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Data-Driven Precision Irrigation for Increasing Water Use Efficiency

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Water is a fundamental resource in agriculture, essential for crop production, food security, and sustainability; however, increasing water scarcity, climate change, and inefficient irrigation practices to make necessary improved water management strategies. Agriculture accounts for nearly 70% of global freshwater withdrawals, placing significant pressure on limited resources (Ringler et al., 2022), making the enhancement of water use efficiency (WUE) critical for sustainable productivity. Water management strategies focus on intelligent precision irrigation by integrating soil moisture sensors, remote sensing, Internet of Things (IoT), and machine learning (ML) for data-driven irrigation management. Sensors such as tensiometers, granular matrix sensors, and FDR, TDR are used to monitor soil moisture dynamics, while remote sensing techniques, including optical, microwave, and thermal drone imaging, provide information on vegetation indices, canopy temperature, and soil moisture for accurate crop water assessment (Wu et al., 2019; Wang et al., 2023). Machine learning models such as Random Forest and Artificial Neural Networks analyse complex datasets to predict irrigation needs and optimize scheduling (Sun & Scanlon, 2019; Elbeltagi et al., 2020). The integrated framework ultimately improves WUE, reduces water wastage, and supports sustainable agriculture.

Keywords: Precision irrigation, water use efficiency (WUE), Internet of Things (IoT), Soil moisture sensors, Remote Sensing, Machine learning, Sustainable agriculture

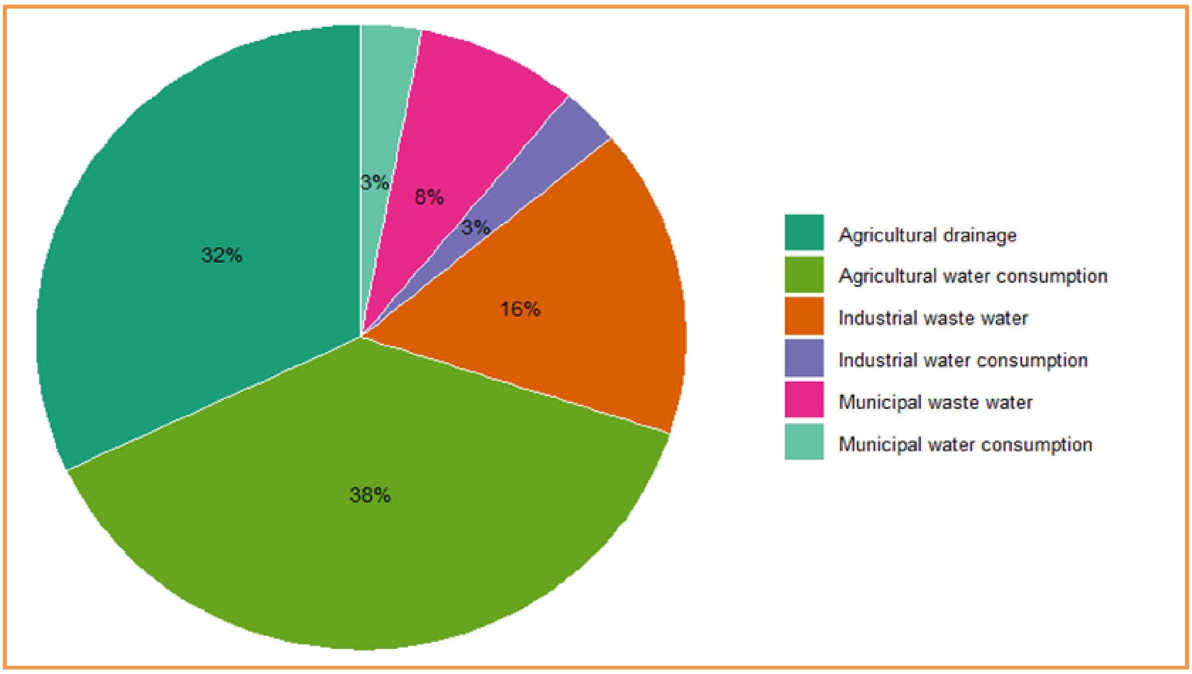
Introduction

Water is a fundamental resource in agriculture, playing a critical role in food production and security worldwide (Ringler et al., 2022). As the primary input in crop cultivation and livestock rearing, water availability and quality directly influence agricultural productivity and sustainability (Molden et al., 2007). In recent years, the escalating challenges of **water scarcity and climate change** have underscored the urgent need for optimizing water use in agriculture (Ingrao et al., 2023). The significance of water in agriculture is profound. It is essential for physiological processes such as photosynthesis, nutrient transport, and maintaining soil structure and health. The agricultural sector is the **largest consumer of freshwater resources (about 70%)** (Ringler et al., 2022). This substantial demand exerts immense pressure on freshwater supplies, increasingly threatened by over-extraction, contamination, and erratic climatic patterns (Mishra, 2023). **Water scarcity is an escalating issue** in many regions, exacerbated by climate change, which affects precipitation patterns, increases the frequency and severity of droughts, and depletes water sources (Mahato et al., 2022). These challenges necessitate innovative and efficient water management strategies to ensure that agricultural needs are met without compromising the sustainability of water resources. Efficient water management practices, such as drip irrigation and precision farming, have demonstrated significant potential in enhancing water use efficiency and reducing wastage (Ringler et al., 2022). **Sustainability in water management** involves maintaining a balance between water needs for agriculture, ecosystems, and human consumption (Russo et al., 2014). Techniques such as water recycling, rainwater harvesting, and integrated water resource management (IWRM) are pivotal in promoting sustainable water use. These practices help conserve water, reduce dependency on freshwater sources, and enhance the resilience of agricultural systems to climatic variability (Ringler et al., 2022).

Global Water scarcity

A pictorial overview of the various sources of water scarcity across the world and the remedial strategies through innovation and water-efficient agricultural practices

World's water consumption and wastewater by sector



Source: United Nations, Department of Economic and Social Affairs (UN DESA), 2025

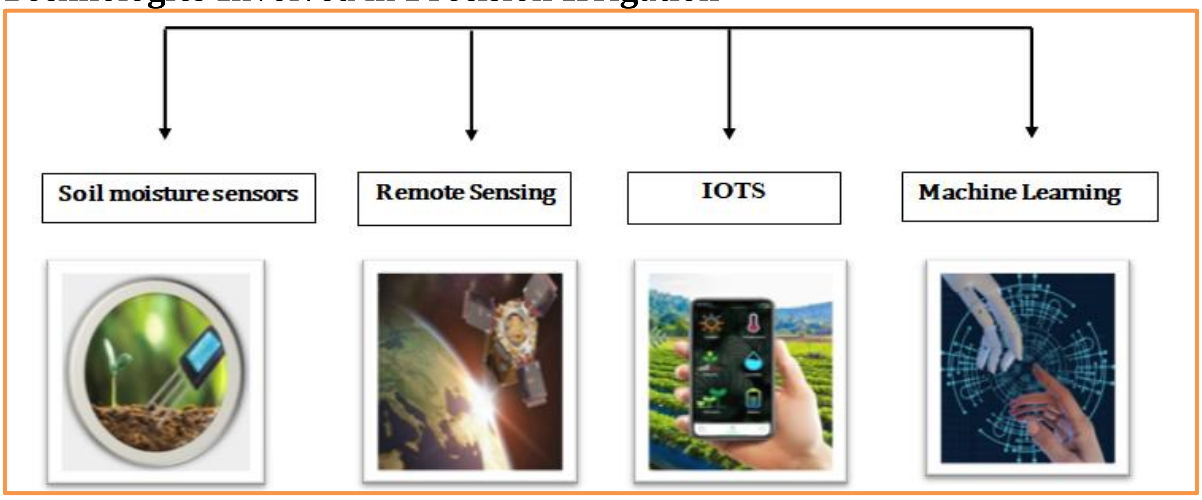
Importance of Water Use Efficiency (WUE) in Agriculture

Water Use Efficiency (WUE) is a critical concept in modern agriculture, particularly under conditions of **water scarcity and climate stress**. It is widely regarded as a key factor influencing crop yield, drought resistance, and sustainable agricultural productivity (Blum, 2009; Farooq et al., 2009). Improving WUE ensures that crops produce more yield per unit of water used, often described by the principle **"more crop per drop."** Efficient use of water is essential in both rainfed and irrigated systems. Practices such as crop residue incorporation, mulching, and the application of drought-tolerant rhizobacteria, along with the co-application of biochar and compost, improve soil structure and enhance **soil water holding capacity, retention, and nutrient availability** (Li et al., 2010). These practices help conserve moisture and support plant growth during periods of limited water availability. Advanced irrigation strategies also contribute significantly to improving WUE. Techniques such as deficit irrigation, irrigation scheduling, and remote sensing-based approaches enable site-specific water management according to crop needs and stress levels (Zhang & Oweis, 1999). These methods reduce water losses while maintaining crop productivity. Furthermore, automated irrigation systems optimize water application by adjusting irrigation timing in real time based on soil moisture conditions in the root zone, thereby significantly enhancing water use efficiency (Pereira et al., 2012). Although deficit irrigation reduces total water use, it can increase economic returns per unit of water, making it a valuable strategy in water-limited regions (Zhang & Oweis, 1999). Overall, improving WUE is essential for ensuring **sustainable water resource management, enhancing agricultural productivity, and building resilience to climate change** (Farooq et al., 2009).

Precision Irrigation: Definition and Comparison with Conventional Irrigation

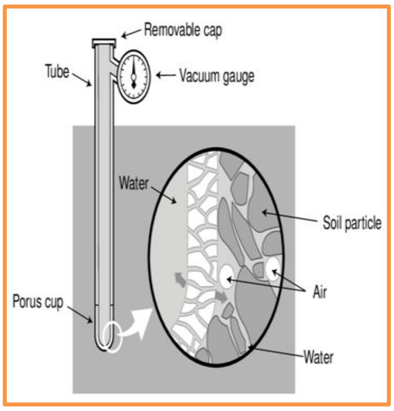
Precision irrigation is an advanced agricultural water management technique that involves applying water to crops in the **right quantity, at the right time, and at the right location** based on crop requirements and real-time field conditions. It utilizes modern technologies such as **soil moisture sensors, remote sensing, and automated irrigation systems** to optimize water application and improve efficiency (Pereira et al., 2012). In contrast, conventional irrigation methods rely on uniform water application across the field without considering spatial and temporal variability in soil moisture and crop needs. This often leads to **uneven water distribution, over- or under-irrigation, nutrient leaching, and increased environmental runoff**, resulting in lower water use efficiency (WUE). Precision irrigation, on the other hand, ensures **targeted water delivery directly to the root zone**, minimizing losses and enhancing both crop yield and resource use efficiency. Additionally, while conventional systems are generally **labour-intensive and less adaptive**, precision irrigation systems are **data-driven, automated, and responsive**, enabling better decision-making and sustainable water management (Zhang & Oweis, 1999).

Technologies Involved in Precision Irrigation



1. Tensiometer

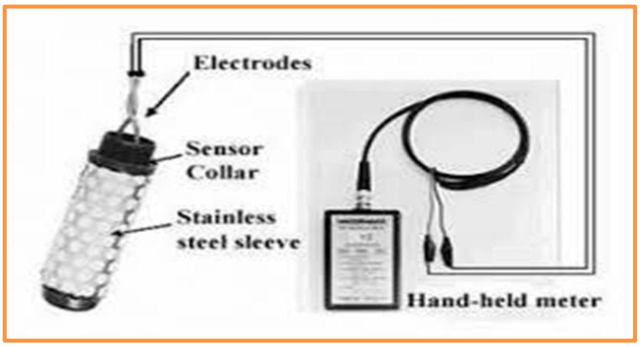
Tensiometers are simple soil moisture tension measuring devices used frequently in irrigation scheduling. A typical tensiometer consists of a **porous ceramic tip connected to a vacuum gauge through a PVC tube**. The tube contains water which should be free from air. The porous ceramic cup is installed into the soil in such a way that soil water pressure is transmitted to the tensiometer and is read by the pressure sensing device mounted on it. This instrument does not measure soil moisture content directly; instead, it measures **soil water tension** (Freeman et al., 2004). Generally, the response time of a tensiometer is **2 to 3 hours** (Zazueta, 1994). There are tensiometers available which can be automated with irrigation systems with the help of a pressure gauge.



Soil moisture tension values for different soils are:

- Sand or loamy soil: **40–50 centibars**
- Sandy loam: **50–70 centibars**
- Loam: **60–90 centibars**
- Clay loam or clay: **90–120 centibars** (Hanson et al., 2002)

2. Granular Matrix Sensor (GMS)



The granular matrix sensor is made of a **porous ceramic external shell with an internal matrix structure containing two electrodes**. The electrodes inside the GMS are embedded in the granular fill material above the gypsum wafer. The water conditions in the granular matrix change with variation in corresponding water conditions in the soil, and these changes are continuously indicated by the difference in **electrical resistance between the two electrodes** in the sensor (Berrada et al., 2014). This resistance between the electrodes is inversely related to soil water (Irmak et al., 2006).

3. Time Domain Reflectometry (TDR)

In time domain reflectometry, a pulse of **radio frequency energy** is injected into a transmission line, and its velocity is measured by detecting the reflected pulse from the end of the line. This velocity depends upon the **dielectric constant**. It measures the moisture content by measuring how long it takes for the reflected pulse to return (Cepuder et al., 2008; Haman et al., undated). The response of a TDR is very quick.

4. Frequency Domain Reflectometry (FDR)

FDR sensor consists of a **pair of metal rings which are formed as a capacitor**, and the soil sample acts as a dielectric. The electrical sensor capacitance is a direct measure of **soil volumetric water content**.

Remote Sensing in Precision Irrigation

Remote sensing plays a vital role in precision irrigation by enabling the **monitoring and management of crop water requirements over large areas** in a timely and efficient manner. It involves the use of satellite, aerial, or drone-based sensors to collect data on crop conditions, soil moisture, and environmental parameters without direct contact with the field. By analyzing spectral information such as vegetation indices (e.g., NDVI), remote sensing helps in assessing **crop health, evapotranspiration, and water stress levels**, allowing farmers to make informed irrigation decisions (Zhang et al., 2002; Jones, 2004).

In precision irrigation, remote sensing supports **site-specific water application**, ensuring that water is applied according to spatial variability within the field. This reduces over-irrigation and water wastage while improving water use efficiency and crop productivity. Additionally, when integrated with Geographic Information Systems (GIS) and decision support systems, remote sensing provides real-time data that enhances irrigation scheduling and resource management (O'Shaughnessy et al., 2015). Thus, remote sensing serves as a powerful tool for achieving **efficient, sustainable, and data-driven irrigation practices** under conditions of increasing water scarcity and climate variability.

Optical Remote sensing

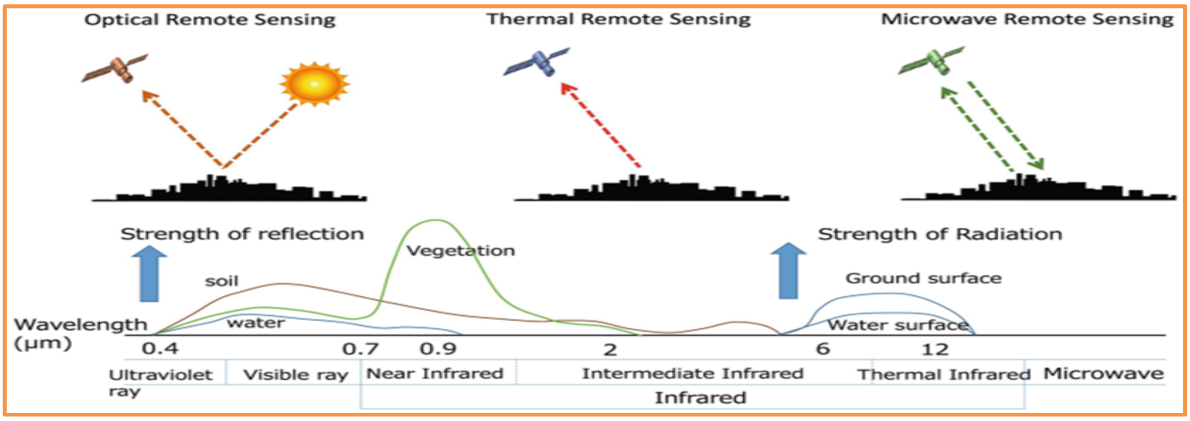
Optical remote sensing is widely used in precision irrigation as it relies on **sunlight reflected from the Earth's surface** to gather information about crop and soil conditions. Sensors mounted on satellites or drones capture this reflected energy in different wavelengths, particularly in the **visible and near-infrared (NIR) regions**. Healthy vegetation reflects more NIR radiation compared to stressed plants, and this property is utilized through vegetation indices such as **Normalized Difference Vegetation Index (NDVI)** to assess **crop health, growth stages, and stress conditions**. In addition, optical remote sensing plays an important role in estimating **evapotranspiration (ET)**, which is essential for irrigation scheduling. However, its effectiveness is limited under **cloudy or rainy conditions**, as clouds obstruct sunlight and reduce data accuracy (Moran et al., 1997; Jones, 2004).

Microwave Remote sensing

Microwave remote sensing operates using **microwave signals (radar waves)** rather than sunlight, making it an **active sensing system**. These sensors emit their own energy toward the Earth's surface and measure the reflected signals, known as **backscatter**. One of the major advantages of microwave remote sensing is its ability to function **day and night and under all weather conditions**, including cloud cover and rainfall. It is particularly valuable for measuring **soil moisture**, as microwave signals can penetrate vegetation and provide information about subsurface conditions. Data from satellites such as **Sentinel-1 Synthetic Aperture Radar (SAR)** are widely used for detecting irrigation events and monitoring water availability. However, compared to optical remote sensing, microwave systems generally provide **lower spatial resolution**, which may limit detailed field-level analysis (Wagner et al., 2007).

Thermal Remote sensing

Thermal Remote sensing is another advanced technique used in precision irrigation, where drones equipped with thermal sensors capture **high-resolution canopy temperature data**. Canopy temperature is closely related to plant water status, as plants experiencing **water deficit exhibit higher canopy temperatures** due to reduced transpiration and cooling. This makes thermal imaging a reliable indicator of **plant water stress**, enabling **early detection before visible symptoms appear**. Such early detection allows farmers to take timely irrigation decisions, preventing yield losses. Furthermore, thermal imagery helps identify spatial variability within fields, highlighting areas that require immediate irrigation and thereby reducing water wastage. When integrated with **soil moisture sensors, weather data, and irrigation algorithms**, thermal drone data supports **real-time, site-specific irrigation scheduling**, ultimately enhancing **water use efficiency and crop productivity** in precision agriculture systems (O'Shaughnessy et al., 2015).

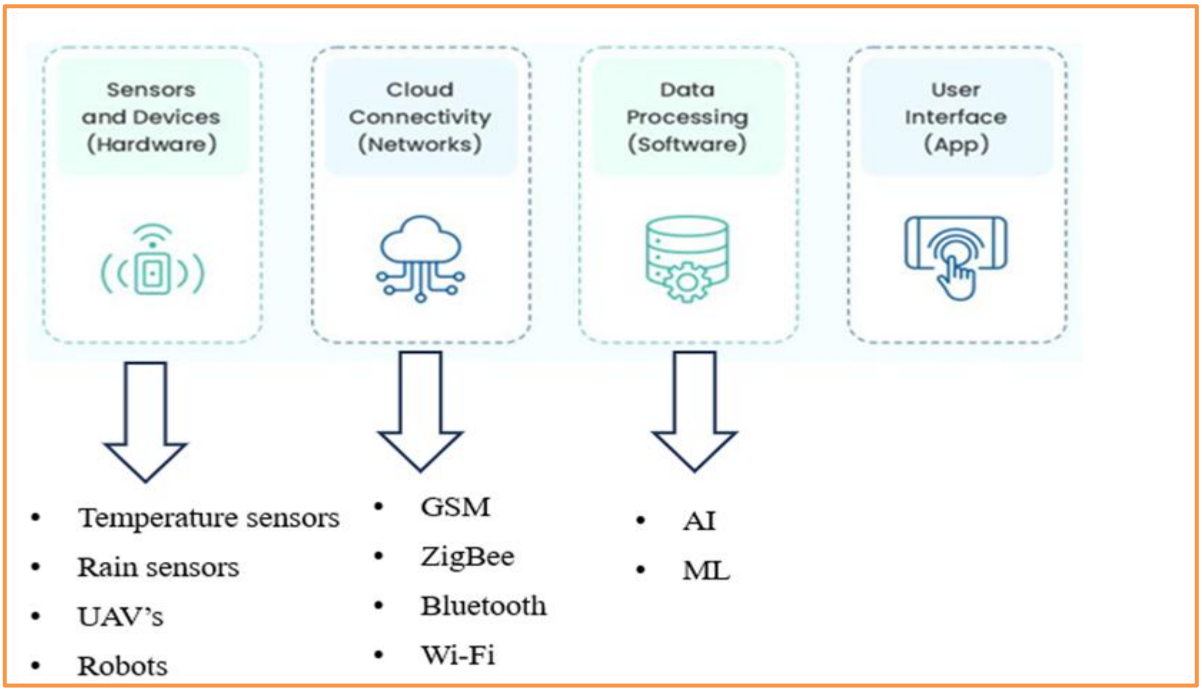


Role of IoT in Precision Irrigation

The Internet of Things (IoT) plays a significant role in precision irrigation by enabling the **connection of physical devices such as sensors, controllers, and irrigation systems** through network connectivity. IoT-based systems use sensors embedded in the field to continuously collect data on **soil moisture, temperature, humidity, and crop conditions**, which is then transmitted over the internet for analysis and decision-making. These interconnected devices can operate with **minimal human intervention**, allowing automatic communication and data exchange between components of the irrigation system (Gluhak et al., 2011).

In precision irrigation, IoT facilitates **real-time monitoring and automated irrigation scheduling**, ensuring that water is applied in the **right amount, at the right time, and at the right location**. By integrating soil moisture sensors and weather data, IoT systems can trigger irrigation only when required, thereby reducing water wastage and improving **water use efficiency (WUE)**. Additionally, IoT enables remote access and control, allowing farmers to monitor field conditions and manage irrigation systems through mobile or web-based platforms. This data-driven approach enhances crop productivity, reduces labor requirements, and supports sustainable water management under changing climatic conditions (Kim et al., 2008; Ojha et al., 2015).

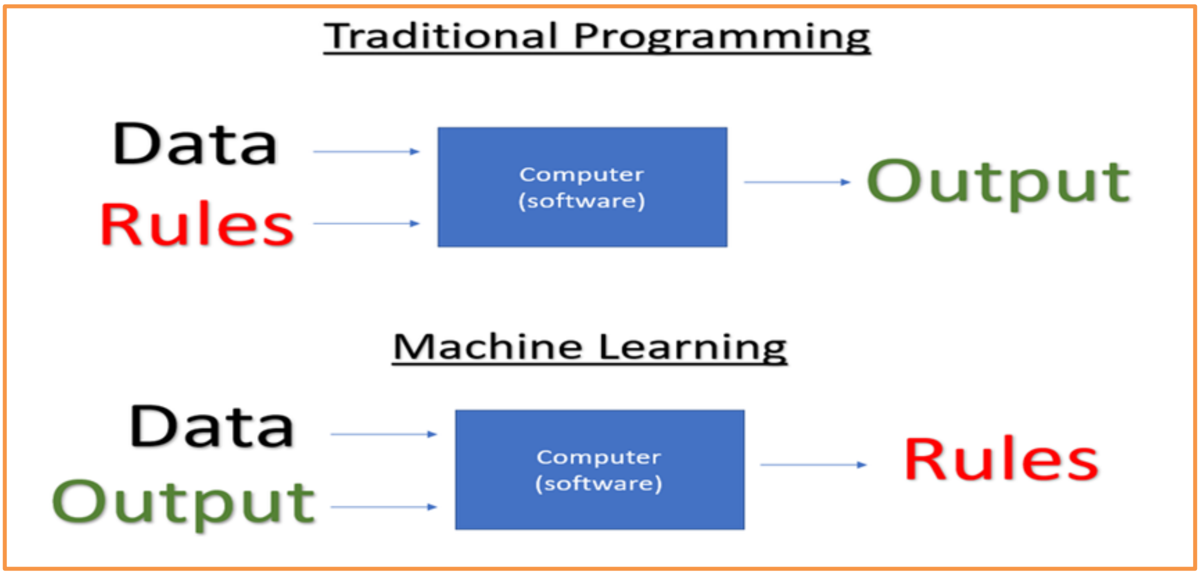
Major components of IoT's



Role of Machine Learning in Precision Irrigation

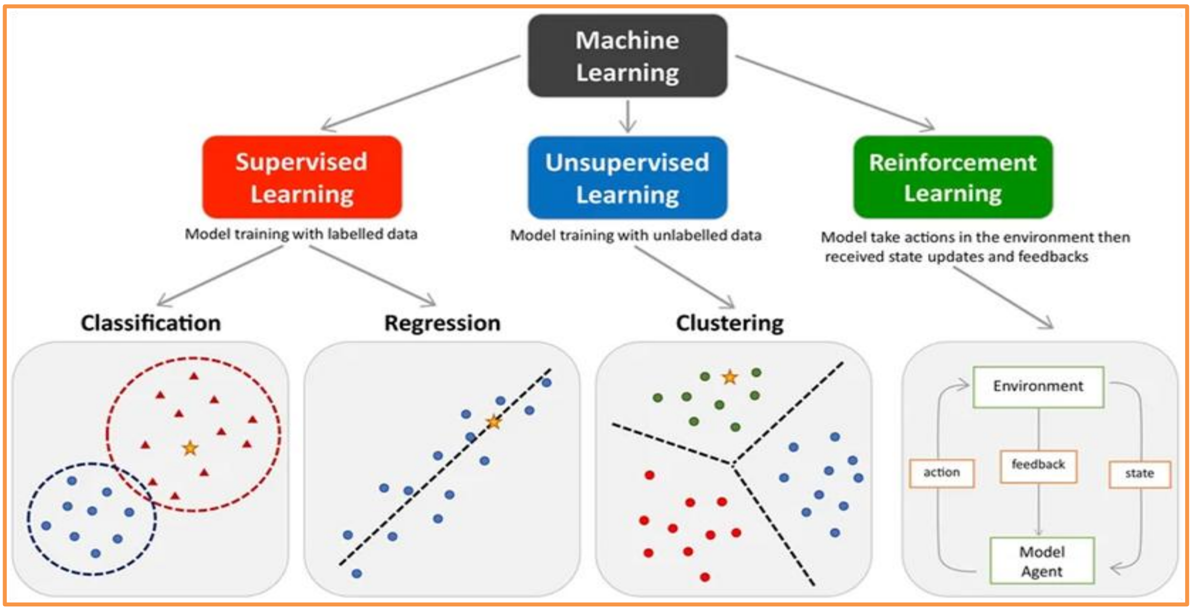
Machine learning, a branch of artificial intelligence, plays an important role in precision irrigation by enabling systems to **learn from data and make decisions without explicit programming**. In agricultural water management, machine learning algorithms analyze large volumes of data collected from sensors, weather stations, and remote sensing systems to identify **patterns related to soil moisture, crop water requirements, and environmental conditions** (Kamilaris & Prenafeta-Boldú, 2018). Using both historical and real-time data as **training data**, machine learning models continuously improve their performance over time. These models can predict irrigation requirements, detect early signs of crop stress, and support efficient decision-making. Unlike traditional rule-based approaches, machine learning systems are adaptive and can respond to dynamic field conditions, enabling **site-specific and optimized irrigation scheduling** (Liakos et al., 2018). Overall, the integration of machine learning in precision irrigation helps improve **water use efficiency, reduce**

resource wastage, and enhance crop productivity, making it an essential tool for sustainable agriculture under changing climatic conditions (Wolfert et al., 2017).

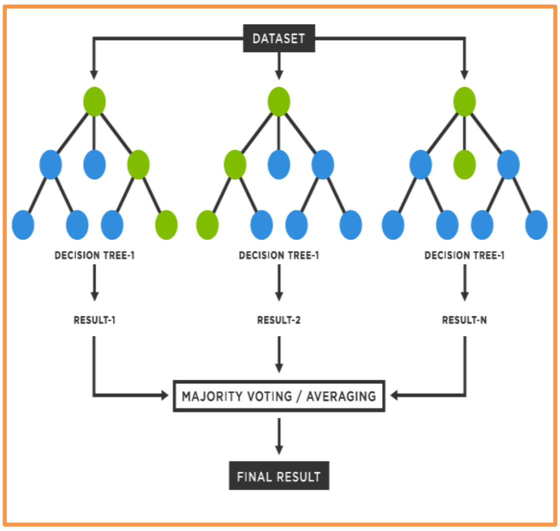


Types of Machine learning

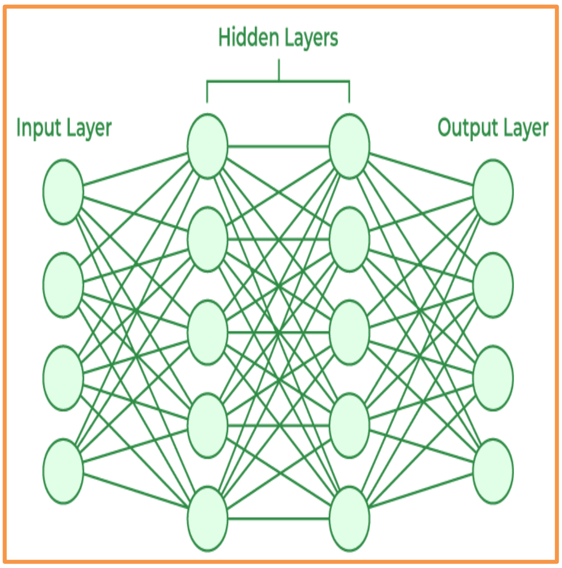
Machine learning in precision irrigation can be broadly categorized into **supervised, unsupervised, and reinforcement learning**, each playing a distinct role in improving irrigation efficiency. In **Supervised learning**, models are trained using **labelled datasets**, where input data such as soil moisture, weather conditions, and crop parameters are paired with known outputs. This allows the model to learn relationships and make accurate predictions over time, such as estimating crop water requirements or irrigation scheduling (Liakos et al., 2018). **Unsupervised learning** works with **unlabelled data** and focuses on identifying hidden patterns or trends without predefined outputs. In precision irrigation, it can be used to group similar field conditions, detect variability in soil moisture, or identify zones within a field that require different irrigation levels. This helps in understanding spatial variability and supports more efficient water management (Kamilaris & Prenafeta-Boldú, 2018). **Reinforcement learning** is based on a **trial-and-error approach**, where the system learns to make optimal decisions by receiving feedback in the form of rewards or penalties. In irrigation systems, it can be used to determine the best irrigation strategy by continuously interacting with the environment and improving decisions over time. This approach is useful for developing adaptive irrigation systems that respond dynamically to changing environmental and crop conditions (Sutton & Barto, 2018).



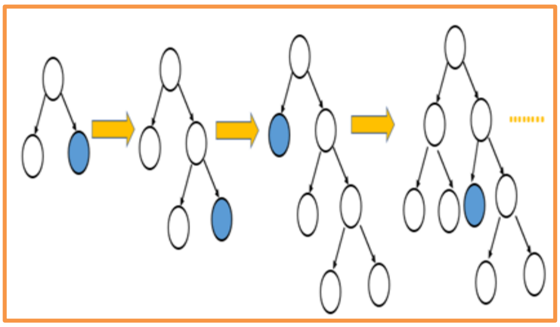
Commonly Used Machine Learning Algorithms in Precision Irrigation



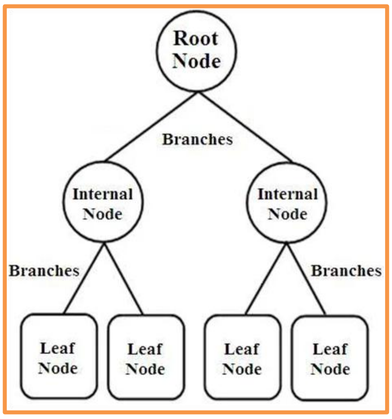
Random Forest (RF) is an ensemble learning method used for both classification and regression tasks. It works by constructing **multiple decision trees** using bootstrap sampling from the original dataset and applying **random feature selection** during node splitting. Each tree produces an independent prediction, and the final output is obtained by aggregating these predictions, often through regression. This approach improves **prediction accuracy and model stability**, making it highly suitable for agricultural applications (Breiman, 2001).



Artificial Neural Networks (ANNs) are computational models inspired by the **human brain structure**. They consist of three main layers: the **input layer, hidden layers, and output layer**. Each neuron processes **weighted inputs using nonlinear activation functions**, enabling the model to capture complex patterns and relationships in data. The hidden layers play a key role in learning these patterns, and their number and depth can be adjusted depending on the complexity of the problem. ANNs are widely used in precision irrigation for modelling nonlinear relationships between environmental factors and crop water requirements (Haykin, 2009).



The **Light Gradient Boosting Machine (LightGBM)** is an efficient gradient boosting framework that uses **tree-based learning algorithms**. It is designed for **fast distributed training**, especially suitable for large datasets. LightGBM employs a **histogram-based algorithm**, which reduces memory usage and speeds up processing. It also provides **higher prediction accuracy** compared to traditional boosting methods by focusing on minimizing errors during model training. This makes it effective for handling complex agricultural datasets and improving irrigation predictions (Ke et al., 2017).



Decision Trees are non-parametric supervised learning methods used for classification and regression. They split data into subsets using a **tree-like structure of decisions**, where nodes represent features, branches represent decision rules, and leaf nodes represent final outcomes. Decision trees are **easy to interpret** and can handle both numerical and categorical data. However, they may suffer from overfitting, which can be reduced by setting constraints such as the minimum number of samples per leaf. Their simplicity and interpretability make them useful for decision-making in irrigation management (Quinlan, 1986).

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