Role of Evapotranspiration in Agricultural Water Management

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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.

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1. 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 [1]. 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 [2][3]. Water conservation in E- based irrigation scheduling is a rising concern on a global, as well as local, scale, while improving water productivity [4]. 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 [5]. Li [6] 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 [7]. 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 [8]. Krishna [4] 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 [9].

Evapotranspiration facilitates the continuous energy flux across the hydrosphere, atmosphere, and biosphere [4][10]. 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 [11]. The ET process is significantly contributing to moisture return into the atmosphere [5]. Analyzing the contribution of the three modes of water supply to the ET, Moiwo [12] 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 [13]. 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 [10][14][15][16][17].

2. 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 [18]. Climate change will trigger numerous and complex impacts on water resources and agriculture [19]. 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 [20]. 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 [21]. Lopez [22] 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 [23]. 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 [23]. Entezari [24] 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 [25] 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 [26][27][28]. To assess the spatiotemporal variation in climatic water availability (CWA) and crop water demand using long-term rainfall and temperature data, Salman [29] 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.

3. 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 [30]. 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 [30][31]. 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 [30]. 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 [32]. 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) [33] 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 [34]. 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 [35]. Precise and accurate crop water demand assessment needs the accurate estimation of evapotranspiration. Koech [36] highlighted the requirement of water-efficient technologies and practices to achieve sustainable water resources in agriculture. Furthermore, Blatchford [37] 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 [38]. 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 [39].

4. 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 [34]. Therefore, automated farm management using agricultural automation equipment and systems will be widely used in the future. Deep learning and spectral analysis technology [40] 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 [40]. 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 [5].

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 [41]. 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 [1] 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_2), etc. [42][43][44]. When it comes to extensive terrain, measurements of these parameters are quite difficult and need to be extrapolated or interpolated with limited accuracy [6][45]. 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. Ghiat [44] 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 [44][46]. These field scale measurement systems include lysimeters, Bowen ratio, eddy covariance systems, surface renewal systems, scintillometers, and classical soil water balancing [5][37][44]. 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 [42][44]. According to Subedi [43] and Maina [42], 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 [47][48]. Thus, more focus should be on the estimation of accurate surface resistance. Additionally, Subedi [43] 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 [49] 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 [50] 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 [21]. 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 [11][37][39][51][52]. 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 [53]. 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 [39][54][55][56][57].

Reyes-Gonzalez [8] 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 [58] 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 [59].

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