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Review

# A Review on Evapotranspiration Estimation in Agricultural Water Management: Past, Present, and Future

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**Abstract:** Evapotranspiration (ET) is a major component of the water cycle and agricultural water balance. Estimation of water consumption over agricultural areas is important for agricultural water resources planning, management, and regulation. It leads to the establishment of a sustainable water balance, mitigates the impacts of water scarcity, as well as prevents the overusing and wasting of precious water resources. As evapotranspiration is a major consumptive use of irrigation water and rainwater on agricultural lands, improvements of water use efficiency and sustainable water management in agriculture must be based on the accurate estimation of ET. Applications of precision and digital agricultural technologies, the integration of advanced techniques including remote sensing and satellite technology, and usage of machine learning algorithms will be an advantage to enhance the accuracy of the ET estimation in agricultural water management. This paper reviews and summarizes the technical development of the available methodologies and explores the advanced techniques in the estimation of ET in agricultural water management and highlights the potential improvements to enhance the accuracy of the ET estimation to achieve precise agricultural water management.

**Keywords:** evapotranspiration; agricultural water management; ET estimation



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## 1. Introduction

Agricultural productions heavily depend on complex and dynamic conditions such as weather, climate, and soil moisture. These conditions cannot envisage perfectly and have limited control over the processes [1,2]. Irrigated agriculture can generate more agricultural yield and income compared with rain-fed agriculture [3–5]. In addition, irrigated agriculture comes with reliability, and a wider and more diversified choice of higher-value crops [6]. Irrigated agriculture utilizes 20% of cultivated lands throughout the world and produces 40% of total crop production [5], which is a significant contribution in terms of food security [7,8]. In 2016, agriculture accounted globally for nearly 92% of total freshwater withdrawals [9]. The Food and Agriculture Organization (FAO) projected the global water demand for agriculture up to 2050 and identified that there will be an 11% increment from the 2006 baseline [10].

Water has been identified as the most vital resource in agriculture [11]. The expected growth of the world population will increase the demand for food and the demand for water in agriculture [12–15]. Moreover, Chartzoulakis [11] highlighted the low efficiency of irrigation across the agricultural industry, with only less than 65% of the applied water actually being utilized by the crops. In addition, irrigation water consumption is approximately about 70% of the water extraction globally and it has been identified as the major cause of the water depletion in most countries [16]. This increases the stress on the available limited water resources for domestic, industrial, energy generation, associated recreational and cultural uses, and, most importantly, the allocations for environmental improvements and ecosystems [17]. Careful analysis shows that the areas experiencing water shortages

were due to poor and inappropriate water management [18]. Encouraging the farmers who practice water conservation technologies and implementing regulatory authorities that limit water allocations in agriculture can drive towards sustainable water resources management in agriculture. However, when compared with other issues, water management in agricultural industry is a serious issue which can be confronted with the advancement of the technology.

Currently, the investment of one unit of water for infrastructure development and industries can earn a higher economic rate of return than agriculture does. However, irrigated agriculture is supposed to generate much more in the future, applying lesser water than it uses now [19,20]. Sustainable management and more efficient practices are essential to meet the growing demand under scarce water resources. Water resources management plans in many river basins mainly target to reduce the water consumption without affecting the agricultural production [21]. In this regard, water sensitive irrigation practices and tools can be used. For example, semi-dry cultivation (SDC) and alternate wetting and drying (AWD) can reduce the water use by nearly 50% compared with traditional irrigation practices [22,23]. Evapotranspiration is a major consumptive use of agricultural water. Traditionally, evapotranspiration, in terms of actual crop water requirements, is assessed by the field observations of plants and soil, including soil moisture [24]. Evapotranspiration (ET) contributes to the highest water loss in cultivated semi-arid regions [25,26]. Furthermore, the identification of ET's effect on the water budget is essential for water resource management as well as forest growth and species diversity, sustainable crop production, food security, and social stability [8,17,19,27–29]. Therefore, applying more efficient ET-reduction strategies are important to achieve efficient and sustainable water use [30,31]. Consequently, these strategies will balance the water distribution among industrial, domestic, ecological, and agricultural sectors [27,32–34].

The objective of this systematic review is to identify the significance of ET in agricultural water management and identify the evolution of ET estimation up to the digital agriculture era. This review helps to enhance the understanding of the present status, benefits, and limitations of technologies and methods used in ET estimation in agricultural water management. It also shows the future opportunities of technical developments and potential improvements for sustainable agriculture.

## 2. Role of Evapotranspiration in Agricultural Water Management

Evapotranspiration (ET) represents the combination of evaporation and transpiration, where evaporation is vaporization from soil surface, or water surface, and transpiration is plant water absorption from the root zone [35]. Both precipitation and ET represent the climate of a region and are used as a decision support tool for water management in agriculture. While contributing to the surface energy balance, ET quantifies the water requirement for efficient water management [32,34]. Water conservation in E-based irrigation scheduling is a rising concern on a global, as well as local, scale, while improving water productivity [36]. Not only in irrigation assessments, but also in the accurate modelling of river basin hydrology, estimation of local ET is one of the essential tasks [17]. Li [37] quantified that approximately 60% of the average precipitation will be subjected to ET from the land surface. Additionally, for vegetated lands, ET rates are the same as the water absorption rates of the vegetation and, thus, ET can be used as a measure of plant water stress [38]. With the insufficient water allocations, a cut down on water supply may affect the harvest and, ultimately, intimidate food security. In this regard, optimizing the water management system and the accurate estimation of evapotranspiration are very important [31]. Krishna [36] highlighted that the accurate estimation of ET is important because understanding and quantifying the processes governing ET clarifies the uncertainties in the behavior of the hydrologic cycle with the changing climate. Since ET is a critical factor in water balance at plot scale to global scale, well-grounded ET estimations are required to regulate the components of the irrigation system: the size of canals and dams, and the capacity of pumps [39].

Evapotranspiration facilitates the continuous energy flux across the hydrosphere, atmosphere, and biosphere [33,36]. Since the crop water requirement is a dynamic parameter, it should capture the water stocks, fluxes, and their change over time. All measurements can be particularly challenging, as they require adequate devices and sensors for consistent monitoring and data recording [40]. The ET process is significantly contributing to moisture return into the atmosphere [17]. Analyzing the contribution of the three modes of water supply to the ET, Moiwo [27] concluded that precipitation is the major contributor to ET (39.0%), followed by soil water (36.3%), and then irrigation (24.7%). Every aspect of productivity in the ecosystem is depending on ET [41]. In most cases, ET estimation is affected by the heterogeneity of vegetation, and it is more complicated during dynamic flux periods following precipitation and irrigation [33,42–45].

### *2.1. Climate Change and Agricultural Water Crisis/Demand*

Agriculture is one of the sectors most sensitive to, and greatly influenced by, climate change and climate variability. The Intergovernmental Panel on Climate Change (IPCC) and the Food and Agriculture Organization (FAO) have identified the agriculture industry as one of the most vulnerable industries affected by climate change, particularly in developing countries. This has raised the concern of the scientific community and, due to recent technological developments, drone technologies have been integrated into an Innovative Agrometeorological Methodology for the Precise and Real-Time Estimation of Crop Water Requirements [46]. Climate change will trigger numerous and complex impacts on water resources and agriculture [47]. It is evident that climate change will alter the soil water balance, which causes changes in evaporation and transpiration. Repercussions can be drastic changes in agricultural production, effects on the availability and quality of water, and increases in the frequency and severity of extreme droughts and floods [48]. As the mitigation and adaptation of climate change impacts on agricultural water, particularly agricultural water saving, improving the efficiency of water consumption and reusing agricultural water are state-of-the-art technologies in agriculture [49]. Lopez [50] proposed a sustainable water management method to reduce the extensive groundwater extraction for irrigated agriculture and highlighted the importance of sustainable water management policies under possible climate change scenarios.

Atmospheric temperature is projected to increase with the climate change, and it provides more energy to cause more evaporation. Unfortunately, evaporated water cannot be used for agricultural production [51]. The rising temperature and reduced precipitation will drastically reduce crop production and yield. Therefore, it is important to understand the role of evapotranspiration to reduce the effects of future water crisis under the changing climate [51]. Entezari [18] has investigated the possibility of recycling the evapotranspiration water within a greenhouse for sustainable agriculture and air–water harvesting technology (AWH) has been introduced to get liquid water in arid or desert areas. Analyzing the impacts of climate change on agricultural water resources, Xing-Guo [52] used the Global Climate Model (GCM) composite projections with three scenarios and showed that there has been a significant change in the climate on the study region over the past 60 years. They found that regional average ET will increase in all three scenarios and, when compared with the 1990s, ET will increase by 6–10% in the 2050s. However, GCMs are too coarse in assessing local changes. Many researchers use Regional Climate Models (RCMs) to address climate change and possible effects on water availability and mentioned the effects of model resolution on projection accuracy [53–55]. To assess the spatiotemporal variation in climatic water availability (CWA) and crop water demand using long-term rainfall and temperature data, Salman [56] used simple water-balance equations and identified that when the temperature increases it contributes to an increment in evapotranspiration, which leads to a large increase in crop water demand and a decrease in climatic water availability.

## 2.2. Importance of Accurate ET Estimation in Precision Agriculture

Precision agriculture can be defined as optimizing the growth conditions of crops using state-of-the-art sensors [1]. Smart agriculture is the further development of precision agriculture with optimization using partial or complete automation. Digital agriculture consists of applications of the methods of “Precision and Smart agriculture” including interconnected components and processes of the farm operated by web-based data platforms together with Big Data analysis [1,57]. Big Data analysis plays a main role in data management in digital agriculture. However, it is difficult to implement the digitalization of agriculture in most countries due to the lack of required technology, such as efficient mobile telecommunication infrastructure and facilities [1]. The conventional farming practices, which used to manage agricultural fields without considering the heterogeneity in geomorphology, soil parameters, crop growth stages, and other agronomic parameters, cause inverse impacts such as nutrient leaching, environmental contamination, and loss of profit [15]. However, precision agriculture uses spatially distributed information with accurate information processing and reliable decision-making tools. Geographic information systems and remote sensing (GIS & RS), Global Navigation Satellite System (GNSS), harvest monitoring, and variable-rate irrigation technology (VRT) [58] are the compelling feature of precision agriculture.

In precision agriculture, evapotranspiration (ET) plays a major role. As evapotranspiration is the most challenging component in agricultural water management, accurate ET estimation is required to understand the water balance and hydrological processes, climatic variations, and ecosystem processes. Accurate ET estimation is required for drought monitoring, hydrological model validations, weather forecasts, and to predict forest fires [59]. Since the irrigation water is insufficient for the total agricultural demand, precise crop water requirement is very important for accurate management and conservation of agricultural water [60]. Precise and accurate crop water demand assessment needs the accurate estimation of evapotranspiration. Koech [61] highlighted the requirement of water-efficient technologies and practices to achieve sustainable water resources in agriculture. Furthermore, Blatchford [62] identifies the crop water productivity (CWP) through digital technologies to evaluate the water-use efficiency in agriculture. As precision agriculture contains concepts of monitoring, measuring, and responding to variability in the crops, it basically expects reduction in the cost of cultivation, optimized resource use, and higher efficiency through real-time facts and figures sent via the sensors attached to the farm machineries in the field [63]. In semi-arid and arid regions, higher efficiency in irrigated agriculture can be achieved through the precision agriculture applications. For example, drip irrigation techniques combined with remotely sensed canopy air temperature measurements will improve the water-use efficiency and minimize the runoff and percolation losses [64].

## 2.3. Current Status of the ET Estimation in Agricultural Water Management

In the 21st century, the general agreement was that advancements of ET technology have still been used in research rather than in applications. Usage of spatial science techniques such as remote sensing and satellite technology for ET estimation in agriculture has been very popular recently. It provides a consistent and cost-effective solution for field-based measurement methods. Generally, sensors in the field provide the input recommendations and regulate the water and nutrients requirement. Spatial variation of these requirements will be captured by GPS receivers [59]. Therefore, automated farm management using agricultural automation equipment and systems will be widely used in the future. Deep learning and spectral analysis technology [65] can be identified as examples for them. Moreover, computer vision supported by artificial intelligence (AI) functions can be used to achieve economical, reliable, and the steady performance of the agricultural automation systems [65]. Most importantly, the recorded spatial and temporal variation of ET data must be accessible in productive and successful precision agriculture. Future studies on ET-based agriculture water management will be benefitted through

the development of open-access ET databases. This concept is under development by various organizations such as the US Geological Survey, US Department of Agriculture, the Commonwealth Science and Industrial Research Organization of Australia, and the Chinese Academy of Sciences [17].

Accurate estimation of evapotranspiration is a tedious task. However, it is required for water management in agriculture and the design and functioning of irrigation systems [66]. Although the water balance approach is the simplest way in the estimation of evapotranspiration, the unknown water movements through the boundary causes errors in the water balance method. Nolz [35] proposed to identify these movements through an advanced sensor arrangement system by obtaining details about the occurrence and the movement of subsoil water and groundwater. Conventional ET estimation techniques are associated with field measurements such as leaf temperature and leaf area, wind speed, vapor pressure, surface roughness, gas concentration (water vapor, CO<sub>2</sub>), etc. [67–69]. When it comes to extensive terrain, measurements of these parameters are quite difficult and need to be extrapolated or interpolated with limited accuracy [37,70]. The empirical methods have the advantages of computational timesaving and less requirements of ground-based measurements over homogeneous areas, but over the regions with great variability of land surface characteristics, it cannot always function successfully. Ghat [69] specifies the Penman–Monteith equation, Stanghellini model, Priestley–Taylor model, and Hargreaves–Samani into the mechanistic and empirical model category. However, the accuracy of these empirical models is compromised by the integration of empirical constants, and it leads to the over estimation of ET. The physically based, analytical methods are able to provide ET estimations in good agreement with measurements, but generally have a large data requirement [69,71]. These field scale measurement systems include lysimeters, Bowen ratio, eddy covariance systems, surface renewal systems, scintillometers, and classical soil water balancing [17,62,69]. Sometimes it may not be financially feasible to setup instruments throughout the catchment. Most of the cases of the FAO Penman–Monteith method is accepted as the representative ET estimation and crop coefficient (K) estimation method because it works with accurate lysimeter observations [67,69]. According to Subedi [68] and Maina [67], Penman–Monteith equation is the most representative ET estimation method. However, the aerodynamic terms used in the Penman–Monteith equation can be calculated without ambiguity and the most complicated part is the calculation of the canopy surface resistance [72,73]. Thus, more focus should be on the estimation of accurate surface resistance. Additionally, Subedi [68] highlighted one shortcoming of the Penman–Monteith equation in advective condition as it cannot incorporate the horizontal movement of sensible heat flux perfectly.

The application of the Penman–Monteith method is not possible where detailed meteorological data is not available. In such a case, Lang [74] compares three radiation-based methods (Makkink, Abtew, and Priestley–Taylor) and five temperature-based methods (Hargreaves–Samani, Thornthwaite, Hamon, Linacre, and Blaney–Criddle) with the Penman–Monteith method on a yearly and seasonal scale. The key finding was that radiation-based methods for PET estimation performed better than temperature-based methods among the selected methods in the study area. Furthermore, for low latitude, warm regions most suitable methods are Makkink and Abtew and, for regions with complex geographic features, the Makkink method is suitable. Tegos [75] presents a new parametric radiation-based model to estimate PET which shows excellent predictive capacity. The only drawback of this model is that it requires local calibration to apply for similar watersheds. In addition, the field measurement of evapotranspiration with the lysimeter experiment is very accurate, but costly and time consuming. Therefore, ET is often predicted based on climatological data.

Many researchers assessed both temperature-based and radiation-based methods in estimating ET for different case studies. In addition, some researchers successfully used state-of-the-art technologies in the estimation of the spatial and temporal distribution of ET [49]. Remote sensing technology is heavily used in the field of agricultural research

as they widely use various soil parameters, climatic factors, and other physio-chemical variations which vary spatially and temporally [40,62,64,76,77]. The well-established use of remote sensing technologies and the ever-growing availability of EO data lead to the development of global PET datasets by means of remote monthly temperature data [78]. Remote sensing can also be used for crop classification, crop monitoring during the growth season, and crop production assessment. In this regard, the remote sensing technology with global positioning systems (GPS) and geographical information systems (GIS) can be used to improve the efficiency in agricultural activities such as farmland extent estimation, crop growth stages monitoring, soil moisture and fertility evaluation, crop stress detection, diseases and pest disperse, drought and flood situations monitoring, and weather forecasting [7,64,79–81].

Reyes-Gonzalez [31] identifies that satellite-based remote sensing can be used to estimate the evapotranspiration to estimate the crop water use efficiently. They have investigated key elements that control the ET rates, such as weather factors, crop factors, and soil factors including meteorological measurements, crop information, and geo-hydraulic properties. Furthermore, due to spatial heterogeneity of these parameters, estimated ET values are varying in space and time with the variation of climate and growth stages of plants. Wu [82] highlighted that the implications of uncertainties in spatial ET modelling are often overlooked in water accounting frameworks due to difficulties in the ground measurements. Therefore, to capture the spatial and temporal variability of ET, satellite images can be identified as a useful tool [83].

According to the analysis of Stisen [84], the technology in remote sensing has improved a lot in the past years and more reliable ET mapping can be obtained. Usage of remote sensing for ET estimation has increased as it provides a consistent and cost-effective solution for field-based measurement methods as data scarcity is a general issue in most studies [81,85,86]. Additionally, when there are measurements in larger catchments (such as trans-boundary river basins), sometimes there can be accessibility restrictions with political issues. Indirect satellite-based measurements with high temporal frequency can be a solution for these issues [87]. Remote sensing of thermal infrared can predict the water stress levels. Thus, surface energy balance (SEB) models based on remote sensing of thermal infrared are widely used. However, those models highly depend on land surface temperature (LST) data measured from satellite observations [83]. Wagle [88] has compared and evaluated commonly used one- and two-source energy balance models and emphasized the importance of precise ET estimation to predict the adverse effects of climate change on agriculture and food security. Studies based on spatially distributed ET and plant water status have used reflectance, thermal radiance, vegetation index-based crop coefficients, and soil water balance [40,89]. Alvino [76] identified a positive relationship between crop-water status and yield and recommended more attention on remote sensing studies to improve productivity. Remote sensing has the potential to accurately map ET at unprecedented resolution and potentially with much less effort as these methods become easily operational [89]. The main advantage of the reflectance-based models is the capability of estimating the potential crop transpiration using crop coefficients ( $K_c$ ) and the actual ET values obtained from remote sensing methods [40]. Reyes-González [90] concluded that ET maps derived from remotely sensed multispectral vegetation indices can be used to estimate the crop water requirement at regional and field scales. Furthermore, the results indicated that the seasonal water requirement could reduce by 18% when proper ET estimation is used in irrigation schedules [90].

Digital infrared thermography in remote sensing has been used to measure the canopy temperature for early crop water stress detection and saving water with site-specific irrigation management. CSIRO in Australia has developed an IrriSatSMS system (Irrigation Water Management by Satellite and SMS) with satellite data, mobile phones, and web-GIS platform [40]. Wireless soil moisture sensors and unmanned aerial systems (UAS) are other important remote sensing techniques which increase the efficiency of site-specific irrigation management by monitoring and assessing groundwater and plant growth in precision

agriculture [76]. These techniques are capable of capturing soil moisture status and some physical properties, predicting harvest, canopy status and crop water status, and pests [91].

Andriambeloson [92] stated that remote sensing is more practical for ungauged watersheds. In addition, they noted that the accuracy of the remotely sensed near-surface parameters of the energy balance equation, such as wind speed, air temperature, and humidity, need to be improved. Another issue is the disturbance to the radiometer of the satellites from the airspace between the earth surface and sensors of the satellites as this alters the accuracy of the measurements [37]. Yang [71] showed that ET measurements highly depend on solar radiation and temperature but were less associated with relative humidity and wind speed. ET controls the matter and energy exchange between the plants and atmosphere. Therefore, crop growth and production highly depend on ET. Agricultural performance can be measured at high spatial and temporal resolutions with the latest remote sensing options [62]. Reviewing the reliability of remote sensing platforms to predict the scattered behavior of the actual evapotranspiration, precipitation, and land use, Karimi [17] showed that the evapotranspiration estimation can be performed with 95% accuracy. Furthermore, they highlighted that more research work is required in the areas of spatial mapping of precipitation and land use/land cover with multiple space-borne sensors.

Application of machine vision tools in agriculture has been enabled by machine learning algorithms which have been used to analyze extensive volumes of data precisely and accurately [63,93]. Based on surface energy balance, several tools and functions to estimate the actual ET using satellite measurements have emerged recently. Furthermore, Karimi [17] provided a list of algorithms and measurement tools required to estimate the surface temperature, which is estimated by the space-borne radiometers and will be used in ET algorithms. These algorithms are varied from each other with the configuration of sensible heat flux (H), model assumptions, and the required input data. Soil moisture data can be identified as one of the most important pieces of data required in ET estimations, which can be obtained from thermal measurements or from microwave measurements. The significant advantage of microwave measurements is that they can be measured for any climate with any spatial scale [17].

The evaporation process requires energy. Therefore, increasing evapotranspiration can decrease the surface temperature of tree canopy [94]. This concept has been used in ground-based thermal remote sensing and it can be identified as one of the accurate evapotranspiration and drought stress estimation methods in agriculture water management [87,95]. Due to the scattered and diversified canopy cover in agriculture lands, it is difficult to measure canopy surface temperature. Therefore, ground-based thermal remote sensing tools are mainly applied for homogeneous croplands. However, sophisticated thermal cameras, providing precise canopy surface temperatures while removing the noise from the soil and background, enable applications in heterogeneous croplands as well [96]. In advanced irrigation scheduling, plant water status information is usually obtained by leaf water potential or leaf stomata conductance estimation, which requires more time and resources [97]. Since the leaf temperature is a function of transpiration and stomata opening, this can be carried out with infrared thermography (IRT), which is a non-contact and pragmatic method. It is possible to capture overgrown leaf cluster and, therefore, it can provide physiological status information for all crops within the field. However, leaf temperature depends on some more factors such as air temperature, radiation, humidity, and wind speed, which can cause errors in thermography-based water status detection [97]. Hence, the integration of advanced techniques including remote sensing and satellite technology for ET estimation provides higher accuracy and significant improvement in agricultural water management.



### 3. Future Research Developments

Reviewing the methods of ET estimations and applications in agricultural water management reported in the literature, the potential and viability as well as several drawbacks of available evapotranspiration estimation techniques can be identified. Two decades back, the conveyance of findings in ET modelling into field practices remains slow [98,99]. However, recent research findings are practiced in most agricultural regions of the world [100,101]. When applying remote sensing techniques to estimate ET, key issues that restrict the applications to an accurate level are: physical interpretation surface variables, the representation of land surface fluxes, scaling spatial and temporal data, validation of modelled latent heat flux, and obtaining the near-surface meteorological data. Since ET is not possible to measure directly from space, it should be physically derived as an energy variable with several measurements. To understand the seasonal variations and magnitudes of ET fluxes, knowledge of information on phenology, vegetation cover, and movement of water from the land into the atmosphere is required [102].

When taking remote sensing technology as a method to determine ET, the advanced space-borne observation systems used to capture the energy flows at the top of the atmosphere. However, the energy flows at the earth's surface have not been captured well as it is a collective effort of satellite and ground-based data measurements. Ustin [103] identified that this gap can be filled in coming decades with the qualitative information retrieved from optical, thermal, radar, and LiDAR imagery. Furthermore, Jing [93] emphasized that there is no universal model which could be used regardless of the variations in land surface parameters in different climates and terrains without any correction to obtain the ET from satellite data. Therefore, the link between the remote sensing and distributed hydrological modelling should be enhanced for accurate estimation of ET in future applications [104]. Additionally, higher-resolution ET data is required as it is the steering factor of satellite-based ET measurements which applies water management and hydrological studies [17]. In addition, integration of machine learning algorithms to analyze the extensive volumes of observed data leads to increased accuracy. The changing climate scenario should also be considered in future research methodologies and the modification of existing methods should also be considered [36,104].

### 4. Conclusions

Accurate estimation of the water use over agricultural areas is important for agricultural water resources planning, management, and regulation. Insufficient water allocations affect the growth of crops, harvest, and, ultimately, food scarcity. Evapotranspiration (ET) contributes to the highest water loss in agricultural areas. Applying more efficient ET reduction strategies are important to achieve efficient and sustainable water management in agricultural areas. Furthermore, the atmospheric temperature is projected to increase with climate change, and it provides more energy leading to more evaporation. Therefore, improvements of water-use efficiency and sustainable water management in agriculture must be based on the accurate estimation of ET.

Taking these facts into account, this comprehensive review summarizes the technical development of the methodologies, tools, and approaches in the estimation of ET to enhance the agricultural water management. The available studies in the literature mainly revealed two main approaches: the identification of more efficient ET reduction strategies, which compromise the crop growth, and the development of precise ET measuring tools and approaches. Accuracy of the ET estimation is of prime important to achieve precise agricultural water management. It was also identified that the gap between the existing knowledge and technology to identify energy interaction needs further improvement, as there is large uncertainty in the understating of energy interaction in different crop growth stages. Applications of precision and digital agricultural technologies lead to an increase in the accuracy of the estimation of ET. The integration of advanced techniques, including remote sensing and satellite technology, and usage of machine learning algorithms to

analyze the data in ET estimation provides higher accuracy and significant improvement in agricultural water management.

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