Chapter 15
Precision Agriculture Technologies for Climate-Resiliency and Water Resource Management

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Abstract This chapter explores how precision farming techniques and technologies are used to manage water resources and tackle the challenges brought by climate change in agriculture. Precision farming relies on automation, sensors, drones, and/or telemetry systems to monitor soil conditions, water availability, and weather patterns. By doing so, farmers can optimize productivity, use resources efficiently, and reduce greenhouse gas emissions. Precision water management helps farmers make learned decisions about irrigation, saving water, and making crops more resilient to extreme weather. Additionally, climate-resilient crops, sensing techniques, and agrivoltaics help manage water efficiently and reduce climate risks in farming. Technologies like remote sensing, wireless sensors, and agrivoltaics provide promising solutions for water resource management, ensuring sustainable farming practices despite water scarcity. These approaches improve water efficiency, boost crop yields, and enhance resilience to climate change, building a sustainable future for agriculture.

Keywords Precision agriculture · Climate-resilient · Crop yield

15.1 Introduction

Imagine earth as a big puzzle where climate, soil or land and water are important segments. Removing any one of these components can throw off the balanced cycle that sustains all living organisms. Climate is continuously changing and as

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A. Nanda et al. (eds.), *Navigating the Nexus*, Water Science and Technology Library 102, https://doi.org/10.1007/978-3-031-76532-2_15

there are more people inhabiting the planet over time, the demand to increase food production by utilizing natural resources is increasing. Simultaneously, the weather is becoming increasingly unpredictable, seasons are shifting, and extreme events are happening more often. At the same time, the water we need for farming is also going through a lot of upheavals leading to—drought, flood or glacial melts. As climate change accelerates, its consequences are reverberating through the foundation of our agricultural systems. Consequently, conventional farming practices are being challenged by abrupt weather patterns, changing growing seasons and crop shifts, and an increasing frequency of extreme events. Concurrently, water resources are being affected by shifts in precipitation, melting glaciers, and changing river patterns. In the context of evolving water resource challenges, it is notable that global water usage has escalated dramatically, nearly six-fold since 1900 (Chellaney 2013). The largest share of this usage is agricultural, consuming 69% of water withdrawals, while industrial uses account for 19%, and municipal needs 12% (Plappally and Lienhard 2012). These trends and the impact of human activities and climate change on water systems highlight the growing need for effective water resource management tools among professionals like hydrologists and engineers, particularly in areas where traditional monitoring methods are insufficient. This chapter sheds light on the complex web of interactions, the cascading effects of climate change, and the delicate balance between precision agriculture, water resources, and optimization strategies.

15.1.1 Climate-Resilient Agricultural Practices

In the context of sustainable water management, resilience is defined as the capacity of agriculture system to maintain or enhance productivity by preventing, mitigating, or managing risks; adapting to changes in water status during stressed conditions, recovering from the impacts of climate changes and extreme weather events. In response to climate change, the concept of climate-smart agriculture has emerged as a comprehensive approach to promote adaptation and food security while effectively addressing climate change issues; often referred to as triple win (Lipper et al. 2014). These extreme weather events involve challenges associated with drought conditions, flooding, heat or cold waves, erratic rainfall patterns, prolonged dry spells, insect or pest population explosions, and other perceived threats as a result of climate change. These factors play a crucial role in determining the threats to global food security and the need to adopt resilience practices for cropping systems. Strengthening resilience involves the implementation of short and long-term climate mitigation and adaptation strategies. Additionally, ensuring transparent and inclusive participation of stakeholders in decision-making processes is crucial for the effectiveness of these strategies. Strengthening the grit of agricultural production systems in the face of climate challenges is important for sustaining global food security.

Climate resilient agriculture offers a multidisciplinary approach to tackle the interdependent issues of food security and climate change, with a focus on three primary goals outlined by Rao (2016). (1) sustainably enhancing agricultural productivity to ensure a fair increase in farm incomes and bolster food security; (2) building an adapting and resilient production system to climate change at multiple levels; (3) minimizing greenhouse gas emissions from agriculture (including livestock, fisheries, etc.), to the extent possible. In the realm of climate-smart agriculture, a diverse range of agricultural technologies and practices comes into play. These practices include conservation agriculture, agroforestry, soil and water conservation, advancements in crop genetics, and integration of precision farming. For instance, concerning water management, resilient **farm-scale** practices may include managed aquifer recharge, in-situ moisture conservation, farm ponds, and implementation of efficient irrigation systems. Moreover, **crop-scale** practices may include the use of drought and flood-tolerant varieties, intercropping systems, etc. Additional climate resilient practices include the adoption of diversified cropping systems for soil conservation, crop-livestock integration, developing disease-resistant crops and livestock breeds, and formulating risk management strategies to adapt to changing climate while enhancing farm profitability.

The adoption of climate smart agriculture yields several positive outcomes. Diversified cropping systems with incorporated cover crops contribute to nitrogen fixation and other nutrients in the soil, potentially eliminating the need for additional synthetic inputs. Crop-livestock integration improves soil health by directly synergistic with biogeochemical nutrient cycling and restoring grasslands, particularly when maintaining an appropriate animal grazing density. Such practices lead to increased resource use efficiency, reduced water, and energy requirements, decreased soil runoff and erosion, enhanced aggregate stability, and carbon sequestration in soils. Moreover, these practices enhance pest and disease resistance, thereby improving yield stability and resilience to extreme weather events.

15.2 Precision Farming Techniques for Resilient Agriculture

Precision farming has revolutionized modern agriculture, enhancing efficiency through automated and control systems, data-processing software, mobile apps, and web-based applications (Balasundram et al. 2023). Precision farming employs technologies such as the use of drone technologies, wireless sensor networks, satellites, sensors, robotics, Internet of Things (IoT) based automation, and mobile apps, which can be used to continuously monitor, evaluate, and manage several abiotic factors to enhance productivity and economics benefit. Satellites and high-resolution drone imagery are utilized to track the quality of crops, their water levels, soil moisture levels, and soil salinity. It also helps to generate yield maps and identify crop stress and soil health. The automation tools contribute to smart irrigation and adapting precision technologies even in remote areas.

Adaptation and mitigation strategies, related to precision tools and management practices, provide solutions to achieving higher yields with fewer inputs. Inappropriate irrigation and nutrient management practices significantly contribute to greenhouse gas emissions. Major anthropogenic greenhouse gases, methane, and nitrous oxide, consist of a global warming potential of 27.9, 273 times that of carbon dioxide in a 100-year timeframe (Arias et al. 2021). To mitigate these gas emissions and improve resource use efficiency, sensible use of water and nutrients through precision farming can be employed. For example, increasing nutrient use efficiency with the exact source, rate, place, and application method using precision input management reduced nitrous oxide emissions, mitigating greenhouse gas emissions.

As the impact of climate change persists, building climate resilience through precision and digital agriculture strategies becomes progressively vital enabling farmers to make informed decisions, conserve water resources, and enhance crop productivity. Resilient to drought and other extreme weather events can be put into force with such technologies. By optimizing irrigation practices, precision farming can help maintain the water levels at various aquifers, reservoirs, rivers, canals, and other water sources with easy access even in drought. Alongside precision farming, the adoption of climate-resilient varieties, rainwater harvesting, groundwater recharge, minimum tillage practices, crop diversification, slow-releasing fertilizers, carbon sequestration, and sustainable land use management plays an important role in moderating greenhouse gas emissions in the current scenario of climate change.

15.3 Technologies for Water Resource Management

Water stands as a fundamental and indispensable resource for agriculture playing an important role in ensuring food security. Conventional tools and techniques of irrigation scheduling and crop water use measurements pose significant challenges due to their time-consuming and labor-intensive nature, rendering them impractical for large-scale agricultural operations. By 2050, over half of the global population (57%) is projected to inhabit regions experiencing at least one month of water scarcity annually (Boretti and Rosa 2019). Consequently, mitigating water scarcity and improving water usage efficiency are critical aspects of contemporary water resource management. Precision agriculture facilitated by technological advancements offers a promising solution to this challenge. Precision irrigation preserves and enhances crop yields while conserving water by at least 15% or more than 50% (Zotarelli et al. 2009). By providing insights into spatiotemporal variability, recent research has explored precision technology as an alternative to conventional field tools for assessing plant stress indicators. Precision technologies include a range of methods including remote sensing, wireless sensor networks, LiDAR irrigation, and agrivoltics. These technologies enhance water use efficiency and are integral to sustainable agricultural goals.

15.3.1 Remote Sensing Tools

Remote sensing is a valuable tool in irrigation water management by providing spatial (space) and temporal (time) information on crop water content, particularly for large fields where ground-level measurements or point-based data are impractical to make decisions for entire fields or farms. It offers various avenues for integration into irrigation management, with the most effective method being the detection of water stress levels within plants to schedule irrigation appropriately (Bello et al. 2014). When plants experience water stress, their temperature rises above absolute zero emitting thermal infrared radiation which can be detectable by specialized sensors. This temperature data, coupled with air temperature and pressure allows the construction of water stress indices providing insights into crop water stress levels. Leaf spectral reflectance is also utilized to estimate crop coefficients for irrigation scheduling, leveraging bands at specific wavelengths affected by stress conditions (Bausch 1995). Several indices, including the normalized difference vegetation index (NDVI), and crop water stress indices (CWSI) play crucial roles in measuring water stress across visible and near-infrared spectral ranges. Additionally, the photochemical reflectance index (PRI) offers a substitute for thermal remote sensing, using affordable image sensors with high spatial resolution capabilities not feasible in the thermal domain (Suárez et al. 2010). With advancements in high-resolution and high-frequency remote sensing technologies, monitoring spatial changes in crop water and evapotranspiration at the field level has become increasingly accessible (Debangshi and Sadhukhan 2023).

15.3.2 Wireless Sensor Network (WSN)

Wireless Sensor Networks (WSNs) are highly efficient in irrigation systems due to their dynamic application, flexibility, self-monitoring capabilities, scalability, accuracy, and inter-sensor node collaboration (Hamami and Nassereddine 2020). WSNs comprise sensor nodes distributed throughout fields, communicating wirelessly via handheld devices. They facilitate long-term irrigation assessment without necessitating sensor removal for field operations, thus minimizing equipment damage and data loss (Debangshi and Sadhukhan 2023). WSNs prioritize intelligent controller valves and pumps during irrigation, aiming to allocate water equitably to meet all demands (Al-ammri and Ridah 2014). Advanced WSNs include a wide-area network comprising underground nodes connected to a single above-ground hub or base station, enhancing efficiency. These systems utilize sensor arrays and web-based decision support tools to gather real-time soil moisture data from farmers. This data is then transmitted to a server, enabling farmers to monitor their fields in real time. Moreover, the system employs irrigation management indicators to evaluate water efficiency with smart programming facilitating rapid irrigation recommendation calculations (Jha et al. 2022).

15.3.3 Light Detection and Ranging (LiDAR)

Light Detection and Ranging, a remote sensing technology that measures distances by sending laser pulses and analyzing the light that is reflected, is similar to radar but uses light pulses instead of radio waves; and operates by measuring the time it takes for light pulses to travel to collision points and back to sensors with precision (Rivera et al. 2023). These systems emit light pulses periodically, generating a map of the surrounding environment based on detected collisions.

Various types of LiDAR find applications in agriculture, with bathymetric LiDAR being notable for its use of green light to penetrate water for detection and mapping purposes. This technology aids in identifying water sources and suitable areas for well digging. Moreover, it enables the creation of maps indicating where irrigation may be unnecessary, such as in flood-prone areas or where soils retain moisture at saturation levels. Recent advancements in 3-dimensional LiDAR imagery coupled with natural color offer precise estimation of water stress and its location. The short-band laser light effectively penetrates crop canopies facilitating the detection of water stress within plants (Ahmad et al. 2021).

15.3.4 Agrivoltaics

Agriculture plays a critical role in ensuring economic stability and ensuring global food security. However, this sector is currently facing issues such as climate change, with restricted water resources being the most crucial limitation today. A potential solution to address this challenge is agrivoltaics, which integrates solar photovoltaic (PV) systems with agricultural practices. Agrivoltaics, also known as solar sharing or agri-photovoltaics, involves using land for both generating solar energy and doing agricultural activities. It can help reduce climate change by increasing agricultural production and reducing water usage, while also meeting the growing needs for food, energy, and renewable technology. The National Renewable Energy Laboratory (NREL) foresees that by 2030 utility-scale solar installations in the USA will cover 2 million acres, offering farmers opportunities to cultivate crops beneath solar modules, thus enhancing efficiency, conserving water, and promoting sustainable food production (Macknick et al. 2013). In addition to water storage and recycling, the relationship between solar panels and crops can be leveraged to store water in the shelter provided by the panels and to return the water used for panel cleaning for agricultural irrigation. Agrivoltaics not only enhances water management but also increases land productivity by as much as 70% through the integration of agricultural production and energy generation on a single site. By employing this dual land-use technique, the overall agricultural output is increased while resource utilization is optimized. Numerous studies demonstrate a positive correlation between agrivoltaics and water use efficiency (Zainol et al. 2021). For instance, a recent project in the arid regions of Arizona revealed that cultivating crops under solar panels reduces soil evaporation thus reducing irrigation needs by 50% alongside a more than 300% increase in crop yield through agrivoltaics implementation leading to more efficient water use in agriculture (Bello et al. 2014) (U.S. Department of Energy). Moreover, agrivoltaics systems contribute to increased crop resilience and productivity, particularly when adverse weather conditions such as drought prevail. Solar panels generate a favorable micro-climate through the provision of shade, which serves to mitigate heat stress and enhance the water efficiency of crops. In addition, the vegetation situated beneath the panels experiences enhanced energy efficiency, resulting in reduced water consumption for irrigation purposes (Time et al. 2024). Sometimes agrivoltics systems reduce crop yield by providing shade on the crop so to encounter this issue there are agrivoltaics systems based on Concentrated Lighting Agrivoltaics Systems (CAS) (Fig. 15.1) that transmit red, blue, and far-red light from the sun to plants for photosynthesis. Power is generated by the concentration and reflection of the residual sunlight onto photovoltaic panels (Liu et al. 2018). Alternately, grooved glass plates can be positioned between conventional PV panels (Even-lighting Agrivoltaics System) to promote optimal plant growth and uniform sunlight dispersion. Both approaches, which employ Agrivoltaics Spectral Differentiation (AVSD) effectively, have exhibited productive agricultural development and streamlined electrical production (Ali Abaker Omer et al. 2022). By implementing these two technologies, the even-lighting Agrivoltaics System effectively decreased accumulative water evaporation from pan and soil surfaces by 33% and 19%, respectively, compared to the Concentrated-lighting Agrivoltaics System's 11% and 14%. Subsequently, the moisture content of the soil is greater in areas unexposed to sunlight, including the water and soil surfaces beneath the systems (Liu et al. 2018).

15.4 Data Analytics and Decision Support Systems

The most efficient use of irrigation water is a multifaceted operation that depends on several variables and numerous data layers (such as plant development stage, weather parameters, soil condition, etc.), most of which are linked to different degrees of uncertainty (Jha et al. 2022). In regions that are vulnerable to drought, when water becomes scarce, the difficulties of this work become increasingly stressful (Singh Rawat et al. 2019). Since crop evapotranspiration (ET) is primarily used to calculate irrigation volume and schedule, an accurate prediction of the spatial ET (plant-scale) can help prevent overwatering or underwatering and so ensure optimal irrigation practices (Ghiat et al. 2021). Precision agriculture has advanced to the point that it is now feasible to anticipate many plant health monitoring indicators, including high-resolution spatial ET such as, Normalized Difference Vegetation Index (NDVI), Crop Coefficients (Kc), Land Surface Temperature (LST), Enhanced Vegetation Index (EVI), Normalized Difference Water Index (NDWI), Chlorophyll Content, Leaf Area Index (LAI) and many more (Abdulmumin et al. 1987). The primary sources of this data are in-situ radiometric and telemetric sensors (like Arable Mark III, Tule, and CropX), optical remote sensing technology (like satellite data, multispectral

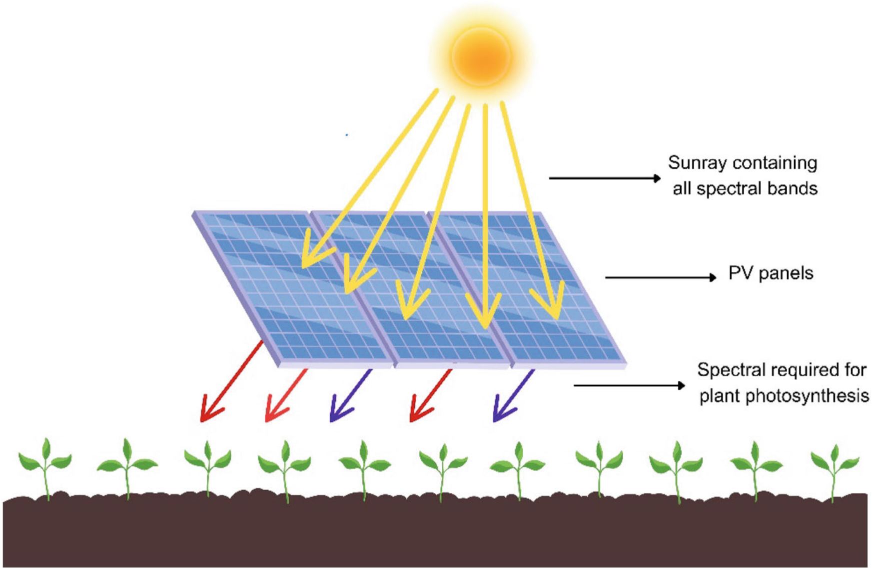

Fig. 15.1 Agrivoltaics systems based on concentrated lighting agrivoltaic systems (CAS)

imagery, etc.), and publicly accessible meteorological data (like Mesonet, the California Irrigation Management Information System (CIMIS), the National Weather Service (NWS), etc.) (Gavilán et al. 2019). The majority of these data are currently accessible to the public via PRISM Climate, Climate Data Online (CDO), and the National Oceanic and Atmospheric Administration (NOAA), among other websites. These resources, easily accessible by farmers, are weather-dependent temporarily and contribute to lower irrigation expenses overall (Ghiat et al. 2021; Guo et al. 2020).

Automated data-driven irrigation strategies can be conceptualized as a structured pipeline incorporating processed based modeling statistical and machine learning techniques, as illustrated in Fig. 15.2. The data collected from optical, telemetric, and radiometric devices including satellites, drones, local weather stations, ground sensors and it serves as the inputs to this pipeline. These inputs undergo sequential processing through distinct stages of the pipeline, outlined as follows.

15.4.1 Feature Selection

The process of selecting a subset of pertinent predictors, that are essential for precisely characterizing the target variable, is known as feature selection (Liu 2011). The input data types are the predictors in this scenario, and ET is the target variable. Numerous

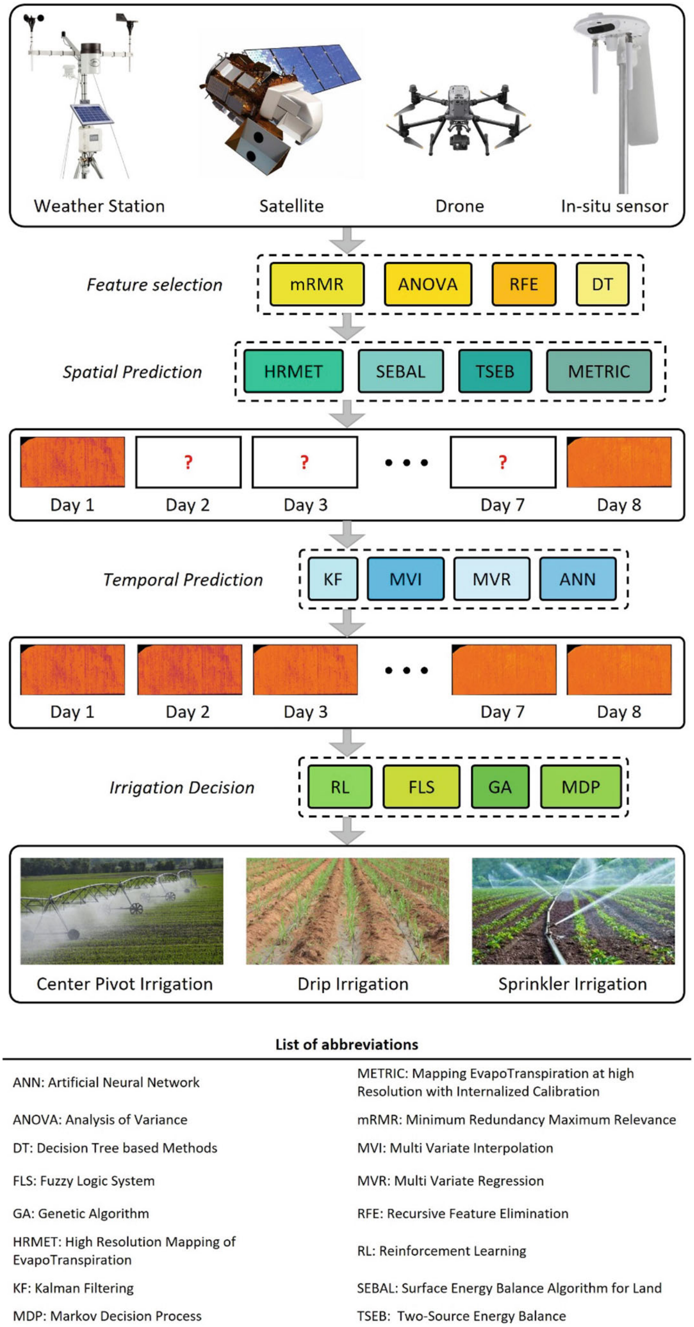

Fig. 15.2 A pipeline of data-driven automated irrigation system

metrics about crop, weather, and soil factors are accessible, similar to most real-world applications. However, not every one of these metrics has a strong correlation with ET. Incorporating extraneous information into the model might lead to needless complexity in computations and perhaps lower prediction accuracy (Guyon and Elisseeff 2003). Techniques for selecting features address this by retaining only the most important elements (Chandrashekar and Sahin 2014).

Several feature selection algorithms work better in certain situations. The kind of data, model assumptions, and quantity of the dataset all influence the method selection (Chandrashekar and Sahin 2014). For instance, model-specific techniques (such Recursive Feature Elimination (RFE) and Decision Tree (DT) based Methods) exist if the prediction model is predetermined (Guyon and Elisseeff 2003). However, there are several model-free techniques (such as Analysis of Variance (ANOVA), Minimum Redundancy Maximum Relevance (mRMR), etc.) that provide users the flexibility to use whatever model they like (Liu 2011; Witten et al. 2017).

15.4.2 Spatial Prediction

Even within a very small agricultural area, ET demonstrates significant spatial heterogeneity based on crop kinds, soil variability, and geographical topography (Wigmosta et al. 1994). Because of this variability, different parts of the field may require different irrigation levels, resulting in overwatering in some places and underwatering in others (Singh Rawat et al. 2019). Although radiometric sensors located on the ground have a good degree of accuracy in their specific region, they frequently do not record field fluctuation, which makes them ineffective for effective micro irrigation (Wang et al. 2020). Thus, the spatial ET prediction at the plant size is an essential component for irrigation water optimization (Ahmad et al. 2021).

With the most significant set of characteristics chosen (or all at once, depending on the feature selection technique), the remotely sensed input data can be used as an appropriate spatial prediction model (Singh Rawat et al. 2019). Other methods use empirical equations and iterative surface energy balance equation solutions to estimate the field ET (Ershadi et al. 2013). The Surface Energy Balance Algorithm for Land (SEBAL), Two-Source Energy Balance (TSEB), Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC), and High-Resolution Mapping of Evapotranspiration (HRMET) are a few of the widely used models in this area (Hoffmann et al. 2016). These models use the field's thermal and multispectral reflectance photos, meteorological data, and accessible surface energy to calculate the sensible heat flux iteratively (Abdulmumin et al. 1987; Ershadi et al. 2013). The difference between the sensible heat flow and the available energy is then utilized to compute the latent heat flux, which is ultimately used to estimate surface ET (Ghiat et al. 2021). As shown in Fig. 15.2, the surface ET images provide a nice visualization and useful metric of plant behaviors.

15.4.3 Temporal Prediction

The data that the spatial ET predictors may produce is only relevant to the day and time of the picture capture (Wang et al. 2023). Daily observations and forecast of plants with ET, help growers to identify plant stress early on and adjust watering schedules appropriately (Ahmad et al. 2021). Frequent and regular gathering of thermal and multispectral spatial data is impractical due to technical limitations (Abdulmumin et al. 1987). For example, Aguilar et al. (2018) assessed the MOD16 algorithm, which estimates evapotranspiration using satellite data. They compared its results with on-ground eddy covariance measurements in five arid or semiarid locations in Northwestern Mexico used for wheat cultivation or hosting natural shrub vegetation. The study found variability in MOD16 performance across these sites, often underestimating evapotranspiration. While MOD16 provided reasonable crop water need estimations for these areas, the lack of extensive ground measurements limits the broader applicability of this satellite-based method.

On the other hand, operating aerial imagery is expensive and requires human effort and hence is not affordable for small-scale farmers (Jha et al. 2022). Consequently, temporal predictions (for each pixel or mini-batches per image) might assist in overcoming the challenge and contribute to a significant reduction in the expenses associated with collecting data (Guo et al. 2020).

Figure 15.2 demonstrates how the days between aerial imagery may be filled up with information via temporal prediction. Assume for the moment that the spatial ET data was available on days 1 and 8, and that the data for days 2 through 7 were absent. In this instance, temporal prediction may be used to estimate these data for the missing data days using the matching weather, soil, and on-the-ground sensor properties. Many intriguing methods exist in this regard, such as deep learning techniques like Support Vector Machine (SVM) regression, Long Short-Term Memory (LSTM), Feedforward Neural Network (FNN), etc.—the latter two models are members of the Artificial Neural Network (ANN) family—or statistical methods like Kalman Filtering (KF), Multi Variate Regression (MVR), Multi Variate Interpolation (MVI), etc. (Witten et al. 2017).

15.4.4 Irrigation Decision

The aforementioned approaches have thus far been relatively straightforward; they merely require the provision of certain input data to an established method. The matching output is either found by the model using empirical and/or statistical calculations, or it is learned via training instances. But in decision-making, the methods might become more inventive and difficult simultaneously (Torres-Sanchez et al. 2020). First, the amount of irrigation may be calculated using linear or polynomial regression approaches by integrating the pertinent data (weather and soil conditions, plant physiology and phenology, availability, and quality of water, etc.) (Torres-Sanchez et al. 2020). These techniques might not be particularly successful or adaptable to real-world circumstances since they oversimplify the irrigation approximation function (Puerto et al. 2013). Second, it is possible to train well-known machine learning models—like Random Forest (RF), Fuzzy Logic System (FLS), Support Vector Machine (SVM), and ANN—to determine the necessary irrigation quantity (Li et al. 2019). When enough training data is provided, the models will ultimately be able to mimic human decision-making. The training data can consist of either historical irrigation practices or expert human judgment (Pluchinotta et al. 2018). Naturally, these abovementioned approaches are mostly directly or indirectly dictated and, hence are limited by anthropogenic solutions (Chen et al. 2021).

The complexity of the process and the vast array of potential alternatives never guarantee a particular solution is the optimal one (Knuth 1974). At the same time, constant observation and quick decision-making are necessary due to the physical systems' dynamism and unpredictability (Torres-Sanchez et al. 2020). Modern artificial intelligence systems, like the Markov Decision Process (MDP), Genetic Algorithm (GA), and Reinforcement Learning (RL), can be used singly or in combination to achieve the highest possible level of water usage efficiency. These systems can even outperform human-provided solutions (Chen et al. 2021; Ding and Du 2022). However, these methods need detailed planning (quite specific to the irrigation system in question) and difficult physical system calibrations, which call for a high degree of human skill (Chen et al. 2021).

After they are set up, smart irrigation controllers (such as those for subsurface drip irrigation and micro-irrigation) may be immediately integrated with the outputs of these automated irrigation decision support systems (IDSS) (Ding and Du 2022). Towards notable contributions to optimizing irrigation and soil moisture management, Gutiérrez et al. (2013) introduced an automated irrigation system that employs a wireless sensor network and a GPRS module for real-time monitoring and control of soil moisture, aiming to conserve water in irrigation practices. For predicting soil moisture Gill et al. (2006) proposed a method using support vector machines relying on air temperature, relative air humidity, and soil temperature data. These studies collectively highlight the potential of integrating advanced technology, such as sensor networks and machine learning algorithms in enhancing agricultural efficiency and resource management. A novel irrigation sensor was developed by Jagüey et al. (2015) using a smartphone camera to estimate soil moisture. This system processes images from RGB to grayscale to determine the wet and dry areas of soil and sends this data to a water motor controller for efficient irrigation management.

15.5 Drones and Satellites; and Their Applications in Agriculture and Water Management

In the last two decades, the agricultural sector has seen a significant rise in the adoption of modern technologies aimed at enhancing various aspects of crop management. These advancements are designed to assist farmers in optimizing their net earnings by adopting recommendations from consultants and researchers, particularly in the sustainable utilization of limited resources such as water and raw materials. The water cycle, supply and demand for water, and the stress placed on the water systems are impacted by anthropogenic disruptions and climate change (Haddeland et al. 2014). With the global water withdrawal and usage in industries, agriculture and other municipal purposes, the amount of pure available water is reduced, making it essential for efficient utilization and management. Monitoring and assessment are essential tools for managing and evaluating the success of investments and agricultural initiatives. When combined with local data gathered through conventional methods that address data volume limits, remote sensing techniques are a potent tool for processing real-time data. Rainfall and evapotranspiration are two of the many aspects where different indices are correlated with water budget and management.

15.5.1 Rainfall for Water Budget and Management

Utilizing remote sensing data, an integrated automated application for the Water Resources and Agriculture Spatial Indicators System (WRASIS) was created to track and evaluate various agricultural development projects, analyzing remotely sensed time series data of (Agriculture Moderate Resolution Imaging Spectra-radiometer MODIS NDVI—Rain-Fall Estimate RFE 2.0) (Zahran et al. 2022). With its unique features of moderate spatial resolution, better spectral resolution, frequent observations, improved atmospheric calibration, and free download for end users, MODIS data packages present an amazing opportunity for land-cover and land-use change research (Xiao et al. 2003). Though most satellite image analysis and GIS software packages now in use lack a defined procedural setup for handling time series image analysis, and they are not tailored to the requirements of agriculture monitoring operations, several comparative analyses of crop monitoring were performed for better understanding (Ji-hua and Bing-fang 2008). The NDVI-MOD13-Q1 classification process comprises discriminating the quantity of vegetation at each pixel level and creating reflection maps of chlorophyll. To distinguish between fields with and without vegetation, the NDVI uses the difference in spectral reflectance in the Red (RED) and Near-Infra Red (NIR) bands, as per the following equation:

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{RED})/(\mathrm{NIR} + \mathrm{RED})$$

Every 16 days, 250 m spatial resolution global MOD13-Q1 data are made available as a unique mesh product in the Sinusoidal projection. To create a composite NDVI, algorithms must process data on a per-pixel level and require several observations over several days in a given area (Zahran et al. 2022).

15.5.2 *Evapotranspiration-Based Irrigation Scheduling*

For a long time, remote sensing has been acknowledged as the most practical way to deliver geographically dispersed regional evapotranspiration (ET) data on terrestrial surfaces (Moran 1994). The data is contemporary and often collected regularly from air or space platforms. The two main approaches are (i) land surface energy balance (EB) approach which makes use of surface temperature (radiometric) from an infrared (IR) thermal band and remotely detected surface reflectance in the visible (VIS) and near-infrared (NIR) regions of the electromagnetic spectrum and, (ii) Crop coefficient (Kc) based on reflectance (Kcr) and reference ET method, in which vegetation indices obtained from canopy reflectance values are linked to the Kc (Gowda et al. 2008).

(i) To estimate ET as a residual of the land surface energy balance equation, EB models translate satellite-detected radiances into land surface attributes such as leaf area index, vegetation indices, surface emissivity, and surface temperature as:

For local estimation: LE = Rn − G − H (Allen et al. 1998).

(where Rn is the net radiation resulting from the short and long-wave incoming and emitted radiation respectively,)

LE is the latent heat flux from evapotranspiration,

G is the soil heat flux, and

H is the sensible heat flux (W m^{-2} units)).

For regional estimation: $\mathrm{Rn} = (1-\alpha)Rs + \varepsilon_a \sigma T_a^4 - \varepsilon_s \sigma T_s^4$ (Jackson et al. 1985) (where a is surface albedo, Rs is incoming short-wave radiation (W m^{-2}), σ is the Stefan–Boltzmann constant (5.67 E^{-08} W m^{-2} K^{-4}), ε is emissivity and T temperature (K) with subscripts "a" and "s" for air and surface, respectively.)

The second method uses measurements of R and NIR reflectance to calculate a vegetation index like the soil-adjusted vegetation index (SAVI) or normalized differentiation vegetation index (NDVI); where data from satellites or local meteorological stations along the timeframe forms the basis of computing ET. Thermal data obtained from satellites to estimate ET using the formula:

$$\mathrm{LE} = \mathrm{R_n} - G - \frac{r_a\ C_p\ (T_s - T_a)}{\mathrm{r}_{ah}}$$

where r_a is air density (kg m^{-3}), C_p is the specific heat capacity of the air (J kg^{-1} K^{-1}), and rah is aerodynamic resistance for heat transfer (s m^{-1}). T_s and T_a are expressed in K.

It is challenging to get accurate estimations of H, mainly when T_s is utilized in place of the (aerodynamic temperature) and when surface emissivity and atmospheric effects are not counted. Hence later, Rosenberg et al. (1983) incorporated the term surface aerodynamic temperature (To) to calculate H. Based on the manner H is estimated, several algorithms and models have been formulated from time to time. These models included the surface energy balance algorithm for land (SEBAL), which uses hot and cold pixels to develop an empirical temperature difference equation, the surface energy balance index (SEBI), which is based on the contrast between wet and dry areas, and the two-source model (TSM), which models the energy balance of soil and vegetation separately and then combines them to estimate total LE (Gowda et al. 2008). Mapping Evapotranspiration with Internalized Calibration (METRICTM); and ET mapping algorithm (ETMA) are some of the recent approaches to calibration (Loheide and Gorelick 2005). SEBI and SEBAL based on the crop water stress index (CWSI) are replaced with planetary boundary layer (PBL) scaling. Two independent, high-quality datasets were collected at the field scale during the soil moisture-atmosphere coupling experiment (SMACEX), which was used to evaluate SEBS, in the Walnut Creek agricultural watershed near Ames, Iowa, USA (Su et al. 2005).

(ii) For the reflectance-based crop coefficient method crop coefficients (Kc) have shown relatedness to vegetation indices like NDVI, and SAVI, where the crop coefficient is calculated mathematically using surface roughness, aerodynamic resistance, and albedo obtained from remote sensing (from LAI), without the requirement of crop development stage. Using multi-temporal, multi-spectral, digital, aerial video images collected during the growth season of a cotton crop, crop coefficients based on reflectance were determined and linked to the SAVI (Neale et al. 1996). In Kenya, crop ET was estimated using the Priestley-Taylor equation to derive crop coefficient (Kcr) based on reflectance from Landsat imagery (Michael and Bastiaanssen 2000).

One of the basic remote sensing platforms is satellites (Bansod et al. 2017). In the early 1970s with the launching of LANDSAT 1, satellite use was started for remote sensing in agriculture (Acker et al. 2014). After passing years of development in satellites for remote sensing, the EOS SAT-1 satellite is the latest one launched at the beginning of 2023. This satellite is unique with the most advanced tools for precision agriculture to date. The Wyoming Game and Fish Department utilizes the EOSDA Crop Monitoring, employing a scouting app for near-real-time field monitoring, streamlining data collection, enhancing efficiency, and enabling prompt response to vegetation issues, thereby reducing costs and improving the overall management of crop damage claims through the analysis of satellite imagery data (Elijah 2022). However, satellites and piloted aircraft record distant images that lack substantial information regarding the spatial and temporal dynamics of crop responses and might not match the resolution occupied by drones or UAVs (Table 15.1). To overcome these drawbacks, the use of drones has evolved in recent years for water management. The sensing systems, spectral and thermal cameras are often integrated or can be mounted on a drone using a gimbal system that is developed specifically for high-resolution mapping of crop water stress on spatial and temporal scales. It is reported that the worldwide agriculture drones market is anticipated to experience substantial growth, increasing from USD 4.5 Billion in 2023 to USD 17.9 billion by 2028, with a compounded annual growth rate (CAGR) of 31.5% over the specified period (Markets 2023).

Drones excel in capturing detailed data from complex environments, overcoming limitations of traditional methods like satellite and aerial imagery. It provides high-resolution spatial and temporal data crucial for managing surface and subsurface water resources, supporting various applications such as water quality monitoring and flood extent mapping. The increased use reflects its value in providing detailed environmental insights and shaping future hydrological studies and water resource management strategies. Advancements in technology have propelled UAVs for water resource management on the spatiotemporal scale (Elmeseiry et al. 2021). The drones offer a quick, accurate, and economically viable means for on-site analysis of water resources, particularly in complex environments. Koparan et al. (2018) developed a hexacopter-based system for on-site water quality measurements using open-source electronic sensors. This system was tested on a 1.1 ha agricultural pond and produced

Table 15.1 Contrasting the pros and cons of satellites and drones

Pros of satellites	Cons of drones
Fully autonomous	Often needs an operator
Unlimited accessibility along its orbit	Limited accessibility in areas which are inaccessible for the operator
Consistent imaging; continuous mapping possible	Inconsistent mapping or loss of continuous mapping due to limited flight time
Image pricing based on size of the area, resolution, and time of capture	Pricing based on duration of operation which is comparatively higher than satellites
Pros of drones	**Cons of satellites**
High-quality and resolution images due to proximity to the ground	Comparatively lower image quality
Weather condition (like cloudy) does not hinder imaging	Bad weather hinders imaging
Ease of timely deployment; can be operated close to land	Reliant on orbital parameters
Works better to record NDVI, MSAVI and GNDVI	Comparatively lower efficiency
Less revisiting time and ease of data extraction	High revisiting time with difficulty in data extraction
Low price with better flexibility of use	High price with lack of flexibility to use

Source Bansod et al. (2017)

accurate spatial distribution maps of parameters like water temperature and dissolved oxygen. However, limitations such as limited flight duration exist.

Ramírez Cuesta et al. (2019) introduced a user-friendly tool integrated with ArcGIS for estimating crop water needs using satellite imagery. This tool, utilizing Landsat 7 and 8, and Sentinel 2A images alongside the dual crop coefficient approach, effectively maps spatial variability in crop water demands with minimal inputs (Serrano et al. 2019) focused on monitoring pasture quality in the Montado ecosystem, crucial for extensive grazing systems. They compared two methods: proximal sensing with optical sensors and remote sensing using Sentinel 2 satellite images. Both methods computed NDVI and PDQI, revealing significant correlations. Values below 0.6 for NDVI and above 0.7 for PDQI indicated a need for supplementary feeding. However, issues like spring cloudiness can hinder remote sensing effectiveness, prompting the recommendation to combine both techniques for optimal pasture management.

Multispectral sensors capture light from the visible to near-infrared spectrum, typically between 400 to 1000 nm. They have a narrower bandwidth compared to RGB sensors but may experience geometric distortions depending on lens characteristics. They can also have spectral and radiometric distortions, requiring additional processing for accurate data interpretation, such as correcting atmospheric interference. Advanced multispectral sensors like the MicaSense RedEdge, Micasenses Altum PT (panchromatic, multispectral—Red, Green, Blue, Red Edge, Near Infrared; and Long Wave Infrared or thermal in the same camera system), and Slant Range 3P often include calibration systems but are costlier and heavier than RGB sensors. They can be integrated into UAVs separately or can be integrated as part of the system.

Hyperspectral sensors represent a significant advancement in remote sensing, offering remarkable spectral resolution across a broad spectral range. While UAV-based hyperspectral imaging provides a cost-effective alternative to satellite methods, challenges include higher costs and compatibility issues with standard UAV software (Adão et al. 2017). Notable hyperspectral sensors include the Resonon Pika-L and Micro-Hyperspec X-series NIR. Gao et al. (2019) explored a novel technique using UAV photogrammetry and image recognition to measure reservoir water levels, yielding reliable results at a Chinese hydropower station after introducing a correction method to counteract UAV drift. Multispectral (multiband) images (MSI) capture discrete and specific wavelengths, often in the visible (VIS) and near-infrared (NIR) regions, through individual images taken at specific wave numbers or wavelengths using filters or LEDs across the electromagnetic spectrum (Vidal and Amigo 2012). MSI consists of individual channel images, each capturing specific wavelengths. Unlike hyperspectral images, MSI discrete wavelength measurements require different treatments (Amigo 2019). Hyperspectral images (HSI) involve the measurement of one continuous spectrum for each pixel, typically expressed in nanometers or wave numbers (Zhang et al. 2022). These images can be acquired through various electromagnetic measurements, including visible, near-infrared, middle infrared, and Raman spectroscopy, showcasing versatile applications beyond traditional imaging modalities (Tran and Fei 2023). Emerging applications of hyperspectral imaging extend to technologies such as confocal laser microscopy scanners, Terahertz spectroscopy, X-ray spectroscopy, 3D ultrasound imaging, and magnetic resonance, showcasing its increasing popularity and diverse usage across various fields (Amigo 2019). In hyperspectral images, spectral resolution refers to the interval or gap between different wavelengths in a specific range, with a higher resolution achieved by acquiring more bands or spectral channels within a smaller wavelength range (Morales et al. 2021).

Thermal cameras capture far-infrared radiation emitted by objects on Earth, correlating directly with their surface temperatures, typically falling within the 3–100 μm range (Reach et al. 1995). The infrared portion of the spectrum can be categorized as near-infrared (NIR, 0.7–1.5 μm), short-wave infrared (SWIR, 1.5–3 μm), medium-wave infrared (MWIR, 3–8 μm), long-wave infrared (LWIR, 8–14 μm), and far-infrared (FIR, 14–100 μm). Thermal sensors operate in the long-wave spectrum, usually between 7.5 and 13.5 μm, allowing them to detect temperatures ranging from − 25 to 135 °C. The landscape, including vegetation, soil, water, and individuals, emits thermal infrared radiation in the 3.0–14 μm range of the electromagnetic spectrum, comprising of medium-wave infrared (MWIR) and long-wave infrared (LWIR), at its normal temperature of ~ 300 K (Sabins Jr and Ellis 2020). They boast a pixel sensitivity as precise as 0.04 °C (Kaplan 2007). Thermal cameras are categorized as uncooled or cooled based on the sort of image detector they use. A cooled infrared thermal camera typically uses mid-wave infrared wavelengths of 3–5 μm. It can offer enhanced resolution and the ability to detect minute temperature variations of the target. Cooled thermal cameras can detect smaller temperature variations for extended periods compared to uncooled cameras. However, its big size, high cost, and significant energy consumption make it unsuitable for use in field environments. Uncooled thermal cameras are lighter and cheaper than cooled ones, making them suitable for deployment on ground-based and UAV-based platforms. Despite causing significant inaccuracies in orthoimage production due to the poor contrast of thermal pictures, this issue can be resolved through calibration, utilizing a thermally controlled flat plate blackbody. Calibration methods were created to precisely calibrate the uncooled thermal camera for increased accuracy. The use of validation panels and temperature-controlled references to calibrate the thermal imagery involved extracting median pixel values from high- and low-temperature references, creating a linear equation to correlate pixel values with known temperatures, and calibrating all other pixels in the mosaic (Han et al. 2020). Thermal imagery has many uses in water management, including irrigation systems, crop water stress (Zhou et al. 2021), canopy water content (Elsherbiny et al. 2021), groundwater (USGS 2019), and plant water relation (Jones and Leinonen 2003). Thermal sensing methods have a non-contact nature, reduced labor requirements, and the ability to provide non-destructive monitoring for assessing crop stress based on leaf canopy temperatures (Grant et al. 2006). Temperature-based indices have demonstrated notable correlations between crop canopy temperature, stomatal conductance, and leaf water potential, with correlations strengthening as stress intensity increases. The most commonly used low-cost

Table 15.2 Optimal spectral values are important for developing spatial and temporal imagery for water management

Sensor	Spectral range	Parameters for water management and ancillary canopy parameters	References
1. RGB	Visible spectrum (450 nm–750 nm) 1. Red (620–750 nm) 2. Green (495–570 nm) 3. Blue (450–495 nm)	Sensitivity for red, green, and blue. Green pixels represent vegetation	Lu et al. (2024)
2. Multispectral	Wavelength ranges from (450–1000 nm) Visible spectrum (450–750 nm) Near infrared (NIR) (700–1000 nm)	Chlorophyll content, stress detection, vegetation cover Vegetation health and biomass	Wang et al. (2022)
3. Hyperspectral	Spectral wavelength from (350–2500 nm) Visible spectrum (450–750 nm) Near infrared (NIR) (700–1000 nm) Short wave infrared (SWIR) (1000–2500 nm)	Plant pigment detection (450–650 nm), nitrogen detection (405 nm), Chlorophyll absorption (687 nm) Biophysical Quantity and Biomass (687 nm–1100 nm) Water content in canopies (970 nm–2100 nm), plant stress (2295 nm), Heavy metal stress (1650 nm)	Chen et al. (2021)

thermal sensors are FLIR, where it combines the accurate temperature measurement with an image up to 1030 °C (Wu et al. 2019) (Table 15.2).

15.5.3 Limitations of Data

- *Spatial and temporal resolution*: For the acquisition of data from satellite images spatial (pixel size) and temporal (repeat frequency) resolution varies from different forms of spectral bands obtained from their respective satellite, varying between Landsat, MODIS, and sentinel images. While Landsat 5 has a 16-day repetition cycle with 30–120 m spatial resolution, MODIS uses the same satellite platform to provide thermal images with a 1000 m resolution, in contrast to the images collected in other bandwidths with a 250 m resolution. Most of the time the pixel size of these maps is larger than a single field, resulting in substantial errors in ET estimation, ET maps derived from remote sensing data obtained by daily-coverage satellite-based sensors like MODIS, GOES (geostationary environmental satellite), and AVHRR (advanced very high-resolution radiometer) are too coarse to be of any use in agricultural regions (Tasumi et al. 2006).

- Accuracy of data: Gaps in data along a timeframe or the efficacy of data based on pixels, the true potential can at times lead to errors in spatial estimation. When TSM hardly requires extreme temperature (T_s) pixels, METRIC, SEBAL, and SEBS are largely dependent on T_s (Gowda et al. 2008)
- Processing time: Instantaneous real-time imagery and data with rapid processing calls the aid of artificial intelligence for increasing efficacy and simplicity of the data processing. More research in this area is needed, even though several studies are now being conducted to examine the transferability of crop coefficients to different locales (Howell et al. 2012).
- Model implementation: Different remote sensing-based ET methods are available for calculating the amount and trends of regional ET, varying in different ranges of complexity. To accurately estimate using observed data, it is necessary to properly utilize the integration of LE pixels while using different heat flux source models (Chávez et al. 2005).
- Governmental policies and limitations: Variations in worldwide data access and their limitations for better resolution images like Worldview data restricting the use of specific algorithms and models globally (Harris and Baumann 2015).

15.6 Emerging Technologies

15.6.1 Nanosensors and Nanobionics

Nanosensors and biosensors strengthen agricultural productivity and safeguard agroecosystems by sensing soil nutrients, microclimate, temperature, moisture, heavy metals, pesticides, plant diseases, and harmful substances. Nanosensors can assist farmers in controlling their farms precisely and identifying plant requirements on time. It transforms conventional farming practices into smart farming, promoting energy efficiency and sustainability. Nanosensors can also detect soil and plant moisture, pesticide residue, and nutrient requirements. Nanosensors outperform traditional sensors due to their high surface-to-volume ratio, quick response time and consistent results. This emerging area of science termed **nanobionics** is an interdisciplinary field that combines nanotechnology with biology to create innovative solutions for various applications. For agriculture water management, nanobionics plays a crucial role in developing advanced technologies that integrate nanomaterials with biological systems to enhance water efficiency, monitor water quality and optimize irrigation practices (Fig. 15.3).

Nanobionics pioneers the use of nanomaterials to optimize water absorption and retention within plants. By delicately modifying plant structures at the nanoscale, nanobionics enhances the efficiency of water transport within crops. Photosynthesis

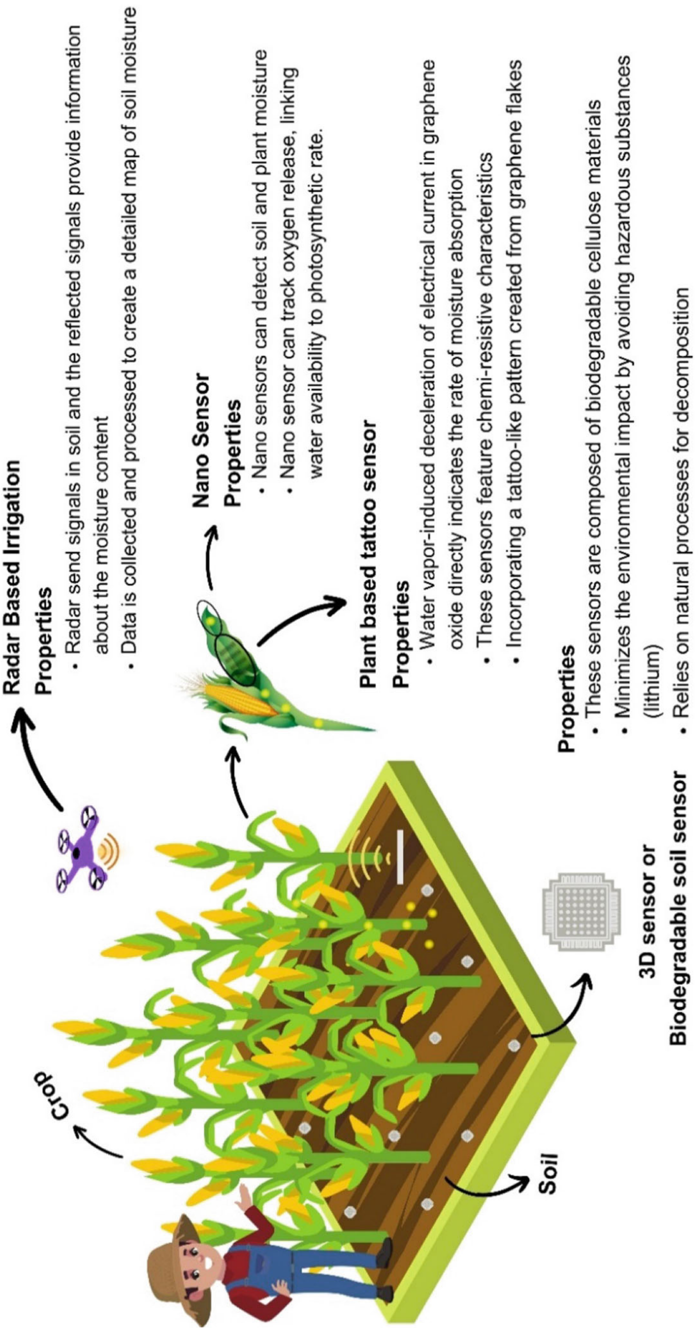

Fig. 15.3 Emerging precision water management technologies for data intensive irrigation

transforms sunlight energy into food with the help of water. The release of oxygen from plants is linked to photosynthesis. In addition, water indirectly influences the photosynthetic rate. When there is not enough water, the stomata close, lowering photosynthesis. Consequently, a correlation can be observed between the availability of water and the emission of oxygen, which can be monitored through the utilization of a nanosensor. Clark-type polarographic electrode sensors have been widely employed in the detection of oxygen current flow.

The gravimetric method of soil water content measurement is reliable, but it is time-consuming and not suitable for continuous monitoring of large fields. On the other hand, modern technologies such as nanosensors can be utilized to continuously monitor soil water. It is affordable and produces rapid results. An optics-based nanosensor developed using an aluminum oxide nano-porous ceramic plate is used for continuous monitoring of soil water (Chen et al. 2019). The sensor is connected to a silicon diaphragm which is sensitive to water stress. When buried in unsaturated soil it experiences a negative pressure which bends the diaphragm. This displacement can be used to measure dry soil saturation (Chen et al. 2019). Leone et al. demonstrated a small, affordable sensor that measures the water content of soil by utilizing an optical fiber with near-infrared-based detection. The sensor is placed in a protective tube buried in a soil tank for soil testing. The probe is generally inserted at different depths of soil which measure the reflected spectrum. The reflected spectrum decreases as the amount of water increases (Leone et al. 2022).

Nanobionics contributes significantly to the development of advanced water filtration systems tailored for agricultural use. Nano-enabled filters act as sentinels, efficiently removing impurities, sediments, and contaminants from irrigation water. The deployment of clean and high-quality water to crops becomes a reality, fostering robust plant health and crop yield. Additionally, nanobionics coatings minimize water evaporation and act as barriers against water loss. The result is a landscape where water retention is optimized, water conservation is prioritized, and efficient irrigation water use becomes a hallmark of sustainable agriculture.

15.6.2 Plant Tattoo Sensors

The ingenuity and fundamental principle underlying plant tattoo sensors reside in their capacity to efficiently and non-invasively monitor water dynamics within crops. Conventional methods employed on the ground to evaluate plant water stress are frequently arduous and time-intensive, and they might fail to furnish comprehensive spatial-scale data which is sometimes essential for large-scale agricultural operations. This sensor allows researchers to gain valuable insights into crop health and water use efficiency by measuring how long it takes for water to move from the roots to different parts of the plant (water dynamics).

In large-scale farm operations, conventional ground-based techniques are insufficient for efficiently and effectively monitoring the water in crops due to their time-consuming and labor-intensive nature. These generate large amounts of data and occasionally produce data points that are not representative of the entire field or are incorrect. Plant tattoo sensors are used for monitoring the dynamics of plant water stress in a non-invasive and efficient way. The plant tattoo sensors possess intricate and chemi-resistive characteristics which are infused with a tattoo-like pattern created from several layers of graphene flakes. Graphene is made up of a monolayer of carbon and oxygen atoms that exhibits excellent electrical conductivity (Hossain et al. 2024). It possesses excellent electrical conductivity and high mechanical strength, ensuring its resistance to breakage. Tattoo sensors designed for plants are attached to the leaf with adhesive tape and connected to small wires (Fig. 15.3). A tiny battery is connected to a device that measures electrical conductivity.

Plants absorb water from the soil and release it through stomata in their leaves. These water vapors are the primary indicator in the plant tattoo sensor. The presence of water vapor reduces the speed of electrical current passing through graphene oxide. The magnitude of the electrical conductivity varies according to the velocity at which water ascends within the plant. This determines the rate at which the plant absorbs moisture from the soil (Oren et al. 2017). With the deceleration of electrical current following the attachment of a sensor to a leaf, researchers can determine the rate at which the plant absorbs water. Researchers from Iowa State University (United States of America) have shown that applying a plant tattoo sensor induces substantial development in corn plants. An accurate result was obtained by measuring the time required for two varieties of corn plants to transport water from their roots to their lower leaves and upper leaves (predictivephenomicsinplants.iastate.edu).

15.6.3 Biodegradable Soil Moisture Sensors

The in-situ monitoring of soil volumetric water content is critical owing to its substantial impact on the hydrological, biochemical, and economic aspects of agriculture (Gopalakrishnan et al. 2022). The most effective instruments for measuring in-situ soil moisture are wireless sensors with telemetry. However, the majority of such sensors are equipped with embedded electronic components and active onboard batteries which increase production and assembly expenses and restrict the number of nodes that can be deployed in the field (Fig. 15.3). Additionally, hazardous substances such as lithium and lead can escape from batteries in sensors which is also not sustainable over time. To address these issues, the integration of radio-transmitting biodegradable sensors in conjunction with antennas and drones is now used in the agricultural field (Oren et al. 2017). All sensor tags are embedded in the soil, and a flying drone collects reflected signals from the sensors while flying. The reflected signals dependent on soil properties, such as volumetric water content (VWC), can be effectively transmitted to signal stations for action. These sensors, composed of biodegradable cellulose materials (paper-based substrates), gradually degrade after a few months to years of operation (Oren et al. 2017). For example, researchers developed a wirelessly powered biodegradable soil sensor. The sensor is made up of a tin conductive line and a nanopaper substrate that has been coated with a natural wax for protection. The sensor is mostly decomposed by soil bacteria and the other components are also environmentally friendly (Kasuga et al. n.d.).

15.6.4 Radar-Based Variable Rate Irrigation (VRI) Systems

Radar technology, known as radio detection and ranging, works by transmitting and receiving electromagnetic waves that reflect from objects. By analyzing the time, frequency, and angle of these reflected waves, radar systems can provide characteristics and changes in objects, including their distance, speed, shape, and movement. These systems are adaptable, functioning within different frequency bands like X-band, C-band, L-band, or P-band, tailored to specific requirements for resolution, range, and penetration.

The integration of radar sensors, such as ground-penetrating radar (GPR), has revolutionized agricultural practices, particularly in precision irrigation (Fig. 15.3). The GPR enables continuous and non-invasive monitoring of soil moisture content, allowing farmers to implement variable rate irrigation based on real-time and in-situ soil moisture data. Farmers can precisely adjust water application rates, minimizing water wastage, reducing operational costs, and optimizing crop yields. Additionally, for remote sensing methods for soil characterization, radar technology has emerged as a valuable tool for mapping soil conditions over large areas. Techniques like satellite imaging, Synthetic Aperture Radar (SAR), radiometry, Time Domain Reflectometry (TDR), and GPR, radar offer unique advantages in measuring soil water content and topsoil thickness as soil moisture changes in real time. The radar technology in agricultural systems like Autonomous Pivot (https://www.autonomouspivot.com/) further improves water use efficiency and management efforts. By integrating a GPR system into the moving pivot, farmers can accurately detect soil moisture status and adjust water application rates accordingly. Radar-equipped drones also play a pivotal role in augmenting water management practices in agriculture. These drones outfitted with radar sensors such as P-band radar, efficiently survey large agricultural areas, providing detailed insights into underground water profiles and soil moisture distribution (Frid and Frid 2024). Leveraging cloud computing and intelligent software, radar-equipped drones process and analyze data in real-time, enables the generation of tailored irrigation plans suited to specific field conditions (Sinchi et al. 2023).

15.7 Challenges and Opportunities

Precision water management represents a promising approach to address the complex challenges posed by climate change and water resource management. However, its successful implementation is accompanied by a set of challenges that need to be navigated effectively. One of the primary hurdles lies in the availability and quality assurance of data validation for informed decision-making. Remote sensing technologies offer extensive datasets, but sometimes ensuring their accuracy, reliability, and consistency can be a significant challenge. Data acquired from drones and satellites may be subject to errors, noise, and inconsistencies, if it does not have validation and calibration processes accounted during photogrammetry or image processing steps.

Moreover, the technical complexity for farmers associated with precision water management presents another obstacle. Integrating diverse datasets, sensor technologies, and analytical tools into existing water management frameworks can be daunting. Challenges such as interoperability, data compatibility, and system integration need to be addressed to ensure seamless operation. Stakeholders may require specialized expertise and resources to navigate and overcome these technical barriers effectively. The cost of adopting precision water management practices poses a significant financial challenge, especially for resource-constrained regions and small-scale irrigated farms impacted by drought. High initial investment costs, subscription fees for data services, and the need for specialized equipment and software contribute to the financial burden.

Furthermore, human capacity and institutional readiness are critical factors influencing the successful implementation of precision water management strategies. Effective utilization of remote sensing data and technology requires a skilled workforce with expertise in water resource management, data analytics, and technology deployment. However, there is often a shortage of trained professionals and institutional capacity to train for adoption of emerging technologies effectively. Investing in human capacity through training programs, knowledge exchange initiatives, and academic collaborations is essential to address this challenge. Technological innovations and advancements in remote sensing technologies, machine learning algorithms, and data analytics hold potential for improving the accuracy and efficiency of water management data, strategies and decisions.

15.8 Summary

Precision farming has offered a scientific approach to modern agriculture, using sensors and drones to monitor soil, water, and weather conditions. By making informed decisions on *per drop per crop* and adopting resilient crop varieties, farmers can enhance crop resilience and conserve water resources. Innovations in sensing systems and aerial imagery have further contributed to sustainable farming practices enriching soil health, and maximizing productivity while minimizing environmental impact. Technologies and telemetry have enabled precise water management, optimizing crop growth and resource use efficiency. To sum up, the ideas covered in this chapter, precision farming has the potential to help with climate change issues and provide food security in the future. Increased adoption of these technologies can help farmers nurture resilient and eco-friendly agricultural systems, safeguarding the welfare of both humanity and the planet.

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