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Performance of Remote Sensing in Scheduling Irrigation: A Review

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IRRIGATION management is crucial for sustainable agriculture, particularly in water-scarce regions such as arid and semi-arid zones. Soil moisture and evapotranspiration are critical parameters that need to be estimated with a high degree of uncertainty to enhance irrigation practices and sustainable water management. This review examines various remote sensing techniques, for assessing soil moisture and ET with special emphasis on their applicability in agricultural water management. We consider the necessity of ET in irrigation scheduling and explain its contribution, as well as the use of remote sensing for evaluating crop water demands. Key approaches reviewed include multispectral and radar remote sensing, in addition to models for instance the Penman-Monteith equation, surface energy balance algorithms (SEBAL), and vegetation index (NDVI) for monitoring crop health and water demand. This review also explores the issues related to ET estimation, which is based on remote sensing including calibration, temporal and spatial resolution variability, The findings are summarized to compare the remote sensing approaches to determining the volumetric water content of soils and irrigation management in arid regions. Hypotheses and the use of remote sensing, and real-world data augmentation superior to augmentation methods such as data-casting and deep learning techniques are discussed. The discussion covers hypotheses, the use of remote sensing, and real-world data augmentation, which proves superior to methods like data-casting and deep learning techniques. However, limitations such as ground truth difficulties, model calibration, and spatial resolution mismatches remain obstacles. Although this review presents a concise summary of the current knowledge on remote sensing for estimating soil moisture and evapotranspiration, it is expected that its contribution will be worthwhile for supporting future innovations in efficient and sustainable irrigation applications and water management in agriculture.

Keywords: Remote sensing, evapotranspiration, soil moisture, vegetation index, sustainable irrigation systems.

Abbreviations

- **ET**: Evapotranspiration
- **RS**: Remote Sensing
- **GIS**: Geographic Information Systems
- **ETd**: Daily Evapotranspiration
- **ETo**: Reference Evapotranspiration
- **AET**: Actual Evapotranspiration
- **NDVI**: Normalized Difference Vegetation Index
- **LST**: Land Surface Temperature
- **CWSI**: Crop Water Stress Index
- **SEBAL** - Surface Energy Balance Algorithm for Land
- **MODIS**: Moderate Resolution Imaging Spectroradiometer
- **SEBS**: Surface Energy Balance System
- **TSEB**: Two-Source Energy Balance
- **METRIC** - Mapping Evapotranspiration at High Resolution with Internalized Calibration
- **Kc**: Crop Coefficient
- **Kcb**: Basal Crop Coefficient
- **FC**: Fractional Vegetation Cover
- **EEFlux**: Earth Engine Evapotranspiration Flux
- **USGS-FEWS NET**: United States Geological Survey Famine Early Warning Systems Network
- **MCD12Q1**: MODIS Land Cover Product
- **MOD16A2**: MODIS Evapotranspiration Product
- **LAS**: Large Aperture Scintillometer
- **SETMI**: Satellite-based Evapotranspiration and Temperature Model Integration
- **DEM**: Digital Elevation Model
- **ASTER**: Advanced Spaceborne Thermal Emission and Reflection Radiometer
- **SRTM**: Shuttle Radar Topography Mission
- **NDWI**: Normalized Difference Water Index
- **EVI**: Enhanced Vegetation Index
- **INDVI**: Integrated Normalized Difference Vegetation Index
- **ASLE**: Agricultural Soil and Land Evaluation

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- **CNN**: Convolutional Neural Network
- **EVI**: Enhanced Vegetation Index
- **GIS**: Geographic Information System
- **LULC**: Land Use/Land Cover
- **MODIS**: Moderate Resolution Imaging Spectroradiometer
- **NDVI**: Normalized Difference Vegetation Index
- **P-band SAR**: P-band Synthetic Aperture Radar
- **RGB**: Red, Green, Blue (color channels in imaging)
- **SAR**: Synthetic Aperture Radar
- **SMAP**: Soil Moisture Active Passive (satellite mission)
- **SSA**: Singular Spectrum Analysis
- **UAS**: Unmanned Aerial Systems (drones)
- **FAO**: Food and Agriculture Organization
- **Fc**: Field Capacity
- **IWC**: Irrigation Water Consumption
- **LAI**: Leaf Area Index
- **RS-ET**: Remote Sensing-based Evapotranspiration
- **SAMIR**: Satellite Monitoring of Irrigation
- **SWB**: Soil Water Balance
- **WP**: Wilting Point
- **UAV**: Unmanned Aerial Vehicle
- **SSM**: Surface Soil Moisture
- **SM**: Soil Moisture

1- Introduction

Irrigated agriculture remains largest sector of water consumption in the world, However, the potential for future profitability of large-scale irrigated agriculture is threatened by new water scarcity conditions that include high population pressure densities, global climatic changes, and competition with other sectors of the economy (Abdelraouf et al., 2019). These indicate clearly that, like any other necessity whose major concern would be most essential in the arid regions, water should be managed to the optimum in these areas. This in turn requires the determination of the water needs of the crops and/or irrigation frequencies, with ET as one of the considerations (Abdelraouf et al., 2020; Kharrou et al., 2021**;** Alhashimi et al., 2023; Hani et. al., 2025)**.**

Effective water resource management seems to be a golden base of agricultural sustainability in arid and semi-arid regions (Abdelraouf et al., 2016; Sabra, et al., 2023; Hany et al., 2025). Evapotranspiration (ET) is a critical hydrological phenomenon in such ecosystems. ET comprehension and its accurate assessment are extremely important for proper irrigation management since it defines crop requirements for irrigation water and overall water use efficiency.

A proper system of irrigation is a technique for conserving the water supply for future needs. At this time, energy, water, and costs are also saved. Hence, the study of the dynamics of the ET as well as the deployment of the right management measures is important in the pursuit of efficiency for suitable measures and practices in maintaining water security and sustainable farming. (El-Shirbeny et al., 2021; Abdelraouf and Ragab 2018)

ET is defined in terms of millimeters of water and directly calculates the amount of water let into the atmosphere starting from the surface of the earth and hence is dependent on intensity and blackness of fame, temperature, humidity, wind, and vegetation. In arable, horticultural, and plantation farming, accurate assessment of ET is more critical in the evaluation of irrigation demands and water rationing for other uses. (Cha et al., 2020; Abdelraouf 2019; Abd El Lateef, et al., 2025; Abdelraouf et al., 2024)

The conventional methods, like the FAO Penman-Monteith equation for class A surfaces, are the most accurate and reliable because of the genuine and controlled climate data involved. But they are very expensive, require major maintenance, and only offer a relatively small coverage area. This method require high-quality data and knowledge, and that is why it is hard for their implementation, it provides accuracy in the estimation of evapotranspiration.

Different techniques used to estimate evapotranspiration from remote sensing are effective and efficient in terms of vast area coverage and frequent data acquisition, which can greatly aid in large-scale agricultural evaluations and basin water supply estimations. Such methods employing satellite imagery and UAV provide valuable inputs about vegetation vigor and the status of moisture in the soil without much requirement of massive ground supports. Despite this, remote sensing is relatively less accurate than ground sensing because the sensors' readings can be distorted by cloud existence. Ground data to calibrate and validate should be necessary, which also raises the scale and is more error-prone yet allows more scientific and rational overall management of larger bodies of the area through better irrigation, commanding fuller information.

Due to the challenges associated with the determination of ET, its calculation is important and relevant in order to enhance efficient irrigation practices and water conservation in agriculture. Other prior approaches for calculating ET involved in situ measurements and crop coefficient estimation. In general, methods used in estimating ET have progressed invigoratingly, especially with the advancement in remote sensing techniques offering geographically and temporally consistent data across large areas (Mahmoud and Gan, 2019).

RS application in agricultural water stress monitoring is useful in scheduling irrigation, and productivity of water and land alike to improve crop yields. The incorporation of RS approaches with GIS improve the spatial analysis of ET trends and provide better decision and management traits and sustainable water utilization strategy (ElShirbeny et al. 2021)**.**

Familiarizing themselves with the dynamics of ET helps farmers adjust their irrigation time and frequency and, hence, get the right amount of water for their crops without wasting a lot of water. When irrigation is excessive, water may stagnate, form excess nutrients, and even lead to high energy usage, while on the other side, limited irrigation causes crop stress, loss, and low returns. These findings enlighten farmers, and they are capable, through the quantification of ET, of making suitable choices of the irrigation time, frequency, and amount, thereby improving crop production and water use efficiency (Cha et al., 2020).

Mapping irrigated areas and precisely calculating irrigation parameters like frequency, time, and amount is critical for long-term water resource management in semi-arid and arid countries. (Chen et al., 2018) **.**

Irrigation water management is critical for agricultural sustainability, especially in semi-arid regions prone to water constraints. Despite its importance, precisely quantifying irrigation water remains difficult due to the intricacy of soil-plant-atmosphere interactions (Jalilvand et al., 2019; Abdelraouf et al., 2021))**.**

Irrigated agriculture is critical to global food security, yet accurate data on irrigation water amounts is typically unavailable. Traditional methods for monitoring irrigation are limited by characteristics such as temporal and geographical resolution, stressing the need to use remote sensing techniques for improved irrigation water management. (Zappa et al., 2021)**.**

2. Remote sensing

2.1. Optical Remote Sensing

Wu et al., (2019) employs a method of optical remote sensing, for measuring soil moisture with consideration to the existence of vegetation cover. Targeting and acquisition of optical remote sensing data will contain useful information on the surface of the Earth like vegetation indices and soil moisture. Out of all the indexes, the authors paid the closest attention to spectral signatures and vegetation indices to make improvements in the estimation of soil moisture. The objects identified by a type of remote sensing used in the analysis of (Wang et al., 2023) are air pollutants, wind velocity, specific humidity, pressure, temperature, solar irradiance, and precipitation with the precision of correct inversion of the soil moisture. Backscatter which is derived from SAR data and depends on the soil moisture content. Multispectral photographic and optical instruments provide information on the vegetation cover and the overall nature of the entire land surface. Compiling results from multiple data sources, the research creates a unified dataset for the estimation of soil moisture under various circumstances and types of land covers

There are three key steps: (a) The process of remote sensing data required to be stored, preprocessed, and analyzed; (b) The utilization of machine learning approaches for the interpretation of the remote sensing data; (c) The research and development on multi-disciplinary applications based on remote sensing data and intelligent computing approaches. These algorithms are designed to perform efficiently when operating on large datasets and learn what the more important aspects of the data are in the process, thereby improving the soil moisture estimates. The great thing about this study is how all of these remote sensing inputs can be viewed from a single lens and then the exemplified machine learning approach which enables near real-time measurement of soil moisture.

In the case of soil moisture content estimation, (Wang et al., 2023) utilize multiple sources of remote sensing data and deep learning. They have divided remote sensing data into Satellite-based sensors including Synthetic Aperture Radar (SAR), Optical Imaging, and Multispectral Sensors, which constituted the key data used in the study. Thus, the data sources are described, analyzed, and combined to obtain the final structural database of inverted soil moisture.

The SSA-CNN version is essential to the study's technique. SSA is used to cut up remote sensing information into several additives, setting apart noise and growing the soil moisture sign. The processed facts are then analyzed by the use of the CNN structure, which lets in for the extraction of complex patterns and traits indicative of soil moisture fluctuations (Wang et al., 2023). The use of SSA and CNN permits high stages of accuracy in soil moisture measurement, in particular in tough agriculture regions.

2.2. Microwave Remote Sensing

Microwave satellite sensors are a viable alternative, detecting soil moisture changes independent of weather. Because soil moisture products have low spatial resolution, microwave sensors have been used in most studies for irrigation mapping. For instance, (Jalilvand et al., 2019) employed microwave remote sensing to estimate the quantity of water that is held in the ground. They employed synthetic aperture radar (SAR) data, as it operates independently of anyone’s weather patterns and gives spatial density. SAR stays in a position to make continual moisture measurements of the soil even if there are clouds, which indicates that it is ideal for semi-arid areas with relatively frequent.

Microwave remote sensing techniques were applied and decreased Sentinel-1 SAR records for the assessment of ground soil moisture following a study that was conducted by (Zappa et al., 2021). Earthy-colored topographical data obtained from the Sentinel 1 SAR information has all atmosphere flexibility and an extraordinary spatial solution favorable position, making it the perfect tool for observing soil moisture on a regional scale. This research study would be able to identify irrigation instances through the analysis of the data from Sentinel SAR, which is sensitive to changes in surface soil moisture.

In addition, they rely on satellite information, including Sentinel-1 project data, which contains high-resolution soil moisture data with average frequency. Remote sensing of microwaves is significant in estimating soil moisture, mainly because it can go through both the vegetative and the soil covers to produce the soil (Soylu and Bras, 2024). This does so by combining several remotely sensed data points with hydrological strategies to estimate irrigation and its impacts on power and water-restricting agroecosystems. Hydrological information is obtained from satellite-primarily based remote sensing techniques to look at and quantify the moisture content of soil and, thus, the availability of water in numerous agricultural jurisdictions. An assessment of plant life is done with multispectral sensors, while microwave sensors are used in the assessment of soil moisture.

2.3. Thermal Remote Sensing

To estimate the soil moisture that is prevalent in arid regions, (Mohamed et al., 2020) primarily used optical and thermal imagery. Optical remote sensing measures reflected sunlight and near-infrared light to simulate the character of the surface, while thermal remote sensing transmits thermal energy to gauge the temperature of the surface. From this data, the scientists were able to make estimations of soil moisture with the help of the temperature of the surface and features, the latter being a parameter associated with the surface of the land. This assessment of surface properties was made adaptive, which means it responded to the variation in environmental conditions that specify arid zones. Based on the study (Paridad et al., 2022), soil moisture is here derived from optical and thermal infrared imagery. RGB images captured by UAS can depict the surface of the area and the presence of vegetation cover, and thermographs indicate how the temperature changes across the area, suggesting soil moisture. (Paridad et al., 2022) assumed that accurate estimation of the soil moisture conditions in arid and semi-arid regions should be achieved with the help of RGB and thermal images collected at different time points and sites.

In the works of (Kragh et al., 2024), four approaches utilized in the quantification of irrigation have been explained, and they are as follows: The four approaches to the quantification of irrigation are based on remote sensing Sentinel-1, Sentinel-2, Landsat, and MODIS satellite observations, which offer varying prospects for the monitoring of irrigation. The authors provide quantitative and qualitative evidence of the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI), which are used for measuring changes in vegetation cover density. These indices are calculated using different reflectance bands in the visible and near-infrared range, captured by multispectral satellite sensors, and have become standard indices to monitor the dynamics of vegetation cover (e.g., crop development) via its response to seasons and climatic conditions. Also, (Kragh et al., 2024) look at radar-based approaches, with an emphasis on Sentinel-1 Synthetic Aperture Radar (SAR) statistics. SAR data can impact irrigation activities by providing statistics on soil moisture content. This method is excellent for monitoring irrigation in all-weather conditions, given that cloud cover does not affect SAR facts. Thermal-primarily-based strategies are also explored, which use satellite-derived thermal anomalies to pick out changes in land surface temperature associated with irrigation. These versions can propose irrigation techniques and provide insights into water use performance.

3. Remote sensing-based estimations

Numerous methods have been developed to estimate evapotranspiration (ET) using remote sensing technologies. These methods differ in terms of input requirements, spatial and temporal resolution, and underlying algorithms. Table 1 provides a comparative overview of the most commonly used remote sensing-based ET estimation methods, highlighting their key features, advantages, and limitations.

Downscaling of remote sensing data with evapotranspiration Equations like the Penman-Monteith model enable the accurate derivation of references for evapotranspiration (ETo) and actual evapotranspiration (AET). These models apply different meteorological factors, including net radiation, air temperature, wind speed, and vapor pressure, to the determination of water loss through evapotranspiration.

Moreover, using remote sensing data simplifies the creation of land cover maps and crop coefficients that are needed for determining the extent of irrigation and the needed amount of water for specific crops. Thus, regression models formulated from NDVI data facilitate the determination of crop coefficients based on the number of days in the growing season and therefore enhance the determination of the ET. (Mahmoud & Gan, 2019). RS data provides actual information regarding the demand for water required for agricultural activities so that we can recognize or map the areas of differential water demand. Normalized difference vegetation index (NDVI), land surface temperature (LST), and crop water stress index (CWSI) ratios derived from RS decreased over the Sahel region, which is significant for crop health, water stress, and irrigation.

For irrigated regions and to estimate seasonal ET for crops (El-Shirbeny et al., 2021) and timely utilize remote sensing images to control crop water demands in line with irrigation requirements. They use Landsat and MODIS images within the SEBAL model to estimate the energy balance. According to the study carried out by (Cha et al., 2020), the suggested estimating methodology entails the estimation of the daily evapotranspiration (ETd) value and adopting the constructed ET systems to estimate ET during the growth period of the crop. There are two methods of evaluating seasonal ET: one is the trapezoidal or geometric mean method, while the other is the sinusoidal or harmonic mean method. The trapezoidal technique uses temporal evapotranspiration difference pictures to come up with later on, as well as the sinusoidal method by integrating time series of MODIS and multitemporal ETd images. (Kharrou et al., 2021) assess the possibility of characterizing the temporal and spatial variability of ET and irrigation water requirements at the field scale through remote sensing-based techniques in the semi-arid environment. The CROP-WATER model uses the FAO-56 Soil-Water

Balance model integrated with high-resolution satellite imagery, specifically the Normalized Difference Vegetation Index (NDVI) data, for deriving basal crop coefficients and fractional vegetation cover. The technique of studying the areas irrigated by water and IWC through the use of remote sensing. To generate the maps of present and historical irrigation extent, digitally classified maps of the multi-temporal data of Landsat 8 and Sentinel-2 were prepared. The standard deviation of temperature was examined for NDVI and Kc, from which the crop evapotranspiration (ET) was computed. To back up these estimations and upload ET maps to the IWC for the whole nation, ground data synthesis was conducted (Chen et al., 2018) **.**

3.1. Energy balance method (*SEBAL)*

To describe evapotranspiration (ET) as the ratio of the energy appearing at the interface of land and atmosphere, (Mahmoud & Gan, 2019) utilized energy balance methods and reconstructed land surface energy exchanges. Such approaches rely on the estimation of incoming radiation at the surface from the sun, thermal radiation emitted back to space, and the turbulent transfer of sensible heat to provide the ET estimates. While studying the energy balance components, it was possible to establish the amount of energy used for evaporation and plant transpiration, which hadn't been possible before due to the insufficiency of the data sets, allowing for more comprehensive knowledge of the water cycle processes. (El-Shirbeny et al., 2021) used Farinelli's conservative spectral model to estimate LST using energy balance methods. LST is defined as the temperature inside the crop canopy (Tc) and the thermal environment of the plants. The LST was calculated by conjoining To and Eo, which is NDVI, and thermal emissivity converted into Eo. with the help of NDVI, which is derived from satellite data and categorizes a wide range of land surface features under reflectance red (R) and near-infrared (NIR) waves. The two were determined using a calibration constant for radiance in a given band. The versatility of LST analysis lets researchers identify water stress levels in crops besides their physiological condition; it helps in deciding the irrigation process and yield improvement.

The last term in the surface E balance equation that represents latent heat is employed to estimate evapotranspiration (ET) is used by the study by (Kharrou et al., 2021). These methods involve making estimations of thermal differences by incorporating the thermal sensors and thus arriving at the energy fluxes. In the TSEB, SEBAL, and METRIC models, energy balance is used, which divides the total net radiation into sensible and latent heat flux densities. To estimate evapotranspiration and IWC, the energy balance ratios along with vegetation indices were used. The energy balance-based ET calculation was based on the SEBAL (Surface Energy Balance Algorithm for Land) model for the energy balance-based ET value, and we used NDVI for defining the crop coefficient and for the ET calculation. The correlation established between monthly average NDVI and Kc constructively aided in achieving an accurate representation of evapotranspiration and consequently converting it to IWC(Al-Bakri et al., 2023)**.** (Abou Ali et al., 2023) utilized the Eddy-Covariance system to compare estimates of transpiration and energy exchange and meteorological sensors to quantify other parameters such as radiation and heat exchange from the soil. Moreover, there were established soil moisture sensors to measure the water content in the root zone near the EC tower at different depths. As applied in the SEBAL model, ET was estimated from satellite data at specific time steps, and, therefore, ET fluxes in specific time steps for the overpass time were predicted (Barman and Kamila, 2023). Organized meteorological data was obtained from IMD for the study, which includes air temperature, wind speed, relative humidity, and sun radiation. These parameters were implemented to introduce environmental factors to the SEBAL formula. Furthermore, slope, which is very important in ET estimates, was determined from other DEMs from the ASTER and SRTM datasets.

Kader et al., (2015) used the surface energy balance to calculate evapotranspiration (ET), which quantified the energy exchanges at the surface of the ground as applied by (Mahmoud & Gan, 2019). Such methods rely on the remote sensing data as well as the actual meteorological conditions to estimate the adjusted ET, accounting for the incoming short-wave radiation, surface temperature., and vegetation characteristics. Researchers were also able to estimate spatially explicit ET with the help of surface energy balance methods, which allowed researchers to quantify the dynamics of water usage and describe crop water requirements in larger areas.

Surface energy balance methods of (El-Shirbeny et al., 2021) were used to estimate CWUE focused on crop water stress index. The CWSI developed by Idso et al. (1981) and Jackson et al. (1981) is based on the method that computes crop water stress levels through the variation between potential soil temperature (LST) and air temperature (T air). Thus, by comparing the LST and Tair data from a time perspective, researchers will be able to determine the extent of the crop's water deficit. Also, the surface energy balance methods involve the computation of crop water consumptive use using evapotranspiration (ETo) and crop coefficients (Kc). ETo, which is provided by the FAO-Penman-Monteith model, provides climatic features affecting water demand, while Kc considers crop characteristics. These help the researchers bring into equations water use efficiency (WUE) as well as the right irrigation techniques that lead to better yields.

Energy balance techniques applied by (Cha et al., 2020) consist of SEBAL, which stands for Surface Energy Balance Algorithm over Land, as its name suggests. Separate radiative energy balance (SEBAL) works on ideal radiation and energy balance, with resistances for momentum heat and water vapor transfer incorporated in each pixel. SEBAL then comes up with instantaneous evapotranspiration (ETinst) by using multispectral satellite imagery data, meteorological data, and digital elevation models. These values are obtained from other parameters using the necessary parameters of the energy balance equation, including albedo, corrected NDVI, TS, and emissivity. SEBAL is employed for calculating ETinst, the results of which, integrated with LE and other data, enable the researcher to comprehend the spatial patterns of ET comprehensively across different terrains.

Surface energy balance algorithms that try to estimate ET according to the instance in (Kharrou et al., 2021) partly do so depending on energy flows at the Earth's surface. Crop ET is derived from models like the FAO56 dual crop coefficient approach, which involves combining rationalism's major postulates and a system of coefficients. Superimposed upon ETo for standard grass, by employing crop coefficients (Kcb) and evaporation coefficients (Ke), the FAO56 technique refines ETo to crop-specific rates. Instead of directly specifying the values of Kcb and fc, the NDVI time series are used in the calculation of Kcb and fc. As it was mentioned before, the linear relationship between NDVI and VIs facilitates the possibility of continuing Kcb calculation without restrictions in connection with the given conventional approaches. Moreover, adjustment of the parameters used in the estimation of the rate of soil evaporation enhances the computation schemes of surface energy balance for various levels of soil moisture content.

In a study by (Ayyad et al., 2019), a structured approach was taken to assess satellite-derived data and irrigation efficiency in Egypt. The researchers initially used the MODIS land cover product (MCD12Q1) to pinpoint regions. They compared three products, namely (EEFlux), USGS FEWS NET SSEBop, and GOTTHARD/2 MODIS, monthly actual evapotranspiration products: MOD16A2. Those products were evaluated with data at the same time, with the Normalized Difference Vegetation Index (NDVI) embedded for seasonal and annual assessment, Since capturing images of wheat fields, (Gómez-Candón et al., 2023) have used aerial vehicles (UAVs) fitted with multispectral cameras. The images captured were then digitally enhanced to develop vegetation indices such as the Normalized Difference Vegetation Index (NDVI), which provides information on the health condition and vigor of the crop. Other energy balance algorithms, like the Surface Energy Balance Algorithm for Land SEBAL, were used to estimate ET using energy balance over the dark crop surface. Regarding the remote sensing aspect of the study in question, introduced by (Elfarkh et al., 2023), ET and related parameters were indirectly measured based on a differentiated high-resolution satellite image. The Sentinel 2 satellite, with its function of capturing different types of images, employs spectral bands and has a resolution of between 10 and 60 meters. This detailed data enables the assessment of the vegetation cover, which can be used to estimate evapotranspiration by using the SEBS method.

SEBS then estimates the retrieval of ET based on energy balance at the uppermost layer of the earth using satellite data on temperature, reflectance, and color similar to NDVI. On the ground, it validates its ET estimation with oversight, especially when there are areas that need repair due to the effects of Mother Nature. Satellite data adds to the vast voluminous data acquired using eddy covariance on the ground and offers rich insights into ET and related phenomena. Nevertheless, it is revealed that the integration of both approaches offers a more comprehensive picture of ET in regions with intensive olive trees. (Elfarkh et al., 2023)

This has been confirmed in the study done by (Scintillometer et al., 2024), where the authors employed both ground observations and remote sensing approaches for their strategies. Ground-Based Observations: This technique enabled the researchers to measure sensible heat flux over a long distance using the Large Aperture Scintillometer (LAS). This data was then used to estimate ET using the energy balance method. Here, the net radiation, Rn, sensible heat, H, and latent heat flux, LE, were measured and used in the following equation. Indeed, by performing net radiation balance, heat conduction, and sensible heat transfer, they were able to deduce the latent heat transfer, which is highly correlated to ET. As a part of the ground-based observations, the use of the SETMI model was also involved in performing the remote sensing of the atmosphere.

The following model forecasts ET from satellite data, but for a wider range of calibration scales. Using the data obtained from the meteorological department, together with the data received from communication satellites, the SETMI model can determine the bye-areal value of ET. The authors, in distinct ways, used data from satellite imagery from Landsat and MODIS to accomplish vegetation indices that are an essential input to the SETMI model. These vegetation indices offer significant and extremely useful data on vegetation health and activity in a particular region, which are mandatory for the right computation of ET. By integrating the data gained through LAS and the predictions given out by the SETMI model, the researchers were finally able to arrive at a multifaceted estimate of ET in some geographical regions.

3.2. Vegetation indices

In their study (Mahmoud & Gan, 2019), crop coefficients (Kc) estimation used vegetation indices from remote sensing data, including the MODIS normalized difference vegetation index (NDVI). Through NDVI, helpful data about vegetation density and vigor, as well as the phase of their growth, could be obtained based on spectral reflectance evaluation. These indices were employed in input functions for modeling Kc so that further research correlations and physical links between NDVI and Kc estimates could be built, which might be pivotal for assessing agricultural water requirements on large geographical scales.

Researchers, including (El-Shirbeny et al., 2021), used vegetation indices, including NDVI, to classify land surface targets according to their spectrally distinctive characteristics. The vegetation density and vigor can be determined using NDVI, which is extracted using the satellite data that is present in the R and NIR bands. This study involved the use of NDVI to work in tandem with energy balance methods to come up with Eo, which in itself is vital in the computation of LST. Scientists may employ the values of NDVI in their studies for vegetation condition assessment, crop status, and water deficit determination.

Meteorological global ET can be assessed through physiographic data or remote sensing with vegetation indices such as the NDVI. From the satellite data, the NDVI work (Cha et al., 2020) is received from the nearby infrared or red bandwidth, with the help of which the vegetation health condition can be known. A high NDVI value shows that it has dense vegetation cover, which implies efficient photosynthesis, which in turn leads to losses through evapotranspiration. In this manner, using the NDVI in models of ET estimation, researchers are provided with numerical capabilities that help enable the identification of the extent to which plant cover change influences water vapor exchanges within the biosphere and species' transpiration as a consequence, increasing the accuracy of estimations.

(Kharrou et al., 2021) cited that vegetation indices (Vis) are a strong tool for analyzing biophysical properties from satellite data and that the NDVI is the most popular tool among them. Specifically, NDVI is derived from the NIR and R reflectance and provides information about whether the vegetation conditions are healthy or vigorous. Kcb and fc times series can be directly derived from the NDVI time series; interpolation is then used to determine temporal patterns of the biophysical components. For estimating the ET, it is indispensable to identify Kcb and fc with the help of linear relationships between some NDVI and VI, which are determined.

The study that was under consideration, namely (Kadri et al., 2023), used both techniques based on the analysis of remote sensing data as well as soil-water modeling. The remote sensing part is accomplished by using synthesized images with a spatial resolution of near-infrared and thermal infrared from the satellite in an attempt to estimate the ET. Here, the data from both Sentinel-2 and Landsat bands is used to make indices such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI). These indices are often used for establishing vegetation cover and are intricately linked with ET. The method referred to as the soil water simulation implies estimating ET as a function of the simulation of the soil water balance. It covers variables including humidity, temperature, rainfall, and other weather factors. In the hydraulic interpretation, the process is modeled as the soil-water balance.

Wang et al., (2023) utilized a remote sensing ET through the agricultural model to model the ET and yield of wheat and maize crops. The scientists used the Surface Energy Balance Algorithm for Land (SEBALs) technique to estimate ET from the satellite images. The model computes heat flux in terms of meteorological data and remote sensing without direct representation of ET values at time durations. Imagery data from sources including Landsat and MODIS was used in this study to fill the data requirements for this research. In addition, the assessment of the model was based on ground-based data, much to the success of the entire process. Specific to the canopy water status, which can be estimated by the spectral vegetation index, the study used the remote sensing technique as described by (Solgi et al., 2023). The researchers in the study collected data from irrigated winter wheat fields using satellite-based sensors and unmanned aerial vehicles at various scales. These photographs wash the usage and were subjected to an activity called enhancement, which resulted in the creation of vegetation indices, for instance, the NDVI and NDWI, which, as the abbreviation stands for, the vegetation health status as well as levels of water, respectively. The NDVI is therefore derived using the values of the near-infrared band and the red band to produce a ratio of the vegetation's light absorption. Similarly, NDWI for wetness and near-infrared and shortwave infrared bands are considered. The combination of all the above variables provides full-blown information on the canopy water condition and provides a way for monitoring changes.

3.3. Soil Moisture

Accurate estimation of soil moisture content is essential for hydrological modeling, irrigation planning, and drought monitoring. Remote sensing technologies offer several approaches for estimating soil moisture over large spatial scales with varying degrees of accuracy and resolution. Table 2 presents a comparison of various remote sensing methods used to estimate soil moisture content, outlining their principles, data sources, and typical applications.

With remote sensing, the amount of water used for irrigation has been monitored through proportional measurements of soil moisture. Some rules of irrigation from the work of (Jalilvand et al., 2019) include that adequate time for irrigation has to be chosen depending on the developmental stage of plants and the weather conditions. They then began to pinpoint periods of irrigation by looking at the variation of the soil's moisture content at different times and in different locations. By adapting methods that are used in hydrology and meteorology, it was possible to approximate the ratio, indicating the actual amount of water utilized for the irrigation process without losses due to evapotranspiration as well as drainage.

The study conducted by (Wu et al., 2019) proposed a method that targets providing accurate estimating and mapping of soil moisture while including the effect of vegetation cover. Colleagues opted to use a procedure where data from different remote sensing platforms was fused and sophisticated signal processing techniques were applied to determine signals resulting from the difference between soil and plants only. Some of the steps that were involved in this approach were the pre-processing of remote sensing data, vegetation indices standardization, model calibration for assessing soil moisture, and methodology confirmation through the measurement of ground data.

In the study conducted by (Mohamed et al., 2020) on the impact of soil moisture on crops using geospatial data and analysis, the authors built a method that uses resident data on crops and geospatial analysis to map the soil moisture and crop distribution in arid regions. As explained by the procedure outlined in (Mohamed et al., 2020), the researchers then collected information from different sources, such as optical and thermal images, to derive soil moisture data. Once the samples of the soil were taken, the team used mathematical models, also known as algorithms, to predict the level of moisture in the ground. To analyze the correlation between soil moisture and crop efficiency more deeply, the researchers used other remote sensing technologies like spatial statistics, which include spatial interpolation of data, and regression modeling, which looks into the level of association between two parameters. Once through the above process, the team compared their findings to come up with a conclusion on how water availability impacts crop yield in the desert.

A recent study by (Zappa et al., 2021) calibrated the SSM from Sentinel-1 to estimate the irrigation water amount, and it was done at a 500–500-meter scale by using SM data. It therefore implies that before getting into the analysis of the Sentinel 1 satellite data presented, there was a need to carry out calibration, which is the process of correcting systematic errors, and validation, which endeavors to compare the result with that of ground-based measured data. By adopting a statistical analysis that adopts a change detection framework, the team was able to investigate the actual instances of irrigation in regard to the degree of change in soil moisture. Once the timing of the irrigation episodes had been established, the researchers calculated the quantity of water that was applied during each event. To validate the results derived from the team's methodology, the amount of irrigation from the farmer respondents at the field level was checked with the results of the study. These works exemplify how high-consequence technologies and data analysis can be applied to learn about the moisture of the ground and effectively use water in areas that are arid for agriculture.

Zappa et al., (2021) used satellite soil moisture data to decide irrigation timing and quantities. They analyzed how soil moisture changed over time and the use of satellite records. Their purpose changed into discovering times of irrigation and calculating how much water was utilized by searching for changes in soil moisture levels. To recall the vertical motion of water that affects soil moisture, they blended soil moisture statistics with a formulation for evapotranspiration (water loss from plants and soil) and drainage. On the other hand, (Paridad et al., 2022) predicted soil moisture through the use of unmanned aerial structures (UAS) prepared with RGB and thermal sensors. They flew those UAS over to have a look at the vicinity to capture RGB and thermal pictures. At the same time, in addition, they took direct measurements of soil moisture with the use of sensors positioned inside the ground. By studying the photos and organizing relationships among the RGB/thermal values and soil moisture, they have been capable of determining soil moisture values across the entire study region.

To examine whether or not the land is appropriate for cultivation, a holistic strategy was used in trying to check whether or not the analysis was stated (Abdelrahman, 2019). This technique entailed the act of data reading and information sensing beyond a certain geographical space and geographical information system. To comprise the entire take-a-look-at location, 40 soil profiles were chosen deliberately. These profiles were then tested for various physical and chemical properties, including touch sensation, organic matter content, conductivity, pH, and cation exchange capacity. The one that has been looked at in the preceding is a consideration of two mechanisms for evaluating land talents. Features that were considered by the ASLE program included weather, soil texture, drainage, and fertility to determine the nature of the land. Information used for the assessment was based on the Modified Storie Index, which involved rankings according to weighted factors that reflected soil parameters capacitive of the land. Integrated with these strategies and as the outcome of collecting data, the researchers were able to draw knowledgeable conclusions as to whether or not the particular land was suitable for agriculture.

To assess if the land is appropriate for farming, the study conducted by (Abdelrahman, 2019) used a further method that embraced factual soil data, bibliographic faraway sensing, and GIS software. So, they agreed to select forty soil profiles to investigate the region of interest. These profiles have additionally studied various bodily and chemical properties, which include texture, organic reminiscence content material, electrical conductivity, pH extent, and cation exchange capacity. For instance, in the case of ASLE application, factors such as weather, soil type, drainage, and fertility level were deemed essential in evaluating land talons. On the other hand, the Modified Storie Index gave ratings emphasizing weighted factors each drawn from parameters obtained from soil for assessment of land abilities.

The procedures used in (Ma et al., 2022b) use time series records from Sentinel-1 and Sentinel-2 to discover irrigation episodes and investigate agricultural dynamics. Sentinel-1's radar information enables all-climate monitoring, imparting huge records on soil moisture content, material, and irrigation styles. Sentinel-2's multispectral information provides statistics on plant indices that may be used to screen agricultural increase and health (Ma et al., 2022b), mixed with several satellite statistics sources to generate a time collection that tracks adjustments in soil moisture and flower cover. The authors use Sentinel-1 radar backscatter to determine soil moisture modifications that imply irrigation episodes. Sentinel-2's multispectral facts are used to create flora indices, which include the Normalized Difference Vegetation Index (NDVI), which allows the authors to study crop dynamics and growth degrees.

To study the impact of irrigation scheduling schemes on soil moisture and crop output (Schattman et al., 2023), have a look at using a combined-methods approach that protected discipline trials and questionnaires. Field checks have been executed in two places (Maine and Vermont) over growing seasons, utilizing three irrigation scheduling strategies: the "feel" technique (guide soil texture assessment), granular matrix sensors, and timer-primarily based irrigation. These techniques were used to monitor soil moisture content to decide how they affected soil-water conditions, leaching, and crop production.

Supriyasilp et al., (2022) offered an intensive explanation of the remote sensing techniques used in the research. Microwave sensors have been used for subsurface moisture assessment, supplying statistics about soil moisture at various depths inside the root zone. Optical remote sensing techniques used surface reflectance features to estimate soil moisture content, while thermal remote sensing diagnosed surface temperature fluctuations that indicated underlying soil moisture levels. Integrating more than one remote sensing modality improved the accuracy and reliability of soil moisture estimation. (Stefan et al., 2021) used several remote sensing strategies to quantify soil moisture content: Use of excessive-resolution SMAP-derived information: The researchers analyzed information from the Soil Moisture Active Passive (SMAP) satellite assignment to create entire soil moisture estimates. Applying an exponential filter model: Adopting an exponential clear-out model affords a new perspective on digesting SMAP-derived facts for estimating root-quarter soil moisture. This model, which is customized to diverse land cowl kinds, exhibits resourcefulness in dealing with the complicated spatial and temporal complexities of soil moisture dynamics. (Ma et al., 2022a) address the critical need for excessive-resolution soil moisture records that are required for effective water aid management, agricultural making plans, and weather studies. The observation determined that combining Sentinel-1 and Sentinel-2 statistics considerably improves soil moisture map accuracy. The incorporated approach captures soil moisture spatial variability rather than unmarried-source records. Validation in opposition to floor-based measurements results in an extensive improvement in estimating accuracy, confirming the approach's robustness and reliability.

Integrating numerous modern remote sensing techniques with a novel optical-trapezoid model improves soil moisture estimation accuracy and agricultural tracking skills (Ma et al., 2022a). Advanced remote sensing techniques were used in the (Ma et al., 2022 a) investigation, consisting of high-resolution multispectral snapshots from Sentinel-2 to perceive soil from plants and vegetation indices along with NDVI to estimate soil moisture. The optical-trapezoid model analyzes spectral records to determine soil moisture. Temporal evaluation monitors versions of soil moisture and crop boom during the season, providing useful insights into agriculture.

Combining radar and optical remote sensing records from Sentinel-1 and Sentinel-2 satellites. Sentinel-1 radar pixels (Steinhausen et al., 2018) take into consideration surface roughness and moisture records, while Sentinel-2 optical photographs collect particular surface attributes. They are up-to-date and have preprocessed the statistics to deal with worries about cloud cover. They extracted crucial functions by using Sentinel-2 vegetation indices and Sentinel-1 backscatter readings. These statistics were incorporated and processed with the use of system getting-to-know strategies, yielding more correct LULC maps. This technique handles cloud cover and environmental fluctuation efficaciously, bearing in mind splendid accuracy in recognizing vegetation areas.

Fluhrer et al., (2024) use superior techniques like P-band SAR polarimetry, hydrological, and multi-layer scattering models to estimate soil moisture. P-band SAR digs deep into the soil, giving specified moisture information. Hydrological fashions simulate water motion, displaying moisture changes through the years. Multi-layer scattering fashions improve accuracy by considering distinct soil layers. Results show that this incorporated method gives extra-accurate soil moisture. Integrating high-decision soil hydraulic parameters with Earth observations substantially enhances the accuracy and spatial resolution of root region soil moisture (Thomas et al., 2023) and makes use of exclusive remote sensing methods consisting of optical imagery that looks at the land cowl, plant life, and surface temperature to peer how they affect soil moisture, radar imagery like Sentinel-1, which examines soil residences and moisture even via clouds and vegetation, and thermal imaging.

3.4. Land surface temperature (LST)

Land Surface Temperature (LST) is a key remote sensing parameter representing the radiative temperature of the land surface and serves as an integrated indicator of soil moisture, vegetation activity, and surface energy balance, especially in arid and semi-arid environments. Unlike air temperature, LST is highly sensitive to surface properties such as soil composition, color, and vegetation cover, and responds directly to seasonal variations in soil moisture and climatic conditions. Research in desert and semi-arid regions, such as the work of Ali and Shalaby (2012), has demonstrated that topsoil features and LST exhibit pronounced seasonal fluctuations, with higher temperatures during dry, barren periods and moderated values when soil moisture and vegetation increase. These dynamics make LST a valuable tool for diagnosing environmental stress, monitoring drought, and guiding sustainable land and water management. Contemporary advances in satellite thermal infrared technologies have further enhanced the ability to map and interpret LST patterns, empowering researchers and practitioners to monitor landscape functioning and land degradation risks in near real-time (Shahfahad et al., 2023).

4. Performance of remote sensing methods for evapotranspiration estimation in arid environments

a. Methodological Approaches and Techniques

i. FAO Penman-Monteith Method with GIS

Mahmoud and Gan, (2019) used the FAO Penman-Monteith method with GIS techniques to create a spatial model of reference evapotranspiration (ETo) on a grid. This combination, along with empirical NDVI-Kc relationships, greatly enhanced the accuracy of estimating actual ET (AET) at the pixel level.

ii. Soil Water Balance (SWB) Model

Mahmoud and Gan, (2019) also used the SWB model, but to simulate daily AET with very good agreement to observed values. With validation against observed values, we can assess whether the model fits relatively well. Note that there are discrepancies in relative humidity (%) indicated with dots occurring in certain months, suggesting the need for ongoing refinement of the model.

b. Spatial and Temporal Patterns of Evapotranspiration

i. Monthly and Annual AET Maps

Higher AET values have been observed in irrigated croplands, and (Mahmoud & Gan, 2019) developed maps illustrating geographical changes in water demand; this notable change suggested a favorable trend in long-term daily AET.

ii. Soil Moisture Dynamics

El-Shirbeny et al., (2021) employed wilting point (WP) and field capacity (Fc) to get insights into crop water availability. His research emphasized the need for targeted irrigation because of soil property variability by highlighting geographical changes in FC and WP.

c. Performance Evaluation and Model Applications

i. SEBAL (Surface Energy Balance Algorithm for Land) Model

Despite its accuracy, the SEBAL version's effectiveness in estimating ET for cotton in the Kai-Kong River Basin changed as demonstrated with the aid of (Cha et al., 2020). However, the limited availability of Kc records made it hard to validate ET for various plants, indicating that move-crop validation and the usage of lysimeter measurements have to be the focus of destiny research.

ii. FAO56 Model

Kharrou et al., (2021) applied the FAO56 version in SAMIR (Satellite Monitoring of Irrigation) software program to estimate ET for wheat and olive trees. The model confirmed promising accuracy, but variability in irrigation practices and climate changes revealed an opening between modeled and actual practices.

d. Agricultural Water Management

i. Mapping Irrigated Areas and Estimating IWC (irrigation water consumption)

The need for proper water management turned into underlined by (Al-Bakri et al., 2023) who employed remote sensing to map irrigated zones and estimate irrigation water consumption (IWC). Discrepancies among pumped groundwater and pronounced abstraction highlighted problems inclusive of illicit abstraction.

ii. Daily ETa and LAI (leaf area index) Estimates

Gómez-Candón et al., (2023) estimated daily cumulative ETa and leaf area index (LAI) for wheat, a positive asymptotic relationship between crop yield and ETa was found, with genetic analysis suggesting opportunities for selecting resource-efficient wheat varieties.

iii. Optimization of Crop Irrigation

Abou Ali et al., (2023) focused on optimizing irrigation to reduce water loss and improve efficiency, high deep percolation rates indicated a need for better irrigation scheduling. Derived Kc values provided insights into citrus crop water requirements at different growth stages.

e. Combined Methods and Addressing Uncertainties

i. Combining Ground-Based and Satellite Methods

Abou Ali et al., (2023) used eddy-covariance at ground level and SEBS derived from satellites to estimate ET that method proved effective in giving both the field and regional estimations of ET. Nevertheless, there were issues in methods of scaling and verification concerning remote sensing of environmentally variable phenomena.

ii. Assessing Uncertainties in RS-ET Estimates

Tran et al., (2023) presented approaches for estimating uncertainties in remote sensing-based ET estimation; it was also highlighted that validation against ground measurements with the eddy covariance method was crucial. The review pointed out that future studies should enhance spatial and temporal resolutions and identified that they ran into issues in the validation of their results on the global scale because of the scarcity of data from the ground.

Table 1. compares various methods for Evapotranspiration using remote sensing technologies.

Reference	Remote Sensing Techniques	Input Variables	Satellites / Tools Used	Models Employed / Other Techniques	Advantages	Limitations
(Mahmoud & Gan, 2019)	Energy balance methods	Solar radiation, thermal radiation, sensible heat flux	MODIS, meteorological data	Penman-Monteith equation, surface energy balance algorithms	Comprehensive water cycle understanding, large spatial scale monitoring	Requires detailed meteorological data, complex modeling
(El-Shirbeny et al., 2021)	Energy balance, vegetation indices	LST, NDVI, emissivity, solar radiation	MODIS, Sentinel-2	SEBAL, CWSI, FAO-Penman-Monteith	Assesses crop water stress, detailed physiological status monitoring	High data processing complexity, reliance on accurate emissivity estimates
(Cha et al., 2020)	Optical	ETd, NDVI, LST	Landsat, MODIS	SEBAL, trapezoidal and sinusoidal methods	Seasonal ET estimation, integration of time-series data, comprehensive ET dynamics understanding	Requires multi-temporal data, high computational demands
(Kharrou et al., 2021)	Optical	NDVI, solar radiation, surface temperature	Landsat 8, Sentinel-2	FAO-56 Soil-Water Balance model, TSEB, SEBAL, METRIC	Accurate crop coefficient estimation, high-resolution spatial analysis	Complex integration of models and remote sensing data
(Cohen.2019)	Optical	NDVI, land cover, crop coefficient	Landsat 8, Sentinel-2	Regression models, empirical relationships	High-resolution maps of irrigated areas, effective ET estimation for large regions	Requires extensive ground validation, complex data processing
(Al-Bakri et al., 2023)	Energy balance, Thermal, Optical	NDVI, meteorological data, DEM	Landsat, MODIS, ASTER, SRTM	SEBAL	Accurate ET mapping, integration of multiple data sources	High complexity in data integration, detailed DEM requirement
(Abou Ali et al. 2023)	Eddy-Covariance system	Radiation, soil heat flux, meteorological data	Ground-based sensors, EC system	Energy balance closure (EBC)	High accuracy of ET measurements, validation with ground data	Limited spatial coverage, high cost and maintenance of EC systems
(Barman and Kamila. 2023)	Energy balance, meteorolog ical data	Solar radiation, wind speed, temperature, humidity	SEBAL, DEM	SEBAL	Detailed ET dynamics understanding, integration of meteorological data	Requires detailed DEM, complex data processing
(Ayyad et al. 2019)	Optical, energy balance	NDVI, meteorological data	MODIS, EEFlux, USGS-FEWS NET SSEBop	Surface energy balance algorithms, empirical relationships	Effective irrigation efficiency assessment, multi-sensor integration	High processing complexity, need for extensive validation
(Gómez-Candón et al. 2023)	Optical	NDVI, crop health, radiation balance	UAVs, multispectral cameras	SEBAL	High-resolution ET estimation, flexibility in data acquisition	Limited spatial coverage, high cost of UAV operation
(Elfarkh et al. 2023)	Optical	NDVI, surface temperature, albedo	Sentinel-2	SEBS	Detailed analysis of vegetation cover, accurate ET estimation	High computational demands, reliance on accurate ground calibration
(Scintillomet et al. 2024)	Optical	Sensible heat flux, net radiation, soil heat flux	Landsat, MODIS	SETMI, energy balance approach	Comprehensive ET estimation across different scales, integration of ground-based and satellite data	Complex integration of ground and satellite data, high computational demands
(Solgi, Ahmadi, and Seidel. 2023)	Optical	NDVI, NDWI, canopy water status	Landsat, UAVs	Vegetation indices analysis	Detailed canopy water status assessment, high-resolution spatial analysis	Requires accurate calibration, high data processing complexity

Table 2. Various methods for estimating soil moisture content using remote sensing technologies.

Reference	Remote Sensing Type	Root Depth Estimated	Satellite/ sensor	Models Employed / Other Techniques	Advantages	Limitations
(Jalilvand et al., 2019)	Microwave	0-5 cm	Sentinel-1 SAR	Hydrological and meteorological models	All-weather capability, high spatial resolution, effective in semi-arid regions	Complex processing, need for ground validation
(Zappa et al., 2021)	Microwave	0-5 cm	Sentinel-1 SAR	Statistical algorithms, change detection methods	High resolution, all-weather capability, validated with field data	Calibration and validation with ground data required
(Zappa et al., 2021)	Microwave	0-5 cm	Sentinel-1 SAR	Spatiotemporal analysis, evapotranspiration formulations	Effective for irrigation monitoring, integrates multiple data sources	Complexity in integrating different data types
(Schattman et al., 2023)	Field studies, surveys	Various	Field experiments, surveys	Mixed-methods approach	Practical insights into irrigation practices combine field data and farmer preferences	Limited spatial coverage, dependent on survey responses
(Supriyasilp et al., 2022)	Microwave, optical, thermal remote sensing	Various	Microwave sensors, optical and thermal satellites	Integration of diverse remote sensing modalities	Enhanced accuracy and reliability, combines multiple techniques	High complexity in data integration and processing
(Stefan et al., 2021)	High-resolution SMAP-derived data, exponential filter model	0-100 cm (root zone)	Soil Moisture Active Passive (SMAP)	Exponential filter model	High spatial resolution, tailored model for different land cover types	Requires high-resolution SMAP data, model application complexity
(Ma, Li, and McCabe. 2020)	Sentinel-1, Sentinel-2	0-5 cm	Sentinel-1, 2	Machine learning algorithms		
(Ma, Johansen, McCabe. 2022b)	Radar Multispectral (Sentinel-2)	0-5 cm (surface)	Sentinel-1, 2	Time series analysis, vegetation indices, radar backscatter analysis	Captures soil moisture and vegetation changes effectively, with high temporal resolution	Data preprocessing complexity, integration of multiple data types
(Steinhausen et al., 2018)	Optical	0-5 cm (surface)	Sentinel-1, 2	Machine learning techniques, data fusion	High accuracy in vegetation and urban area identification, effective cloud cover handling	Data correction and preprocessing complexity
(Fluhrer et al., 2024)	Microwave, hydrological models, multi-layer scattering models	0-100 cm Subsurface (deep layers)	Ground-based soil moisture sensors, P-band SAR	Hydrological models, multi-layer scattering models.	Deep penetration for detailed moisture data, high accuracy with integrated models	High complexity in data processing and model integration
(Thomas et al. 2023)	Optical Imagery, Microwave Thermal	Root zone (various)	Ground-based sensors, UAVs equipped with RGB and thermal sensors	Integration of soil hydraulic parameters with Earth observations.	High accuracy and spatial resolution for root zone soil moisture	Data availability and processing complexity
(WU et al., 2019)	Optical Imagery	Surface	Multiple-spectral and hyper-spectral	Advanced algorithms, vegetation indices normalization	Separates soil and vegetation signals, and integrates various data sources for improved accuracy	Extensive preprocessing requires calibration and ground truth measurements
(Mohamed et al., 2020)	Optical and thermal imagery	Surface to root zone (~0-100 cm)	Optical and thermal satellites	Geospatial analysis, spatial interpolation, regression analysis	Combines optical and thermal data, effective in arid regions	Complex data processing, weather dependency
(Paridad et al., 2022)	optical and thermal	Surface	UAS equipped with RGB and thermal imaging sensors.	Image processing techniques, empirical relationships.	High spatial resolution, flexible deployment	Limited coverage area, dependent on flight conditions
(Abdelrahman. 2019)	Optical, GIS tools	Various	Not specified?????	Applied System of Land Evaluation (ASLE) program, Modified Storie Index.	Comprehensive land capability assessment integrates multiple data sources	Extensive soil data and GIS expertise required
(Kragh et al., 2024)	Microwave, Multispectral	Surface to root zone (~0-100 cm)	Sentinel-1, 2 Landsat, MODIS	Various remote sensing and modeling techniques	Wide range of methods for different conditions, effective for irrigation monitoring	Complexity in integrating multiple techniques and data sources

5. performance of remote sensing methods for soil moisture content estimation in arid environments

a. Integration with Geospatial Techniques

Jalilvand et al., (2019) showed remarkable accuracy in identifying irrigation events and water volume predictions. Among the difficulties include uncertainties in irrigation time and limitations in temporal resolution.

b. Soil Moisture Estimation in Vegetated Areas

Wu et al., (2019) revealed a notable increase in accuracy. Significant issues are the complexity of vegetation-soil interactions and calibration/validation methods.

c. Spatial and Temporal Analysis

i. Soil Moisture and Crop Patterns

The detailed maps of soil moisture provided by (Mohamed et al., 2020) investigate crop type correlations and geographical variability. Challenges include limited spatial resolution, algorithm development, and data integration.

ii. Real-Time Monitoring with Sentinel-1

Zappa et al., (2021) reported advantages in the surveillance of irrigation operations. The impact of vegetation cover, soil heterogeneity, and errors in calibration and validation are among the challenges.

d. Advanced Models and Techniques

i. Retrieving Irrigation Timing and Water Amounts

Remarkable findings were obtained from the satellite soil moisture data in (Zappa et al., 2022). The creation of algorithms, validation against ground-based observations, and data assimilation techniques are among the challenges.

ii. Unmanned Aerial Systems (UAS)-Based Remote Sensing

Paridad et al., (2022) discussed the advantages of tracking soil moisture dynamics, recorded spatial variability in soil moisture, and improved irrigation techniques. Surface cover kinds, atmospheric conditions, and sensor limits are some of the challenges.

e. Soil Moisture and Agricultural Practices

i. Agricultural Expansion and Soil Management

Abdelrahman, (2019) recognized potential for agricultural expansion. The issues of improving soil fertility and water use efficiency were emphasized. Advocated for the use of remote sensing and GIS tools to monitor soil moisture and irrigation.

f. Calibration, Validation techniques and challenges

i. Data Augmentation and Machine Learning

Wang et al., (2023) exceeded the conventional methods. Several issues were addressed, such as the need for ongoing calibration and inconsistent data quality from remote sensing.

ii. Vegetation Indices and Thermal-Based Techniques

Kragh et al., (2023) assessed durability and validity. problems related to precise calibration, the impact of outside variables, and variations in vegetation cover and soil moisture have been identified.

g. Challenges

- The dependent quantities that affect estimated irrigation from satellite soil moisture data include the following. These are, among others, errors in precipitation data, noise associated with SM data, the effects arising from spurious signals in SM, and unknown portions of the pixel that are irrigation. (Jalilvand et al., 2019)
- In previous studies, (Ma et al., 2022b) have explored challenges associated with the use of remote sensing data in agriculture, as well as fluctuations that might be linked to the type of ground and the cultivar.

As stated in (Kragh et al., 2023) involves the effect of externalities which are; cloudiness, weather conditions, soil moisture, and vegetation cover.

6. Conclusion

Remote sensing has evolved as a key approach to monitoring, controlling, and optimizing irrigation practices for agricultural management critical constraint. enable practitioners to obtain valuable data for accurate irrigation scheduling. Satellite imagery and energy balance algorithms enable estimation in arid and semi-arid regions where water rationing is a—of evapotranspiration (ET) and soil moisture (SM), providing stakeholders with reliable data for irrigation scheduling. As depicted in the papers reviewed herein, remote sensing measurements appear to be important for soil moisture, vegetation water use estimates, and ET variability. While there is the provision of all-weather capability from SAR technology, the multispectral and optical sensors give excellent results for vegetation health. Integration of remote sensing data with models like Penman-Monteith and energy balance approaches has improved reference ET and actual ET estimates, enhancing precision irrigation. However, challenges remain are insignificant in comparison to these issues. Although data calibration and validation are crucial for accuracy and goals in remote sensing, these data are impacted by weather, crop type, and other environmental factors. This is because variables such as fluctuations in soil moisture content and vegetation cover present difficulties for the application of remote sensing technologies in quantifying irrigation needs. Further complicating matters are temporal resolution issues and the requirement to continuously recalibrate these machine learning models.

Recommendations

- Enhanced Calibration and Validation: To improve the reliability of remote sensing-derived evapotranspiration (ET) and soil moisture (SM) estimates, robust calibration and validation frameworks must be developed. This can be achieved by integrating multiscale in-situ measurements, including eddy covariance flux towers for ET validation and distributed soil moisture sensor networks for SM verification, to ensure data accuracy and operational validity.

- Enhanced Temporal Resolution: Remote sensing systems require higher temporal-frequency observations to accurately capture irrigation dynamics and crop physiological responses. This can be achieved by integrating multi-satellite data streams (e.g. Landsat, Sentinel-1/2 and MODIS) to enable near-real-time monitoring of soil moisture (SM) and evapotranspiration (ET) at field-relevant scales.
- Development of Advanced Algorithms: Future studies should thus strive to advance the algorithms used in estimating soil moisture and ET. Advanced machine learning algorithms, along with data augmentation techniques, can also provide useful support in refining the given estimations.
- Integration with Geographic Information Systems (GIS): Using Geographic Information Systems, remote sensing data can enhance the spatial analysis of irrigation and crop water needs. These integrated models will help to improve the decisions made about water and the long-term management of water systems.

Enhanced Collaboration and Data Sharing: systematic use of remote sensing technologies in agriculture; It will require consultation between researchers, agriculturalists, and policymakers. This might also explain why data sharing in different remote regions and agricultural environments yields different results; this could help in solving some of the challenges that the system encounters and give a more reliable way of quantifying irrigation using remote sensing. Despite existing challenges, remote sensing remains a strategically vital tool for optimizing irrigation management and promoting sustainable agricultural water use. Continuous advancements in innovative methodologies and technologies are driving improvements in both crop productivity and water resource efficiency, particularly in semi-arid and arid regions globally.

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