoudaki, C. Daily irrigation water demand prediction using adaptive neuro-fuzzy inferences systems (ANFIS). In Proceedings of the 3rd IASME/WSEAS International Conference on Energy, Environment, Ecosystems and Sustainable Development, Agios Nikolaos, Greece, 24–26 July 2007; pp. 369–374.
109. Navarro-Hellín, H.; Martínez-del-Rincon, J.; Domingo-Miguel, R.; Soto-Valles, F.; Torres-Sánchez, R. A decision support system for managing irrigation in agriculture. *Comput. Electron. Agric.* **2016**, *124*, 121–131. [CrossRef]
110. Liang, Z.; Liu, X.; Wen, G.; Yuan, X. Influence analysis of sprinkler irrigation effectiveness using ANFIS. *Int. J. Agric. Biol. Eng.* **2019**, *12*, 135–148. [CrossRef]
111. Tabari, H.; Kisi, O.; Ezani, A.; Hosseinzadeh Talaee, P. SVM, ANFIS, regression and climate based models for reference evapotranspiration modeling using limited climatic data in a semi-arid highland environment. *J. Hydrol.* **2012**, *444*, 78–89. [CrossRef]
112. Ehteram, M.; Yenn Teo, F.; Najah Ahmed, A.; Dashti Latif, S.; Feng Huang, Y.; Abozweita, O.; Al-Ansari, N.; El-Shafie, A. Performance improvement for infiltration rate prediction using hybridized adaptive neuro-fuzzy inferences system (ANFIS) with optimization algorithms. *Ain Shams Eng. J.* **2021**, *12*, 1665–1676. [CrossRef]
113. Silva, J.P.M.; da Silva, M.L.M.; de Mendonça, A.R.; da Silva, G.F.; de Barros Junior, A.A.; da Silva, E.F.; Aguiar, M.O.; Santos, J.S.; Rodrigues, N.M.M. Prognosis of forest production using machine learning techniques. *Inf. Process. Agric.* **2021**, *in press*. [CrossRef]

114. Jamroen, C.; Komkum, P.; Fongkerd, C.; Krongpha, W. An intelligent irrigation scheduling system using low-cost wireless sensor network toward sustainable and precision agriculture. *IEEE Access* **2020**, *8*, 172756–172769. [\[CrossRef\]](#)
115. Mousa, A.K.; Croock, M.S.; Abdullah, M.N. Fuzzy based decision support model for irrigation system management. *Int. J. Comput. Appl.* **2014**, *104*, 14–20. [\[CrossRef\]](#)
116. Hang, L.; Kim, D. Enhanced model-based predictive control system based on fuzzy logic for maintaining thermal comfort in IoT smart space. *Appl. Sci.* **2018**, *8*, 1031. [\[CrossRef\]](#)
117. Touati, F.; Al-Hitmi, M.; Benhmed, K.; Tabish, R. A fuzzy logic based irrigation system enhanced with wireless data logging applied to the state of Qatar. *Comput. Electron. Agric.* **2013**, *98*, 233–241. [\[CrossRef\]](#)
118. Izzuddin, T.A.; Johari, M.A.; Rashid, M.Z.A.; Jali, M.H. Smart irrigation using fuzzy logic method. *ARPN J. Eng. Appl. Sci.* **2018**, *13*, 517–522.
119. Robles, C.A.; Cabarcas, J.C.; Llanos, A.P. Low-cost fuzzy logic control for greenhouse environments with web monitoring. *Electronics* **2017**, *6*, 71. [\[CrossRef\]](#)
120. Ji, R.; Qi, L.; Huo, Z. Design of fuzzy control algorithm for precious irrigation system in greenhouse. *IFIP Adv. Inf. Commun. Technol.* **2012**, *370*, 278–283. [\[CrossRef\]](#)
121. Tsang, S.W.; Jim, C.Y. Applying artificial intelligence modeling to optimize green roof irrigation. *Energy Build.* **2016**, *127*, 360–369. [\[CrossRef\]](#)
122. Suntaranont, B.; Aramkul, S.; Kaewmoracharoen, M.; Champrasert, P. Water irrigation decision support system for practical weir adjustment using artificial intelligence and machine learning techniques. *Sustainability* **2020**, *12*, 1763. [\[CrossRef\]](#)
123. Patil, P.; Desai, B.L. Intelligent irrigation control system by employing wireless sensor networks. *Int. J. Comput. Appl.* **2013**, *79*, 33–40. [\[CrossRef\]](#)
124. Abidin, M.S.B.Z.; Shibusawa, S.; Buyamin, S.; Mohamed, Z. Intelligent control of capillary irrigation system for water-saving cultivation. In Proceedings of the 2015 10th Asian Control Conference: Emerging Control Techniques for a Sustainable World, ASCC 2015, Kota Kinabalu, Malaysia, 31 May–3 June 2015; pp. 2–6. [\[CrossRef\]](#)
125. Rahman, M.K.I.A.; Abidin, M.S.Z.; Mohd Saiful Azimi Mahmud, S.B.; Emmanuel, M.H.I.I.A.A. Advancement of a smart fibrous capillary irrigation management system with an internet of things integration. *Bull. Electr. Eng. Inform.* **2019**, *8*, 1402–1410. [\[CrossRef\]](#)
126. Yubin, Z. The control strategy and verification for precise water-fertilizer irrigation system. In Proceedings of the 2018 Chinese Automation Congress (CAC), Xi'an, China, 30 November–2 December 2018; pp. 4288–4292. [\[CrossRef\]](#)
127. Villarrubia, G.; de Paz, J.F.; de la Iglesia, D.H.; Bajo, J. Combining multi-agent systems and wireless sensor networks for monitoring crop irrigation. *Sensors* **2017**, *17*, 1775. [\[CrossRef\]](#)
128. Castañeda-Miranda, A.; Castaño-Meneses, V.M. Internet of things for smart farming and frost intelligent control in greenhouses. *Comput. Electron. Agric.* **2020**, *176*, 105614. [\[CrossRef\]](#)
129. Memoona, K.; Tahira, M.; Warda, I.; Humaraia, A.G.; Rabeea, S. A survey on unsupervised machine learning algorithms for automation, classification and maintenance. *Int. J. Comput. Appl.* **2015**, *119*, 34–39.
130. Ciaburro, G.; Iannace, G. Machine learning-based algorithms to knowledge extraction from time series data: A review. *Data* **2021**, *6*, 55. [\[CrossRef\]](#)
131. Kamilaris, A.; Prenafeta-Boldú, F.X. Deep learning in agriculture: A survey. *Comput. Electron. Agric.* **2018**, *147*, 70–90. [\[CrossRef\]](#)
132. Kamilaris, A.; Prenafeta-Boldú, F.X. A review of the use of convolutional neural networks in agriculture. *J. Agric. Sci.* **2018**, *156*, 312–322. [\[CrossRef\]](#)
133. Nasirahmadi, A.; Gonzalez, J.; Sturm, B.; Hensel, O.; Knierim, U. Pecking activity detection in group-housed turkeys using acoustic data and a deep learning technique. *Biosyst. Eng.* **2020**, *194*, 40–48. [\[CrossRef\]](#)
134. Haghverdi, A.; Leib, B.G.; Washington-Allen, R.A.; Ayers, P.D.; Buschermohle, M.J. Perspectives on delineating management zones for variable rate irrigation. *Comput. Electron. Agric.* **2015**, *117*, 154–167. [\[CrossRef\]](#)
135. Tagarakis, A.; Liakos, V.; Fountas, S.; Koundouras, S.; Gemtos, T.A. Management zones delineation using fuzzy clustering techniques in grapevines. *Precis. Agric.* **2013**, *14*, 18–39. [\[CrossRef\]](#)
136. Method, U.K.; Monem, M.J.; Hashemi, S.M. Spatial clustering of irrigation networks using k-means method (case study of Ghazvin irrigation network). *Iran Water Resour. Res.* **2011**, *7*, 38–46.
137. Metwally, M.S.; Shaddad, S.M.; Liu, M.; Yao, R.J.; Abdo, A.I.; Li, P.; Jiao, J.; Chen, X. Soil properties spatial variability and delineation of site-specific management zones based on soil fertility using fuzzy clustering in a hilly field in Jianyang, Sichuan, China. *Sustainability* **2019**, *11*, 7084. [\[CrossRef\]](#)
138. Yashaswini, L.S.; Vani, H.U.; Sinchana, H.N.; Kumar, N. Smart automated irrigation system with disease prediction. In Proceedings of the 2017 IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI), Chennai, India, 21–22 September 2017; pp. 422–427.
139. Agastya, C.S.; Ghebremusse, S.; Anderson, I.; Reed, C.; Vahabi, H.; Aug, C.V. Self-supervised contrastive learning for irrigation detection. *arXiv* **2021**, arXiv:2108.05484.
140. Albuquerque, C.K.G.; Polimante, S.; Torre-Neto, A.; Prati, R.C. Water spray detection for smart irrigation systems with mask R-CNN and UAV Footage. In Proceedings of the 2020 IEEE International Workshop on Metrology for Agriculture and Forestry, MetroAgriFor 2020, Trento, Italy, 4–6 November 2020; pp. 236–240. [\[CrossRef\]](#)

141. Zhang, C.; Yue, P.; Di, L.; Wu, Z. Automatic identification of center pivot irrigation systems from landsat images using convolutional neural networks. *Agriculture* **2018**, *8*, 147. [[CrossRef](#)]
142. Bellahirich, S.; Mezghani, D.; Mami, A. Design and implementation of an intelligent anfis controller on a raspberry pi nano-computer for photovoltaic pumping intended for drip irrigation. *Energies* **2021**, *14*, 5217. [[CrossRef](#)]
143. Anuslu, T. *Smart Precision Agriculture with Autonomous Irrigation System Using RNN-Based Techniques*; MEF University: Istanbul, Turkey, 2017.
144. Braga, D.J.F.; Coelho, T.L.; Rocha, A.; Coutinho, G.; Magalhães, R.P.; Guerra, P.T.; De Macêdo, J.A.F.; Barbosa, S.D.J. time series forecasting to support irrigation management. *J. Inf. Data Manag.* **2019**, *10*, 66–80.
145. Tang, J.; Arvor, D.; Corpetti, T.; Tang, P. Mapping center pivot irrigation systems in the southern Amazon from Sentinel-2 images. *Water* **2021**, *13*, 298. [[CrossRef](#)]
146. Perea, R.G.; Poyato, E.C.; Montesinos, P.; Díaz, J.A.R. Irrigation demand forecasting using artificial neuro-genetic networks. *Water Resour. Manag.* **2015**, *29*, 5551–5567. [[CrossRef](#)]
147. Li, I.; Yoder, R.E.; Odhiambo, L.O.; Zhang, J. Simulation of nitrate distribution under drip irrigation using artificial neural networks. *Irrig. Sci.* **2004**, *23*, 29–37. [[CrossRef](#)]
148. Sharifi, H.; Roozbahani, A.; Shahdany, M.H. Development of ANN, FIS and ANFIS models to evaluate the adequacy index in agricultural water distribution systems (Case study: Rudasht irrigation network). *Iran. J. Ecohydrol.* **2020**, *7*, 635–646.
149. Jimenez, A.F.; Ortiz, B.V.; Bondesan, L.; Morata, G.; Damianidis, D. Long short-term memory neural network for irrigation management: A case study from southern Alabama, USA. *Precis. Agric.* **2021**, *22*, 475–492. [[CrossRef](#)]
150. Alibabaei, K.; Gaspar, P.D.; Lima, T.M. Crop yield estimation using deep learning based on climate big data and irrigation scheduling. *Energies* **2021**, *14*, 3004. [[CrossRef](#)]
151. Ortiz, B.V.; Bondesan, L.; Morata, G.; Damianidis, D. Evaluation of two recurrent neural network methods for prediction of irrigation rate and timing. *Am. Soc. Agric. Biol. Eng.* **2020**, *63*, 1327–1348.
152. Zhou, J.; Zhang, Y.; Tian, S.; Lai, S. Forecasting rainfall with recurrent neural network for irrigation equipment. In Proceedings of the IOP Conference Series: Earth and Environmental Science, Sanya, China, 24–26 April 2020; Volume 510, p. 042040. [[CrossRef](#)]
153. Delavar, M.; Moghadasi, M.; Morid, S. Real-time model for optimal water allocation in irrigation systems during droughts. *J. Irrig. Drain. Eng.* **2012**, *138*, 517–524. [[CrossRef](#)]
154. Kanmani, R.; Muthulakshmi, S.; Subitcha, K.S.; Sriranjani, M.; Radhapoorani, R.; Suagnya, N. Modern irrigation system using convolutional neural network. In Proceedings of the 2021 7th International Conference on Advanced Computing and Communication Systems, ICACCS 2021, Coimbatore, India, 19–20 March 2021; pp. 592–597. [[CrossRef](#)]
155. Henry, T.; Iv, C. A Deep Learning Approach to Mapping Irrigation: U-Net IrrMapper. Master’s Thesis, University of Montana, Missoula, MT, USA, 2020.
156. Durrant, A.; Markovic, M.; Matthews, D.; May, D.; Enright, J.; Leontidis, G. The role of cross-silo federated learning in facilitating data sharing in the agri-food sector. *Comput. Electron. Agric.* **2022**, *193*, 106648. [[CrossRef](#)]
157. Kumar, P.; Gupta, G.P.; Tripathi, R. PEFL: Deep privacy-encoding based federated learning framework for smart agriculture. *IEEE Comput. Soc.* **2021**, *2021*, 1. [[CrossRef](#)]
158. Wang, X.; Han, Y.; Wang, C.; Zhao, Q.; Chen, X.; Chen, M. In-edge AI: Intelligentizing mobile edge computing, caching and communication by federated learning. *IEEE Netw.* **2019**, *33*, 156–165. [[CrossRef](#)]
159. Sun, L.; Yang, Y.; Hu, J.; Porter, D.; Marek, T.; Hillyer, C. Reinforcement learning control for water-efficient agricultural irrigation. In Proceedings of the 15th IEEE International Symposium on Parallel and Distributed Processing with Applications and 16th IEEE International Conference on Ubiquitous Computing and Communications, ISPA/IUCC 2017, Guangzhou, China, 12–15 December 2018; pp. 1334–1341. [[CrossRef](#)]
160. Chouaib, E.H.; Salwa, B.; Said, K.; Chehbouni, A. A reinforcement learning based approach for efficient irrigation water management. In Proceedings of the 1st African Conference on Precision Agriculture, Marrakesh, Morocco, 8–10 December 2020; pp. 160–168.
161. Chen, M.; Cui, Y.; Wang, X.; Xie, H.; Liu, F.; Luo, T.; Zheng, S.; Luo, Y. A reinforcement learning approach to irrigation decision-making for rice using weather forecasts. *Agric. Water Manag.* **2021**, *250*, 106838. [[CrossRef](#)]
162. Irulkula, S. Reinforcement Learning Based Controller for Precision Irrigation. Ph.D. Thesis, Texas A&M University, College Station, TX, USA, 2015.
163. Bergez, J.; Eigenraam, M.; Garcia, F. Comparison between Dynamic Programming and Reinforcement Learning: A Case Study on Maize Irrigation Management. In Proceedings of the 3rd European Conference on Information Technology in Agriculture (EFITA01), Montpellier, France, 18–21 June 2001; pp. 343–348.
164. Zhou, N. Intelligent control of agricultural irrigation based on reinforcement learning. *J. Phys. Conf. Ser.* **2020**, *1601*, 1954. [[CrossRef](#)]
165. Yang, Y.; Hu, J.; Porter, D.; Marek, T.; Heflin, K.; Kong, H.; Sun, L. Deep reinforcement learning-based irrigation scheduling. *Trans. ASABE* **2020**, *63*, 549–556. [[CrossRef](#)]
166. Overweg, H.; Berghuijs, H.N.C.; Athanasiadis, I.N. CropGym: A reinforcement learning environment for crop management. *arXiv* **2021**, arXiv:2104.04326.
167. Mason, K.; Mannion, P.; Duggan, J.; Howley, E. Applying multi-agent reinforcement learning to watershed management. *Proc. Adapt. Learn. Agents Work.* **2016**, *2016*, 83–90.

168. Binas, J.; Luginbuehl, L.; Bengio, Y. Reinforcement learning for sustainable agriculture. In Proceedings of the ICML 2019 Workshop Climate Change: How Can AI Help, Long Beach, CA, USA, 14 June 2019.
169. Nian, R.; Liu, J.; Huang, B. A review on reinforcement learning: Introduction and applications in industrial process control. *Comput. Chem. Eng.* **2020**, *139*, 106886. [[CrossRef](#)]
170. Gandhi, R. Deep Reinforcement Learning for Agriculture: Principles and Use Cases. In *Data Science in Agriculture and Natural Resource Management; Studies in Big Data 2022*, 96; Reddy, G.P.O., Raval, M.S., Adinarayana, J., Chaudhary, S., Eds.; Springer: Singapore, 2022. [[CrossRef](#)]
171. Kumar, S.A.; Karthikeyan, C. Status of mobile agricultural apps in the global mobile ecosystem. *Int. J. Educ. Dev. Inf. Commun. Technol.* **2019**, *15*, 63–74.
172. Ogubuike, R.; Adib, A.; Orji, R. Masa: AI-adaptive mobile app for sustainable agriculture. In Proceedings of the 2021 IEEE 12th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), Vancouver, BC, Canada, 27–30 October 2021; pp. 1–7.
173. Ruth, L.; Kopecky, F. The Introduction of Smartphones as a Tool for Agricultural Extension in Rural Uganda: A Three-Phase Study. Ph.D. Thesis, Iowa State University, Ames, IA, USA, 2016.
174. Matukhina, O.V.; Votyakova1, L.R.; Zakharova, I.N. SMART-technologies in irrigation management of a remote land plot. In Proceedings of the IOP Conference Series: Materials Science and Engineering, Russky Island, Russia, 6–9 October 2020; Volume 1079, p. 072027. [[CrossRef](#)]
175. Zhang, S.; Li, S.; Ke, Z.; Zhao, H.; Guo, Y.; Yang, J.; Wang, Y.; Li, D.; Wang, L.; Yang, W.; et al. Investigation on environment monitoring system for a combination of hydroponics and aquaculture in greenhouse. *Inf. Process. Agric.* **2021**, *in press*. [[CrossRef](#)]
176. Maina, M.M.; Amin, M.S.M.; Yazid, M.A. Web geographic information system decision support system for irrigation water management: A review. *Acta Agric. Scand. Sect. B Soil Plant Sci.* **2014**, *64*, 283–293. [[CrossRef](#)]
177. Rajeswari, S.; Suthendran, K.; Rajakumar, K. A smart agricultural model by integrating IoT, mobile and cloud-based big data analytics. *Int. J. Pure Appl. Math.* **2018**, *118*, 365–370.
178. Akhter, R.; Sofi, S.A. Precision agriculture using iot data analytics and machine learning. *J. King Saud Univ. Comput. Inf. Sci.* **2021**, *in press*. [[CrossRef](#)]
179. Abdelmoamen Ahmed, A.; Al Omari, S.; Awal, R.; Fares, A.; Chouikha, M. A distributed systemforsupporting smart irrigation using internet of things technology. *Eng. Rep.* **2020**, *2020*, e12352. [[CrossRef](#)]
180. Mohammed, M.; Riad, K.; Alqahtani, N. Efficient IoT-based control for a smart subsurface irrigation system to enhance irrigation management of date palm. *Sensors* **2021**, *21*, 3942. [[CrossRef](#)]
181. Sagheer, A.; Mohammed, M.; Riad, K.; Alhajhoj, M. A cloud-based iot platform for precision control of soilless greenhouse cultivation. *Sensors* **2021**, *21*, 223. [[CrossRef](#)]
182. Osroosh, Y.; Troy, R.; Campbell, C.S.; Zhang, Q. Comparison of irrigation automation algorithms for drip-irrigated apple trees. *Comput. Electron. Agric.* **2016**, *128*, 87–99. [[CrossRef](#)]
183. Bitella, G.; Rossi, R.; Bochicchio, R.; Perniola, M.; Amato, M. A novel low-cost open-hardware platform for monitoring soil water content and multiple soil-air-vegetation parameters. *Sensors* **2014**, *14*, 19639. [[CrossRef](#)]
184. Vellidis, G.; Liakos, V.; Andreis, J.H.; Perry, C.D.; Porter, W.M.; Barnes, E.M.; Morgan, K.T.; Fraisse, C.; Migliaccio, K.W. Development and assessment of a smartphone application for irrigation scheduling in cotton. *Comput. Electron. Agric.* **2016**, *127*, 249–259. [[CrossRef](#)]
185. Ogidan, O.K.; Afia, K.R. Smart irrigation system with an android-based remote logging and control. In Proceedings of the 2019 IEEE AFRICON, Accra, Ghana, 25–27 September 2019; Volume 2019, p. 3953. [[CrossRef](#)]
186. Perea, R.G.; García, I.F.; Arroyo, M.M.; Díaz, J.A.R.; Poyato, E.C.; Montesinos, P. Multiplatform application for precision irrigation scheduling in strawberries. *Agric. Water Manag.* **2017**, *183*, 194–201. [[CrossRef](#)]
187. Pérez-castro, A.; Sánchez-molina, J.A.; Castilla, M.; Sánchez-moreno, J. CFertigUAL: A fertigation management app for greenhouse vegetable crops. *Agric. Water Manag.* **2017**, *183*, 186–193. [[CrossRef](#)]
188. Hassan, A.; Abdullah, H.M.; Farooq, U.; Shahzad, A.; Asif, R.M. A wirelessly controlled robot-based smart irrigation system by exploiting arduino. *J. Robot. Control* **2021**, *2*, 29–34. [[CrossRef](#)]
189. Andrade, M.A.; Shaughnessy, S.A.O.; Evett, S.R. ARSPIVOT, a sensor-based decision support software for variable-rate irrigation center pivot systems: Part A. Development. *Trans. ASABE* **2020**, *63*, 1521–1533. [[CrossRef](#)]
190. Andrade, M.A.; O'Shaughnessy, S.A.; Evett, S.R. ARSmartPivot v.l-sensor based management software for center pivot irrigation systems. *Am. Soc. Agric. Biol. Eng. Annu. Int. Meet.* **2015**, *3*, 2329–2346. [[CrossRef](#)]
191. Colaizzi, P.D.; O'Shaughnessy, S.A.; Lamm, F.R. Web/smart phone based control and feedback systems for irrigation systems. In Proceedings of the 30th Annual Central Plains Irrigation Conference, Colby, KS, USA, 20–21 February 2018; pp. 199–208.
192. Andrade, M.A.; O'Shaughnessy, S.A.; Evett, S.R. A GIS-based decision support tool for center pivot irrigation systems. In Proceedings of the 2016 ASABE Annual International Meeting, Orlando, FL, USA, 17–20 July 2016. [[CrossRef](#)]
193. Stokke, A.F. The Use of Mobile Phones in the Extension and Advisory Service in Rwanda. Master's Thesis, Norwegian University of Life Science, Ås, Norway, 2019.
194. Khan, N.A.; Qijie, G.; Sertse, S.F.; Nabi, M.N.; Khan, P. Farmers' use of mobile phone-based farm advisory services in Punjab, Pakistan. *Inf. Dev.* **2020**, *36*, 390–402. [[CrossRef](#)]

195. Zhishao, T. AgriApp—Adapting ICTs for Mobile Agricultural Information. Available online: <http://knowledgeshare.sainonline.org/wp-content/uploads/2017/04/AgriApp-%E2%80%93-adapting-ICTs-for-mobile-agricultural-information.pdf> (accessed on 20 September 2021).
196. Manonmani, R.; Rose, R.S.S. Participatory GIS for irrigation management in periyar main canal command area—A case study of kumaram village, madurai district. *Int. J. Sci. Res. Sci. Technol.* **2017**, *3*, 865–875.
197. Patel, V.B.; Thakkar, R.G. Agricultural android application. *Int. J. Comput. Sci. Technol.* **2014**, *5*, 326–328.
198. Vuolo, F.; Essl, L.; Atzberger, C. Costs and benefits of satellite-based tools for irrigation management. *Front. Environ. Sci.* **2015**, *3*, 52. [CrossRef]
199. Maiga, J.; Suyoto, S.; Pranowo, P. Mobile app design for sustainable agriculture in Mali—West Africa. In Proceedings of the IOP Conference Series: Materials Science and Engineering, Bandung, Indonesia, 20–21 April 2020; Volume 1098, p. 032037. [CrossRef]
200. Hillyer, C.; Sayde, C. A web based advisory service for optimum irrigation management. In Proceedings of the 5th National Decennial Irrigation Conference Proceedings, Phoenix, AZ, USA, 5–8 December 2010; *1*, pp. 347–357. [CrossRef]
201. Jones, A.S.; Andales, A.A.; Burzynski, A.; Chávez, J.L.; David, O.; Fletcher, S.J.; Forsythe, J.M.; Goodliff, M.; Grazaitis, P.; Kidder, S.Q.; et al. *Integrative Hydrometeorological Applications with Precipitation, Soil Moisture, and Water Vapor Using Phone Apps, GIS, and Data Assimilation*; American Meteorological Society: Boston, MA, USA, 2020. [CrossRef]
202. Okonkwo, C.W.; Ade-Ibijola, A. Chatbots applications in education: A systematic review. *Comput. Educ. Artif. Intell.* **2021**, *2*, 100033. [CrossRef]
203. Agrowetter Irrigation Advice. Geisenheim Research Centre. Available online: [https://www.dwd.de/DE/leistungen/agrowetter\\_prognose/agroprog.html](https://www.dwd.de/DE/leistungen/agrowetter_prognose/agroprog.html) (accessed on 21 September 2021).
204. Haimanote, K.; Bayabil, K.W.; Migliaccio, K.W.; Andreis, J.H.D.; Fraisse, C.; Morgan, K.T.; Vellidis, G. Smartirrigation apps: Urban turf. *EDIS* **2013**, *2013*, *5*. [CrossRef]
205. Migliaccio, K.W.; Morgan, K.T.; Vellidis, G.; Zotarelli, L.; Fraisse, C.; Zurweller, B.A.; Andreis, J.H.; Crane, J.H.; Rowland, D.L. Smartphone apps for irrigation scheduling. *Trans. ASABE* **2016**, *59*, 291–301. [CrossRef]
206. Dahnil, D.P.; Hood, Z.; Adam, A.; Razak, M.Z.A.; Ismail, A.G. Drip irrigation detection for power outage-prone areas with internet-of-things smart fertigation managemant system. *Int. J. Adv. Comput. Sci. Appl.* **2021**, *12*, 745–755. [CrossRef]
207. Brunel, G.; Pichon, L.; Taylor, J.; Tisseyre, B.; Brunel, G.; Pichon, L.; Taylor, J.; Tisseyre, B. Easy water stress detection system for vineyard irrigation management. In Proceedings of the 12th European Conference on Precision Agriculture, Montpellier, France, 8–11 July 2019; Wageningen Academic Publishers: Wageningen, The Netherlands, 2020.
208. Alcaide, C.; González, R.; Fernández, I.; Camacho, E.; Antonio, J.; Díaz, R. Open source application for optimum irrigation and fertilization using reclaimed water in olive orchards. *Comput. Electron. Agric.* **2020**, *173*, 105407. [CrossRef]
209. Fatkhulloev, A.; Gafarova, A.; Hamraqulov, J. The importance of mobile applications in the use of standard. In *International Conference on Information Science and Communications Technologies (ICISCT)*; IEEE: Piscataway, NJ, USA, 2019; pp. 36–38.
210. Andales, A.A. Colorado irrigation scheduler. In Proceedings of the 26th Annual Central Plains Irrigation Conference, Burlington, CO, USA, 25–26 February 2014; pp. 26–33.
211. Riezzo, E.E.; Zippitelli, M.; Impedovo, D.; Todorovic, M.; Cantore, V. *Hydro—Tech—An Integrated Decision Support System for Sustainable Irrigation Management (II): Software and Hardware Architecture*; CIGR: Liege, Belgium, 2013.
212. Todorovic, M.; Riezzo, E.E.; Buono, V.; Zippitelli, M.; Galiano, A.; Cantore, V. Hydro-Tech: An Automated Smart-Tech Decision Support Tool for Eco-Efficient Irrigation Management. *Int. Agric. Eng. J.* **2016**, *25*, 44–56.
213. Simionesei, L.; Ramos, T.B.; Palma, J.; Oliveira, A.R.; Neves, R. IrrigaSys: A web-based irrigation decision support system based on open source data and technology. *Comput. Electron. Agric.* **2020**, *178*, 105822. [CrossRef]
214. Simionesei, L.; Ramos, T.B.; Palma, J.; Oliveira, A.R.; Neves, R. IrrigaSys—A decision support system for irrigation management in the Sorraia Valley region, Portugal. In Proceedings of the EGU General Assembly, Virtual Conference. 4–8 May 2020; p. 9488.
215. Dahane, A.; Kechar, B.; Meddah, Y.; Benabdellah, O. Automated irrigation management platform using a wireless sensor network. In Proceedings of the 2019 Sixth International Conference on Internet of Things: Systems, Management and Security (IOTSMS), Granada, Spain, 22–25 October 2019; pp. 610–615.
216. Vaishali, S.; Suraj, S.; Vignesh, G.; Dhivya, S.; Udhayakumar, S. Mobile integrated smart irrigation management and monitoring system using IOT. In Proceedings of the 2017 IEEE International Conference on Communication and Signal Processing, ICCSP, Chennai, India, 6–8 April 2017; Volume 2018. [CrossRef]
217. Sheikh, J.A.; Cheema, S.M.; Ali, M.; Amjad, Z. *IoT and AI in Precision Agriculture: Designing Smart System to Support Illiterate Farmers*; Springer: Berlin/Heidelberg, Germany, 2021. [CrossRef]
218. Cheema, S.M.; Khalid, M.; Rehman, A.; Sarwar, N. *Plant Irrigation and Recommender System—IoT Based Digital Solution for Home Garden*; Springer Nature: Singapore, 2019; pp. 513–525. [CrossRef]
219. Mbabazi, D.; Migliaccio, K.W.; Crane, J.H.; Fraisse, C.; Zotarelli, L.; Morgan, K.T.; Kiggundu, N. An irrigation schedule testing model for optimization of the smartirrigation avocado app. *Agric. Water Manag.* **2017**, *179*, 390–400. [CrossRef]
220. Vellidis, G.; Liakos, V.; Perry, C.; Tucker, M.; Collins, G.; Snider, J.; Andreis, J.; Migliaccio, K.; Fraisse, C.; Morgan, K.; et al. A smartphone app for scheduling irrigation on cotton. In Proceedings of the 2014 Beltwide Cotton Conference, New Orleans, LA, USA, 7 January 2014; National Cotton Council: Washington, DC, USA, 2014.
221. Andales, A.A. Tactical irrigation management using the wise online tool. In Proceedings of the 29th Annual Central Plains Irrigation Conference, Burlington, CO, USA, 21–22 February 2017; pp. 95–99.

222. Augusto, R.; Dantas, S.; Zyrianoff, I.D.; Kamienski, C.A. The SWAMP farmer app for iot-based smart water status monitoring and irrigation control. In Proceedings of the 2020 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor), Trento, Italy, 4–6 November 2020; pp. 109–113.
223. Campos, N.G.S.; Rocha, A.R.; Gondim, R.; da Silva, T.L.C.; Gomes, D.G. Smart & green: An internet-of-things framework for smart irrigation. *Sensors* **2020**, *20*, 190. [[CrossRef](#)]
224. Rusdi, J.F.; Salam, S.; Abu, N.A.; Sunaryo, B.; Naseer, M.; Rismayadi, D.A.; Kodong, F.R.; Sudarsono, I.; Utomo, E.W.; Pitogo, V.A.; et al. Field reporting irrigation system via smartphone. *J. Phys. Conf. Ser.* **2021**, *1807*, 012012. [[CrossRef](#)]
225. Agricultural Mobile Apps: A Review and Update of Irrigation Apps. Available online: [https://webapp.agron.ksu.edu/agr-social/m Eu\\_article.throck?article\\_id=1011](https://webapp.agron.ksu.edu/agr-social/m Eu_article.throck?article_id=1011) (accessed on 21 September 2021).
226. Bartlett, A.C.; Andales, A.A.; Arabi, M.; Bauder, T.A. A smartphone app to extend use of a cloud-based irrigation scheduling tool. *Comput. Electron. Agric.* **2015**, *111*, 127–130. [[CrossRef](#)]
227. Siddiqui, M.; Akther, F.; Rahman, G.M.E.; Elahi, M.M.; Mostafa, R.; Wahid, K.A. Dimensioning of wide-area alternate wetting and drying (Awd) system for iot-based automation. *Sensors* **2021**, *21*, 6040. [[CrossRef](#)]
228. Talekar, P.S.; Kumar, A.; Kumar, A.; Kumar, M.; Hashmi, M.I. Smart irrigation monitoring system using Blynk app. *Int. J. Innov. Sci. Res. Technol.* **2021**, *6*, 1353–1355.
229. Saab, M.T.A.; Jomaa, I.; Skaf, S.; Fahed, S.; Todorovic, M. Assessment of a smartphone application for real-time irrigation scheduling in Mediterranean environments. *Water* **2019**, *11*, 252. [[CrossRef](#)]
230. Tan, L. Cloud-based decision support and automation for precision agriculture in orchards. *IFAC PapersOnLine* **2016**, *49*, 330–335. [[CrossRef](#)]
231. Osroosh, Y. 5G Technology and Data Privacy Concerns in Agriculture. Available online: <https://www.duruntashlab.com/post/5g-technology-and-data-privacy-concerns-in-agriculture> (accessed on 21 September 2021).
232. Aliev, K. *Internet of Things Applications and Artificial Neural Networks in Smart Agriculture*; Politecnico di Torino: Turin, Italy, 2017.
233. Li, T.; Sahu, A.K.; Talwalkar, A.; Smith, V. Federated learning: Challenges, methods, and future directions. *IEEE Signal Process. Mag.* **2020**, *37*, 50–60. [[CrossRef](#)]
234. Elijah, O.; Orikumhi, I.; Rahman, T.A.; Babale, S.A.; Orakwue, S.I. Enabling smart agriculture in Nigeria: Application of IoT and data analytics. In Proceedings of the 2017 IEEE 3rd International Conference on Electro-Technology for National Development (NIGERCON), Owerri, Nigeria, 7–10 November 2018; pp. 762–766. [[CrossRef](#)]
235. Elijah, O.; Rahman, T.A.; Orikumhi, I.; Leow, C.Y.; Hindia, M.N. An overview of internet of things (IoT) and data analytics in agriculture: Benefits and challenges. *IEEE Internet Things J.* **2018**, *5*, 3758–3773. [[CrossRef](#)]
236. Alves, R.G.; Souza, G.; Maia, R.F.; Tran, A.L.H.; Kamienski, C.; Soininen, J.P.; Aquino, P.T.; Lima, F. A digital twin for smart farming. In Proceedings of the 2019 IEEE Global Humanitarian Technology Conference, GHTC 2019, Seattle, WA, USA, 17–20 October 2019. [[CrossRef](#)]
237. Angin, P.; Anisi, M.H.; Göksel, F.; Gürsoy, C.; Büyükgülçü, A. Agrilora: A digital twin framework for smart agriculture. *J. Wirel. Mob. Netw. Ubiquitous Comput. Dependable Appl.* **2020**, *11*, 77–96. [[CrossRef](#)]
238. Ghandar, A.; Ahmed, A.; Zulfiqar, S.; Hua, Z.; Hanai, M.; Theodoropoulos, G. A decision support system for urban agriculture using digital twin: A case study with aquaponics. *IEEE Access* **2021**, *9*, 35691–35708. [[CrossRef](#)]
239. Moghadam, P.; Lowe, T.; Edwards, E.J. Digital twin for the future of orchard production systems. *Proceedings* **2020**, *36*, 92. [[CrossRef](#)]
240. Neethirajan, S.; Kemp, B. Digital twins in livestock farming. *Animals* **2021**, *11*, 1008. [[CrossRef](#)] [[PubMed](#)]
241. Rahman, M.K.I.A.; Abidin, M.S.Z.; Buyamin, S.; Mahmud, M.S.A. Enhanced Fertigation control system towards higher water saving irrigation. *Indones. J. Electr. Eng. Comput. Sci.* **2018**, *10*, 859–866. [[CrossRef](#)]
242. Anjaly, S.; Sunny, C.; Hakkim, E.C.; Scholar, P. Fertigation automation system for poly houses. *Int. J. Eng. Sci. Comput.* **2016**, *6*, 3061–3067.