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A Review Evapotranspiration Estimation Models, Techniques and Methods: State of Art

Naglaa Elbendary*
FAO Office Cairo, Egypt
*Corresponding author

Asharaf M. Almoustafa
Professor of Engineering Hydrology, Irrigation and Hydraulic Department, Faculty of Engineering, Ain Shams University, Egypt

Sami A. Mohamed
Assistant Professor, Irrigation and Hydraulic Department, Faculty of Engineering, Ain Shams University, Egypt

Sherin A. Zahran
Associate professor, Environmental and Climate Change Research Institute, National Water Research Center, Egypt

Mohamed A. Dawoud
Advisor Environment Quality - Environment Agency – Abu Dhabi, UAE

Abstract
Evapotranspiration (ET) plays a critical role in the global water cycle, significantly impacting water budgets, climate dynamics, and agricultural systems. This complex process results from interactions among the atmosphere, soil, and plants, involving both chemical and biological processes such as photosynthesis and CO_2 emissions, alongside the physical transformation of water between liquid and vapour phases. Due to these interactions, estimating ET accurately remains challenging, particularly in simulating and integrating all associated processes within a single model. ET can be measured with physical devices, like eddy covariance systems and lysimeters, or estimated using physical models and equations informed by measurements, remote sensing data, or a combination of these sources. This paper provides a comprehensive review of the theoretical foundations of ET estimation, observing techniques, and algorithms for estimating ET across diverse landscapes using remotely sensed data. It also addresses the uncertainties and limitations of current estimation methods, reviewing the strengths and constraints of various approaches. Additionally, this paper evaluates existing ET remote sensing products, examining the foundational equations and methods behind their development. Finally, recommendations are offered to enhance future ET estimations, including combining multiple methods to improve the accuracy and reliability of ET flux assessments across varied environments.

Keywords
Evapotranspiration, Land Surface Model, Remote Sensing, Water, Nexus

1. Introduction
The rapid global rise in food demand is exerting intense pressure on food systems to maximize agricultural yields, even as freshwater resources become increasingly scarce. This critical challenge has spurred a shift toward sustainable practices and optimized agricultural operations, with a focus on using water more efficiently. In this context, effective irrigation management is fundamental to sustainable agriculture, largely dependent on accurately assessing crop water needs. A key indicator of these requirements is evapotranspiration (ET), which measures the water vapor transferred from land to the atmosphere through both soil evaporation and plant transpiration (Ghiat et al., 2021). ET, defined as the transfer of water from bare soil and open water sources like rivers and lakes (evaporation), as well as vegetated surfaces (transpiration from plant leaves) to the atmosphere in the form of water vapor (Allan, 1998), plays a pivotal role in the water cycle. The global water cycle itself is a complex system involving various physicochemical processes, such as condensation, groundwater flow, infiltration, plant uptake, precipitation, runoff, sublimation, and water vapor transport (Allan et al., 2020), and it is further influenced by human activities, including water withdrawals, soil moisture use for livestock, crop irrigation, and forestry (Abbott et al., 2019). Figure 1, sourced from Wang et al. (2012), illustrates the ET process,

encompassing evaporation from bare soil, water bodies, and leaf surface droplets, as well as transpiration from leaves. As the second largest component of the terrestrial water cycle after precipitation, ET is significant in that it returns over 60% of precipitation back to the atmosphere, establishing a major constraint on water availability at the land surface. ET also constitutes a critical energy flux, as it consumes more than half of the solar energy absorbed by land surfaces (Trenberth, 2009). Therefore, accurate estimation of ET is not only crucial for meeting the increasing competition for limited water supplies and for reducing irrigation project costs, but it is also essential for understanding potential changes in the global hydrological cycle under various climate change scenarios. The ability to project shifts in water availability with changes in ET patterns is a key aspect of climate-resilient agriculture, enabling policymakers, water managers, and farmers to make informed decisions to sustain agricultural productivity and water security in the face of rising global food demands (Teuling, 2009).

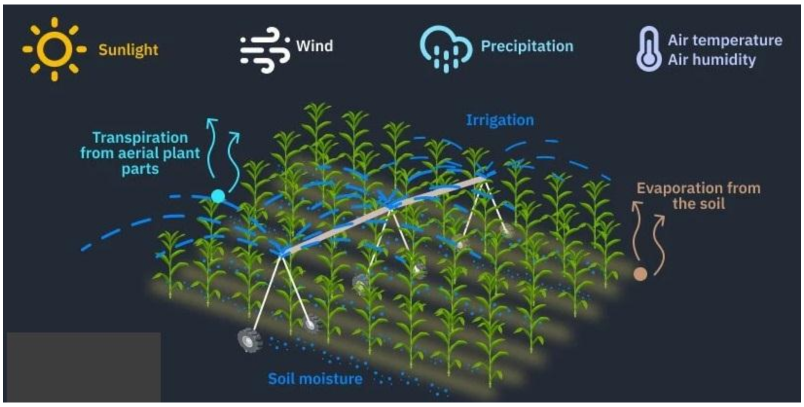

Fig. 1 Transpiration from dry leaves and evaporation from water, surface leaves, and soil as evapotranspiration

Accurately estimating crop water requirements is vital for optimizing irrigation scheduling, ensuring that water is applied at the right time and in the correct amount. By understanding evapotranspiration (ET) rates, growers can meet cultivation goals, boost water-use efficiency, increase crop yields, and lower both energy consumption and environmental emissions. This critical role of ET exemplifies the interconnectedness within the water, energy, and food (WEF) nexus, where each element impacts the others. The WEF nexus provides a holistic framework to evaluate interdependencies across food, water, and energy systems, highlighting both resource trade-offs and synergies. This approach enables a more efficient use of resources, reducing negative environmental impacts across the board. Consequently, adopting a WEF nexus perspective is essential for sustainable agricultural intensification as it addresses the rising demand for nutritious food, conserves both water and energy, and mitigates environmental degradation. Evapotranspiration models have evolved from Penman's initial model, which relied solely on external physical drivers, to Monteith's improved version that includes physiological characteristics. Simplified adaptations of the Penman–Monteith equation have also been developed to require fewer input data, making them more adaptable to diverse meteorological and physiological conditions. Selecting a model that closely matches the characteristics of the system under study is crucial for accuracy, which can be enhanced further through model parameterization based on direct measurements tailored to the target system.

There are multiple methods for estimating ET, from approaches that measure evaporation from water surfaces to various potential and actual ET estimations. However, many focus on ET from a single underlying surface, such as open water, bare soil, or vegetation, often overlooking the broader water balance. This single-surface approach treats ET as a static value rather than a dynamic process within the hydrological cycle. Recent advancements in remote sensing now enable ET estimation on a basin scale, although this technology often provides only instantaneous, rather than continuous, data and remains susceptible to external conditions that can limit accuracy. In contrast, actual ET estimates based on hydrological models consider the influence of both water and energy dynamics and can be calculated across various spatial and temporal scales, making them well-suited for comprehensive water resource assessment and management. Multiple ET estimation methods, developed from existing hydrological models, each have unique data input requirements; however, comparative studies of their output accuracy remain limited. This review aims to bridge this gap by consolidating ET models and measurement techniques, evaluating their applicability to different agricultural environments, and examining the role of ET estimation within the WEF nexus. ET serves as a vital link between the energy and water budgets in the hydrological cycle, with ET modelling initially pioneered by Penman, who developed a model based solely on external physical drivers. Monteith's later enhancement incorporated plant physiological factors, and simplified versions of the Penman–Monteith equation have since emerged to minimize data demands while preserving essential functionality. This review aims to assess key techniques and empirical models for estimating ET, discussing their relevance across diverse agricultural systems, and highlighting measurement techniques for critical parameters such as leaf area index and surface leaf temperature, as well as direct ET measurement methods.

2. Basic Theory of Evapotranspiration

Evapotranspiration (ET) comprises two processes: evaporation, where liquid water vaporizes from surfaces, and transpiration, where water vaporizes from plant tissues and is transferred to the atmosphere. Evaporation is driven by the difference in vapor pressure between the water surface and ambient air (Allen et al., 1998). Transpiration involves water uptake from the soil, its movement through plant tissues, and eventual release as vapor through stomata in the leaves. This process is essential for plant growth, as it enables nutrient and mineral transport within the plant and provides a cooling effect necessary for survival. Meteorological factors, including solar radiation, air temperature, humidity, and wind speed, significantly influence both evaporation and transpiration, while crop characteristics and cultivation methods also affect transpiration. ET models, based on their theoretical approach, are generally classified into four categories: (i) mass transfer, (ii) temperature-based, (iii) radiation-based, and (iv) combination models that integrate both aerodynamics and energy balance (Xiang et al., 2020). Mass transfer models focus on aerodynamics, while temperature-based models, such as the Hargreaves and Samani model, rely solely on temperature inputs. Radiation-based models, like the Priestley–Taylor equation, calculate ET based on energy balance. The combination models, exemplified by the Penman–Monteith model and its FAO56 modification for reference ET (ETo), incorporate both aerodynamic and energy balance components for a comprehensive ET estimation (Xiang et al., 2020).

2.1 Evapotranspiration Measurement Methods

Direct measurements of evapotranspiration are used for experimental purposes to calibrate and validate a certain model. All measurement tools need to be calibrated by a certain calibration coefficient to relate the measurement to reality. The devices used have a limited extent and present local point ET measurements. There are different types of devices used to measure ET such as; lysimeter, eddy covariance, energy balance Bowen ratio, etc. in additional to direct measurements of evapotranspiration, there are some techniques can be used to estimate the evapotranspiration. In this section we will discuss the most used devices for evapotranspiration measurements.

2.1.1 Leaf Area Measurement Method

Measuring evapotranspiration (ET), the combined water loss from soil evaporation and plant transpiration, is crucial for understanding water use efficiency, particularly in agricultural and natural ecosystems. The leaf area index (LAI), representing the total leaf area per unit ground area, serves as an essential metric in ET estimation because it directly influences transpiration rates. Larger LAI values indicate more leaf surface area for transpiration, which correlates with increased water loss through plant canopies. LAI measurements can be integrated into ET models to improve accuracy in assessing the transpiring surface area (Still et al., 2019). Direct LAI measurement techniques, although accurate, are often destructive as they involve harvesting leaves for examination. Indirect techniques are therefore preferred for continuous monitoring, as they non-destructively assess LAI based on radiation interception by the canopy. For instance, ceptometers, which measure photosynthetically active radiation (PAR) above and below the canopy, provide a cost-effective approach for obtaining reliable LAI estimates, particularly in uniform canopies. Similarly, hemispherical photography, utilizing fisheye lenses to capture canopy structure, allows for the analysis of canopy density, position, and gap distribution, which are all factors impacting ET rates. The LAI-2200C leaf area meter by Licor, which assesses blue light interception, and image-based remote sensing techniques, which estimate LAI from vegetative indices, are also effective tools. By capturing LAI variations, these tools contribute to a refined understanding of ET, as LAI data can be integrated into multi-layer canopy models to depict internal resistance and net radiation changes across different canopy layers. Accurate LAI-based ET measurements can enhance water resource management by enabling precise irrigation scheduling and predicting crop water needs, ultimately supporting sustainable agricultural practices and resource conservation.

2.1.2 Leaf Temperature Measurement Method

Estimating ET using leaf temperature measurement is an effective approach that leverages the relationship between leaf surface temperature and transpiration rates. Since transpiration cools the leaf surface, a lower leaf temperature relative to the surrounding air typically indicates active transpiration under healthy growing conditions. Conversely, if leaf temperature equals or exceeds ambient temperature, it often signals crop stress or inadequate water availability. Measuring leaf temperature, therefore, provides critical insights into plant water use and stress levels, improving ET estimates by indicating the rate of gas exchange between the leaf and the atmosphere, which affects vapor concentration within the stomata. Thermocouples are a common tool for measuring leaf temperature, converting temperature changes on the leaf into electric signals. They are economical, lightweight, and have a quick response time, though their direct contact with the leaf can lead to inaccuracies as they may absorb solar radiation and heat by conduction (Yu et al., 2016). Infrared thermometers offer a contactless alternative, measuring the infrared energy emitted by a targeted leaf spot, transforming it into an electrical signal that provides high accuracy and fast response. However, their precision may be affected by environmental factors like dust and steam. Thermal infrared imaging, a more advanced option, captures two-dimensional temperature gradients across larger areas using infrared detectors sensitive to wavelengths between 7–14 μm. These cameras can map temperature variations across extensive crop fields, enabling detection of ET differences at broader temporal and spatial scales than other methods. Though effective, this technique has limitations, including high equipment costs, and potential inaccuracies due to leaf emissivity and longwave radiation effects, especially under outdoor, variable conditions. Corrective software can mitigate some of these errors, but it is often complex and tailored to controlled environments, limiting widespread agricultural adoption (Tarnopolsky and Seginer, 1999).

2.1.3 Eddy Covariance Systems Method

The eddy covariance (EC) method is a direct measurement technique for evapotranspiration (ET), using two primary instruments: an anemometer, which records wind direction and speed, and an infrared gas analyzer (IRGA), which detects air gas concentrations, such as water vapor. Together, these devices enable EC to measure sensible heat flux (H) and latent heat flux (λE) by analyzing variations in heat and moisture flux with vertical wind velocity, using rapid-response sensors operating at frequencies of 10 Hz or higher (Tanny, 2013). EC captures an ecosystem's "breathing," quantifying the exchange of gases, including CO_2, between soil, vegetation, and the atmosphere. This process involves simultaneous measurement of gas concentration changes via the IRGA and the swirling wind's speed and direction via the anemometer. The wind and gas concentration data are then processed through a complex series of calculations to determine H and λE. Originally developed in the 1950s by the Commonwealth Scientific and Industrial Research Organization (CSIRO), EC is recognized as one of the most accurate methods for directly measuring sensible and latent heat fluxes (Stanhill, 2019).

The eddy covariance (EC) method captures turbulent flux data by calculating the covariance between fluctuations in vertical wind velocity and the target physical quantity, enabling direct measurement of carbon, water, and heat exchanges between plant communities and the atmosphere. With current technology, EC can detect even minor air mass and energy fluctuations across multiple timescales (hourly, daily, seasonal, and annual) and spatial scales ranging from 100 to 2000 meters. This technique allows precise, continuous measurements of carbon and water vapor flows within an ecosystem, making it the most effective approach for examining interactions between the terrestrial biosphere and the atmosphere at an ecological scale (Friend et al., 2006; Baldocchi, 2008). Over the past 20 years, more than 500 EC observation stations have been established worldwide, monitoring carbon cycling across various ecosystems and forming both regional and global flux observation networks. The EC method enables continuous carbon flux observations between ecosystems and the atmosphere, recorded hourly with a sampling frequency of 10 Hz. These data, processed through established formulas, indirectly calculate vegetation productivity, providing valuable insights into ecosystem productivity and carbon cycling across representative terrestrial ecosystems.

2.1.4 Weighing Lysimeters

Weighing lysimeters directly measure evapotranspiration (ET) by monitoring changes in the mass of soil and crops within the lysimeter device, providing an accurate assessment of water loss through ET. For precise results, the lysimeter's soil structure, composition, vegetation characteristics (such as height), and climatic conditions must closely resemble those of the surrounding field. Although highly accurate, lysimeter systems are costly and require complex installation and maintenance, limiting their use across large agricultural areas. However, lysimeters offer unique benefits, including data on excess irrigation percolation and soil-water retention—information difficult to obtain from other ET measurement methods. Lysimeters are standard ET measurement tools requiring no assumptions. First constructed in the 1830s, lysimeters typically consist of a round or square tank ranging from 1 to 5 square meters in area and 1 to 4 meters in depth, as illustrated in Figure 2. There are two types of lysimeters: (i) weighing lysimeters, which measure mass changes, and (ii) non-weighing lysimeters, which evaluate ET based on the discharge rate. Precipitation is recorded using a rain gauge, and changes in soil water content are estimated with soil moisture probes. ET can then be calculated as part of the water budget over defined time steps.

$$E = P - \Delta S - Q$$

Where E is evapotranspiration, P is the precipitation, ΔS is the change in the soil water content and Q is the drainage from the system. Non-weighted lysimeter is more suitable for long term estimations with reasonable cost and maintenance plan. The weighted lysimeter is much more costly and need

Fig. 2 Weighing lysimetric station for ET measurement

2.1.5 Gas Exchange Measurement Systems

Gas exchange measurement systems offer a precise method for estimating evapotranspiration (ET) by using an infrared gas analyzer (IRGA) to track gas absorption. Operating in open chambers, these systems measure differential gas exchanges in real-time by comparing water vapours (H_2O) and carbon dioxide (CO_2) concentrations between the chamber's inlet and outlet. By analysing CO_2 exchange at the stomatal level, gas exchange systems provide insights into how varying atmospheric CO_2 levels affect plant transpiration and internal resistance, which directly influence ET rates. Elevated atmospheric CO_2, whether from greenhouse gas emissions or enrichment in controlled environments, impacts plant water use and growth dynamics. In greenhouses, where CO_2 levels are often raised to increase crop yield, understanding its effect on ET is crucial for optimizing environmental conditions. These systems help growers assess optimal CO_2 concentrations, balancing water use efficiency with crop productivity by monitoring how transpiration rates adjust with rising CO_2 levels. Thus, gas exchange systems not only provide accurate ET measurements but also enable researchers and growers to refine atmospheric conditions to support sustainable agriculture. Additionally, by quantifying differential gas exchange, these systems aid research into crop physiological responses to changing CO_2 levels—a crucial area as climate change alters atmospheric composition. As such, gas exchange measurement systems are invaluable in both field and controlled agriculture, delivering data that enhance irrigation strategies and promote resource-efficient productivity.

In addition to gas exchange systems, the energy balance Bowen Ratio (BR) method provides another approach to ET estimation by measuring vertical gradients of air temperature (Ta) and humidity (q). The Bowen Ratio (β) is the ratio of sensible heat flux (H) to latent heat flux (λE), which is determined by dividing the surface available energy into H and λE (Wang et al., 2012). This ratio is derived from the assumption that aerodynamic resistance to heat and water vapor is equal within the constant flux layer, facilitating reliable ET assessments.

$$\beta = \frac{\mathrm{H}}{\lambda\mathrm{E}} = \frac{C_p\,(T_{a1} - T_{a2})}{\lambda(q_1 - q_2)}$$

Where 1 and 2 represents the level BR system is cheaper than EC system and need less maintenance, but it may not be valid for unstable conditions.

2.1.6 Mass Transfer Method

The FAO Penman-Monteith equation provides accurate ETo estimates across various climatic conditions. However, in situations where climatic data are scarce, it becomes necessary to explore alternative ETo equations that can operate effectively with limited data. Mass transfer models, for example, primarily rely on the saturation vapor pressure deficit, as evident in the models' equations presented in Table 1.

Table 1 List of mass transfer equation for reference evapotranspiration estimations

No.	Model Name	Year	Equation
1	Dalton	1802	$ET_o = (0.3648 + 0.07223u_2) \times (e_s - e_a)$ (Dalton, 1802)
2	Trabert	1896	$ET_o = 0.408 \times 0.3075 \times \sqrt{u_2} \times (e_s - e_a)$ (Trabert, 1896)
3	Meyer	1926	$ET_o = (0.375 + 0.0502u_2) \times (e_s - e_a)$ (Meyer, 1926)
4	Rohwer	1931	$ET_o = 0.44(1 + 0.27u_2) \times (e_s - e_a)$ (Rohwer, 1931)
5	Penman	1948	$ET_o = 0.35(1 + 0.24u_2) \times (e_s - e_a)$ (Penman, 1948)
6	Albrecht	1950	$ET_o = (0.1005 + 0.297u_2) \times (e_s - e_a)$ (Albrecht, 1950)
7	Brockamp	1963	$ET_o = (0.543u_2^{0.456}) \times (e_s - e_a)$ (Brockamp, 1963)
8	WMO	1966	$ET_o = (0.1298 + 0.0934u_2) \times (e_s - e_a)$ ((WMO), 1966)
9	Mahringer	1970	$ET_o = 0.15072 \times \sqrt{3.6u_2} \times (e_s - e_a)$ (Mahringer, 1970)
10	Saif	2019b	$ET_o = (0.37 + 0.72u_2) \times (e_s - e_a)$

ET_o reference crop evapotranspiration (mm day^{-1}), e_s saturation vapor pressure (kPa), e_a actual vapor pressure (kPa), and u mean daily wind speed at 2 m (m s^{-1})

2.1.7 Remote Sensing and Satellite Imagery Method

Three major methods have been developed to estimate ET from remote sensing data: (1) empirical/statistical methods which upscale point measured or estimated ET to large scales with remotely sensed vegetation indices which has been addressed in (Pamela L.Naglera, 2005) (Jung, 2010); (2) physical models that calculate ET as the residual of surface energy balance (SEB) through remotely sensed thermal infrared data (Bastiaanssena, 1998, Su, 2002, Overgaard, 2006, Overgaard, 2006, Richard and Allen, 2007); (3) and other physical models such as using the Penman-Monteith logic (Monteith, 1965) to calculate ET (Qiaozhen Mu, 2007, Helen and Cleugh, 2007). ET is inherently difficult to measure and predict over extended or large area. The net solar radiation at the land surface is partitioned into sensible, latent, and ground heat fluxes. Land surface elements, including plants, soil, snow cover and open water bodies, absorb and reemit a portion of this radiant solar energy as latent heat and associated water vapor loss to the atmosphere through evaporation; green plants also lose water vapor to the atmosphere through leaf stomatal pores through the process of transpiration, particularly during photosynthesis. The total evaporated and transpired water is called evapotranspiration (Ea) as the sum of soil evaporation (Es), vegetation evapotranspiration (T), evaporation from open water bodies (Ew), and sublimation of snow and ice (Ei). The latent heat accompanying E is λE, where λ is the latent heat of vaporization. Remote sensing (RS), especially from polar orbiting satellites, provides relatively frequent and spatially contiguous measurements for global monitoring of surface biophysical variables affecting E, including albedo, vegetation type and density. RS based mapping of E is a cost-effective way to estimate and monitor this flux (Zhang et al., 2016). RS-based evapotranspiration estimations are commonly estimated using the energy balance equation and have large footprint (regional coverage). Evapotranspiration remote sensing data use surface energy balance (SEB) equations to calculate ET as a "residual" of the energy balance. Figure 3 illustrate the main components of surface energy balance equation:

$$ET = R_n - G - H$$

Where, ET (Evapotranspiration), H (Heat to air), R_n (Radiation from sun), G (Heat to ground).

The main limitations are imagery availability, cloud cover, and calibration data. SEB models are sensitive to clouds since clouds impact the thermal band. In the model without ground calibration if advection occurs it will introduce errors in the results. In the calibrated mode high quality weather data is required. The development of the ET models demanded a long term and intensive work in each approach.

Remote sensing involves observing and measuring parameters without direct contact, with satellite technologies providing valuable data on biophysical parameters for ET assessment, such as vegetation type, density, and surface albedo. Two main approaches have emerged for estimating ET from remote sensing data in agriculture. The first uses radiometric surface temperature to distinguish between latent and sensible heat, while the second employs vegetation indices (VI) derived from surface reflectance, which can estimate basal crop coefficients at spatial scales. Common vegetation indices, like the leaf area index (LAI) and normalized difference vegetation index (NDVI), aid in estimating surface resistance within the Penman–Monteith model. Radiometric temperature can be refined to determine aerodynamic temperature using semi-empirical or empirical models that account for spatial variations in surface roughness, allowing for its incorporation into the Penman–Monteith equation to estimate ET rates. Basal crop coefficients derived from VIs enable crop-specific ET estimation from reference ET. Remote sensing-derived ET estimates cover large spatial and temporal scales, making them especially useful for large-scale and climate impact studies. However, regions with cloud cover and dust pose challenges for reliable data acquisition. While various methods, such as cloud removal and gap filling, have been explored to address data gaps, model linearity remains a limiting factor. Furthermore, remote sensing data can support data-driven models for ET estimation using techniques like machine learning, regression, and neural networks. These models can be integrated with physical models to parameterize subprocesses, addressing uncertainties and enhancing ET estimation accuracy (Hu et al., 2021).

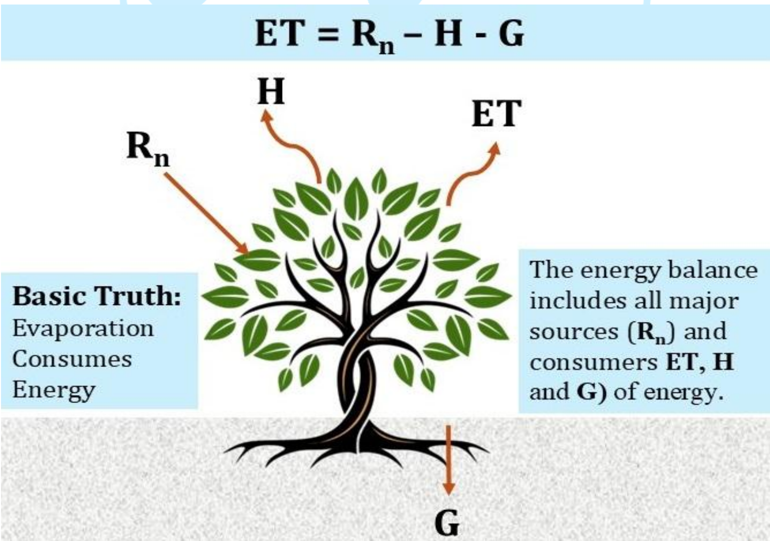

Fig. 3 Demonstration of surface energy balance concept

2.2 Evapotranspiration Remotely Sensed Products

2.2.1 Modis Evapotranspiration

This project is part of the NASA/EOS initiative aimed at estimating global terrestrial evapotranspiration (ET) from Earth's land surface using satellite remote sensing data. The MOD16 global evapotranspiration product is a crucial tool for calculating regional water and energy balance, as well as soil water status, providing essential data for water resource management. With long-term ET data, it is possible to quantify the impacts of climate change, land use changes, and ecosystem disturbances (such as wildfires and insect outbreaks) on regional water resources and land surface energy dynamics. The MOD16 global ET/latent heat flux (LE)/potential ET (PET)/potential LE (PLE) datasets cover a vast 109.03 million km² of global vegetated land and are available at 8-day, monthly, and annual intervals. The dataset spans the period from 2000 to 2010, with two key products available for analysis: 1) Net Evapotranspiration 8-Day Global at a 500 m resolution, and 2) Net Evapotranspiration Yearly L4 at a 500 m resolution.

The development of MOD16 traces back to the original EOS proposal competition in 1989, where leaf area index (LAI), evapotranspiration, and photosynthesis/net primary production (designated as MOD15, 16, and 17, respectively) were proposed. In 1995, during the Algorithm Theoretical Basis Document (ATBD) review for at-launch products, NASA decided to focus more on MOD15 (LAI/FPAR) and MOD17 (PSN/NPP) to develop more theoretically grounded algorithms. As a result, MOD16 ET was deprioritized. However, in the 2003 EOS recompete, NASA selected a new investigator to develop the MOD16 ET product. This investigator shifted the methodology from an energy balance-surface resistance approach to the Penman-Monteith equation, leading to a more successful and globally applicable algorithm. By 2010, NASA had renewed its commitment to the MODIS Science Team, and MOD16, now based on the Penman-Monteith algorithm, was further refined. The new MOD16 algorithm uses daily meteorological reanalysis data and 8-day remotely sensed vegetation property dynamics from MODIS as inputs. The refined global ET datasets developed using this approach have been published in peer-reviewed journals. Table 2 provides an overview of the different MODIS products and their descriptions.

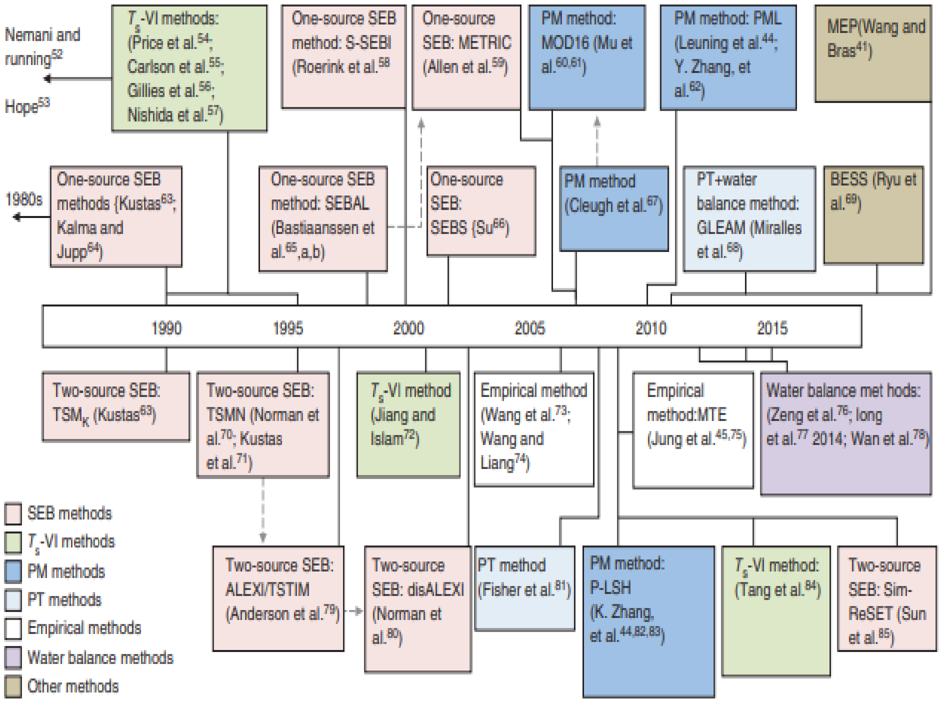

Fig. 4 Key publications that have significantly influenced the development and progression of remote sensing-based evapotranspiration (ET) science.

Table 2 Different MODIS products

Product	Description
• MODIS 8-day FPAR	Vegetation cover fraction quantifies the proportion of surface net radiation distributed between soil and vegetation.
• MODIS 8-day albedo • Daily surface downward solar radiation • Daily air temperature from meteorological data reanalysis	Calculation of surface net radiation and soil heat flux is essential for estimating evapotranspiration (ET).
• Daily air temperature • Daily vapor pressure deficit (VPD) • Daily relative humidity data • 8-day MODIS LAI	Key environmental variables include surface stomatal conductance, aerodynamic resistance, wet canopy conditions, soil heat flux, and others.
• MODIS land cover	Assign a biome type to each pixel.

2.2.2 Wapor Evapotranspiration

The Food and Agriculture Organization's data portal for monitoring Water Productivity through Open-access Remotely Sensed data (FAO, IHE-Delft, IWMI, 2019) provides water productivity (WP) products derived primarily from freely accessible satellite remote sensing data. Actual evapotranspiration (ET) estimates include soil evaporation (E), canopy transpiration (T), and evaporation from rainfall intercepted by leaves (I). ET components are calculated using the ETlook model (Bastiaanssen, 2012), which applies the Penman-Monteith (P-M) equation, originally developed by Monteith in 1948. This approach combines the energy balance and aerodynamic equations, as detailed in the FAO-56 drainage paper (Allen et al., 1998). The ETIa-WPR model calculates soil evaporation and transpiration separately, using Equations (1) and (2). Interception is defined as a function of vegetation cover, leaf area index (LAI), and precipitation (Blatchford, 2020). The FAO portal hosts detailed products on evapotranspiration, transpiration, evaporation, and interception (FAO, IHE-Delft, IWMI, 2019), along with other tools for monitoring water productivity. WaPOR products have become benchmarks in research and publications on evapotranspiration, water resource management, water productivity, and SDG indicators and used in some African countries as shown in Table 3. The WaPOR dataset, available from 2009 to the present, offers 10-day, monthly and annual time steps.

$$\lambda E = \frac{\delta(Rn,soil - G) + \frac{\rho_{air} C_P (e_{sat} - e_a)}{r_{a,soil}}}{\delta + \gamma\left(1 + \frac{r_{s,soil}}{r_{a,soil}}\right)},$$

$$\lambda T = \frac{\delta(Rn,canopy) + \frac{\rho_{air} C_P (e_{sat} - e_a)}{r_{a,canopy}}}{\delta + \gamma\left(1 + \frac{r_{s,canopy}}{r_{a,canopy}}\right)},$$

Blatchford (2020) emphasized the need for continued validation to assess the accuracy of WaPOR products, which are currently considered the highest resolution, near real-time products available. The ETIa-WaPOR product is responsive to general trends in ETIa magnitude across diverse climates and demonstrates strong correlations at both local (Eddy Covariance) and basin (Water Balance) scales. However, in arid irrigated areas, WaPOR tends to overestimate ETIa, particularly at coarser resolutions. The ETIa-WaPOR product shows a Mean Absolute Percentage Error (MAPE) of 26.3% on a monthly, point scale; 40.4% on a daily, point scale; and 29.5% on an annual, basin scale. These results are promising, given that WaPOR provides a nearly real-time, open-access dataset covering the African continent. Analysis of intermediate data components indicates that over- and underestimation of ETIa by WaPOR may primarily stem from an overestimation of soil moisture content, which drives the overestimation of evaporation. Additional validation activities are recommended as new ground data becomes available, especially in cultivated and irrigated regions. In another study, Chukalla (2021) utilized the remotely sensed FAO WaPOR dataset to evaluate irrigation performance indicators at the Xinavane sugarcane estate, segmented by irrigation methods (furrow, sprinkler, and center pivot). This systematic approach offers a framework for using WaPOR and other remotely sensed products to assess irrigation performance.

Table 3 Description of WaPOR V2.0 ETIa-WPR data products, available on the WaPOR portal, used for validation in some African Countries.

	Spatial resolution (m)	Temporal resolution [(a)]	Spatial extent (in Africa)	Satellite (spatial resolution/return period)
Level I (L1)	250	Dekadal	Continental Africa	MODIS (250 m|1-day)
Level II (L2)	100	Dekadal	Benin, Burundi, Egypt, Ethiopia, Ghana, Kenya, Mali, Morocco, Niger, Rwanda, Sudan, Tunisia, Uganda	MODIS (250 m|1-day)[(b)] PROBA-V (100 m|2-day)[(b)]
Level III (L3)	30	Dekadal	Awash, Ethiopia, Egypt Koga, Mali, Niger, Zankalon,	Landsat (30 m|16-day)

Abbreviations:

- MODIS, moderate resolution imaging spectroradiometer;
- WaPOR, water productivity through open-access of remotely sensed derived data.

(a) Dekadal is approximately 10 days. It splits the month into three parts, where the first and second dekads are 10 days and the third dekad covers the remaining days in the month.
(b) MODIS is resampled to 100 m up to 2013 and PROBA-V is used from March 2014.

3. Empirical Models for Estimating of ET

Evapotranspiration (ET) combines two processes: evaporation from surfaces (e.g., lakes, rivers, soil, and vegetation) and transpiration from plants, where water is vaporized and released into the atmosphere. Evaporation requires solar energy to vaporize water, with the vapor pressure difference between the water surface and the air driving the vapor removal. Transpiration involves the movement of water from the soil through plants, eventually evaporating through leaf stomata. This process aids in nutrient transport and provides cooling, which is essential for plant growth. Both evaporation and transpiration are influenced by solar radiation, air temperature, humidity, and wind speed, with crop characteristics and cultivation methods also affecting transpiration. Potential evapotranspiration (ETp) represents the maximum amount of water that can evaporate or transpire from a fully watered surface, while reference evapotranspiration (ETo) is more specific to crop assessments, offering precision by accounting for crop characteristics. ET models can be categorized into four main types: mass transfer models (focused on aerodynamics), temperature-based models (using only temperature, e.g., Hargreaves and Samani model), radiation-based models (based on energy balance, e.g., Priestley–Taylor equation), and combination models, which integrate aerodynamics and energy balance (e.g., Penman–Monteith and FAO56 Penman–Monteith models). ET models can also be classified as analytical, mechanistic, or empirical. Analytical models rely strictly on physical laws, while mechanistic models (like Penman–Monteith) use physical laws and causal relationships to generate estimates. Empirical models (such as the Hargreaves model) are based on observed correlations and are valued for their simplicity, but they lack physical robustness and may not be regionally accurate. Mechanistic models are often preferred for their reliability and physical relevance, especially when sufficient input data is available, as they provide more accurate results compared to empirical models.

3.1 Penman–Monteith Equations

The Hydrologic Engineering Center's Hydrologic Modeling System (HEC-HMS) incorporates the Penman-Monteith method, as outlined by the United Nations Food and Agriculture Organization (FAO) (Allen et al., 1998). This method has been adopted by the FAO as the standard for estimating reference evapotranspiration, providing a consistent baseline for comparing evapotranspiration (ET) across different seasons, regions, and crop types. Evapotranspiration, the combined process of evaporation from soil and water surfaces and transpiration from plant tissues, can be calculated using either energy balance or mass transfer approaches. Evaporation requires energy, either in the form of sensible heat or radiant energy. The rate of ET is controlled by the energy exchange at the vegetation surface and is limited by the amount of available energy. As a result, ET rates can be determined from a surface energy balance. Additionally, ET estimation can be based on the balance of incoming and outgoing water fluxes within the soil or root zone, with the mass transfer approach being particularly useful for longer timeframes (e.g., weeks or more). The Penman-Monteith equation integrates both energy balance and mass transfer approaches (Penman, 1948; Monteith, 1965). The latent heat flux, which represents the ET rate, is derived as follows:

$$ETo = (0.408 * \Delta * (Rn - G) + \gamma * (900 / (T + 273)) * u2 * (es - ea)) / (\Delta + \gamma * (1 + 0.34 * u2))$$

where:

ETo = reference evapotranspiration (mm/day)
Rn = net radiation at crop surface (MJ/m²/day)
G = soil heat flux density (MJ/m²/day)
T = mean daily air temperature (°C)
u2 = wind speed at 2 m height (m/s)
es = saturation vapor pressure (kPa)
ea = actual vapor pressure (kPa)
es - ea = vapor pressure deficit (kPa)
Δ = slope of saturation vapor pressure curve (kPa/°C)
γ = psychrometric constant (kPa/°C)

In this equation, the bulk surface resistance (rs) reflects the resistance to vapor flow through plant stomata and the soil surface, while aerodynamic resistance (ra) reflects the resistance from air flowing over vegetated surfaces. While empirical ET estimation methods exist globally, many are calibrated locally, limiting their global applicability. By defining a "reference surface," the FAO Penman-Monteith method avoids crop-specific calibration. ET rates for various crops are thus calculated relative to this reference surface using crop coefficients. This reference surface represents a hypothetical, well-watered grass crop (0.12 m height, surface resistance of 70 s/m, albedo of 0.23), as defined by the FAO. The assumptions of a uniform, extensive grass surface with one-dimensional fluxes upward simplify global application. The parameterization of the Penman-Monteith method depends entirely on atmospheric conditions such as solar radiation, air temperature, humidity, and wind speed, which should be measured at a standard 2-meter height above the ground.

3.2 Application of Stanghellini Model

The Stanghellini model, developed specifically for greenhouse environments, is widely used to estimate crop evapotranspiration (ET) based on the energy balance method. This model takes into account key parameters like temperature, humidity, solar radiation, and vapor pressure deficit, all of which play significant roles in the microclimate control of greenhouse crops. Unlike models that rely on direct field measurements, the Stanghellini model is designed to operate within a controlled environment, making it especially useful in horticultural production and greenhouse management where climate parameters can vary significantly from open field conditions. The model's primary advantage lies in its precision within greenhouse environments, where external climatic influences are moderated, allowing for better control over variables such as ventilation, shading, and irrigation. It calculates ET based on the premise that greenhouse crop water use can be efficiently managed by controlling internal climate factors, thus reducing water stress and promoting healthier plant growth. However, its application requires precise input data, including accurate readings of solar radiation and temperature within the greenhouse. The model has been applied extensively to a variety of crops, including tomatoes, cucumbers, and peppers, proving effective in supporting optimal irrigation scheduling, which is critical for maximizing crop yield and quality in water-limited settings. Studies comparing the Stanghellini model with other ET models, such as the Penman-Monteith and FAO-56 models, have shown that it often provides a closer approximation to actual ET in greenhouse conditions. Nonetheless, the accuracy of the Stanghellini model can vary depending on the greenhouse setup and crop type. For example, studies have observed that crops with high leaf area indexes or those grown in high-density plantings may experience differences in evapotranspiration rates that require further calibration of the model parameters to ensure precision. Additionally, greenhouse structures with variable ventilation and shading practices may affect the model's reliability, necessitating site-specific adjustments to optimize ET predictions. To address these limitations, modifications of the Stanghellini model have been proposed, such as the inclusion of crop-specific calibration factors that account for unique physiological characteristics, such as stomatal behavior and transpiration efficiency. Furthermore, integrating the Stanghellini model with real-time climate control systems enhances its utility, as continuous monitoring and adjustment of environmental conditions can improve ET estimates and irrigation scheduling accuracy. In modern greenhouse management, coupling the Stanghellini model with automated systems like soil moisture sensors and climate data loggers allows for responsive and efficient water use, reducing the risk of water wastage and enhancing crop water productivity. Despite its greenhouse-focused application, the model has also been adapted for use in semi-controlled environments, extending its relevance in regions where precise water management is crucial due to limited water resources. Overall, the Stanghellini model offers a robust approach to determining crop ET in controlled environments, aligning well with the increasing demand for sustainable water management practices in agriculture, particularly within water-scarce regions and high-intensity farming systems where resource efficiency is paramount. However, for large-scale implementation and adaptability across diverse crop types and greenhouse setups, continuous calibration and validation remain essential to ensure the model's reliability and relevance across varied agricultural conditions.

3.3 Priestley-Taylor Model

The Priestley-Taylor model is a widely recognized approach for estimating evapotranspiration (ET), particularly in scenarios where water is not limited and energy availability predominantly controls ET rates. This model simplifies the complex processes involved in ET estimation by focusing primarily on the balance between incoming solar energy and outgoing heat, assuming that evaporation from open water or well-watered vegetation can be closely approximated by atmospheric conditions. The Priestley-Taylor model uses a simplified version of the Penman equation, omitting the aerodynamic component, which represents the effect of wind and humidity gradients on ET. Instead, it introduces a proportionality constant (often denoted as α, typically valued at 1.26 for wet conditions) that accounts for the energy balance under near-saturated conditions. This constant is crucial, as it adjusts the model to reflect the fact that ET rates are largely driven by available energy rather than soil moisture limitations in well-watered ecosystems. By applying this model, ET can be estimated accurately in regions where water is not a limiting factor, such as wetlands, large bodies of open water, or well-irrigated croplands. One of the Priestley-Taylor model's primary strengths is its relative simplicity, which allows it to be applied with fewer input parameters than other models, such as the Penman-Monteith model. This simplicity makes it especially useful for large-scale applications where detailed data on wind speed, humidity, and vegetation characteristics may be lacking. The model primarily requires net radiation, temperature, and the slope of the saturation vapor pressure curve, making it ideal for broad-scale climatic or hydrological assessments where data collection might be constrained. However, its reliance on the assumption of an abundant water supply limits its application in arid or semi-arid environments, where soil moisture deficits frequently affect ET. In these water-limited conditions, the Priestley-Taylor model may overestimate ET since it does not account for reductions in ET rates due to insufficient soil moisture. This limitation can be mitigated to some extent by adjusting the α constant to reflect varying degrees of water availability, but this requires region-specific calibration and can introduce additional uncertainties. Despite these limitations, the model is still highly applicable in assessing ET for landscapes dominated by water bodies or well-irrigated areas. The Priestley-Taylor model has been widely used in hydrological studies, watershed management, and climate modeling, particularly in understanding how ET responds to changes in energy input due to seasonal variations or climate change. Studies comparing the model with field measurements or more data-intensive models often demonstrate its effectiveness in capturing the overall trends in ET for wet conditions, although it may lack the precision needed for fine-scale agricultural planning or drought-prone regions. Recent advancements have also led to modifications of the Priestley-Taylor model to improve its adaptability, such as incorporating dynamic α values or coupling it with soil moisture data to increase its accuracy across diverse ecosystems. Overall, the Priestley-Taylor model remains an essential tool in hydrology and climatology, especially for studies that require a simple yet reliable estimate of ET driven predominantly by energy availability, making it valuable for large-scale environmental assessments where data availability and simplicity are prioritized.

4. Hydrological Modelling Development Trends

Hydrological models are essential tools for understanding and managing the water cycle, as they simulate the interactions between its various components while simplifying the inherent complexity of these processes. These models serve two primary purposes. First, they are used to study natural hydrological processes, with the goal of understanding the laws governing the water cycle. In this context, models are developed through rigorous experimentation and mathematical formulations that attempt to closely mimic real-world hydrological processes. This often results in complex models, such as the SHE model, which aim to represent these processes in high detail for accurate predictions and analysis. Second, hydrological models are often constructed to address specific practical issues, where the aim is not only to solve a particular water-related problem but to do so in a way that balances accuracy with efficiency. For these applications, simpler models are frequently preferred as they streamline less critical processes, making them easier to apply in diverse scenarios while still providing reliable results. The trend in developing methods for evapotranspiration (ET) estimation within hydrological models reflects these two modeling objectives. On one side, integrated approaches prioritize simplicity, focusing on basic relationships and changes in ET without diving into intricate detail. This trend caters to practical applications where quick, manageable estimations of evapotranspiration are needed. On the other side, classification-based methods are increasingly evolving to embrace complex mechanisms, employing detailed equations to account for water quantities across various forms of evapotranspiration and the associated energy transformations. This method is more comprehensive, capturing the nuances of ET for more precise estimations that factor in diverse conditions and drivers. Thus, two key trends in ET estimation are emerging: a move toward simplified models for ease of practical use and a parallel development of sophisticated models that delve into greater complexity for a more granular understanding of water and energy fluxes. These evolving trends address the dual demands for hydrological models that are both accessible for real-world applications and capable of providing detailed insights into hydrological processes, aligning with the broader goals of effective water resource management.

ET models vary in terms of application, input requirements, and time-step, and can incorporate both mechanistic and empirical approaches with direct or indirect measurements depending on the available data and intended use as shown in Figure 5. The original Penman–Monteith equation is a powerful model for ET estimation, as it integrates both aerodynamic and surface resistances. However, calculating surface resistance accurately requires extensive data collection, which can be a limitation. The FAO56 simplified Penman–Monteith model replaces this variable with a fixed term based on reference crop and standard conditions, offering easier application but sometimes compromising accuracy. The Priestley–Taylor model, which requires fewer inputs, is an alternative when aerodynamic data are unavailable, although it may underestimate ET under advective conditions. Similarly, the Hargreaves and Samani model is useful when limited meteorological data (especially solar radiation) are available, yet the inclusion of an empirical constant can lead to ET overestimations. Several studies have compared mechanistic and empirical models in greenhouse applications. For instance, [15] observed that the Stanghellini model produced more accurate ET estimates in greenhouse environments than the Penman–Monteith model, with a model efficiency (R^2) of 0.872 versus 0.481, likely due to better parametrization of canopy and aerodynamic resistances and sensitivity to the microclimate within greenhouses. Research suggests that ET models may be adapted to greenhouse conditions by collecting temperature and humidity data from within the canopy instead of above it, as this can improve accuracy in ET estimates for greenhouse crops [75]. Accurate leaf surface temperature measurements, through thermocouples, infrared thermometry, or thermal imaging, can also enhance model precision. The Stanghellini model, with its inclusion of leaf area index and net solar radiation adjustments, performs well in greenhouse settings, especially in capturing ET for multi-layered canopy structures where microclimate influences internal canopy resistance. The model has shown to be accurate for unheated, naturally ventilated greenhouses as well as cooled greenhouses with fogging systems. For open-field applications, the FAO56 Penman–Monteith model is generally effective; however, if climate variations or specific stress conditions (e.g., high CO_2 or salinity) affect ET, the original Penman–Monteith model is preferable. In these cases, direct measurements of stomatal and boundary layer resistances can refine ET estimates. Instruments such as weighing lysimeters, eddy covariance, and gas exchange systems, although costly, are useful for high-precision ET estimation in research settings, allowing model calibration for specific climatic and agronomic conditions. Overall, while adapting ET models can improve accuracy, the high cost of precise measurement systems presents a trade-off, especially for commercial agriculture, where these systems are typically reserved for research-focused model enhancement based on location-specific meteorological and agronomic conditions. The Stanghellini model remains the optimal choice for greenhouse environments, adaptable to factors like architecture, ventilation, crop type, and irrigation system, balancing cost with the improved reliability of ET estimates.

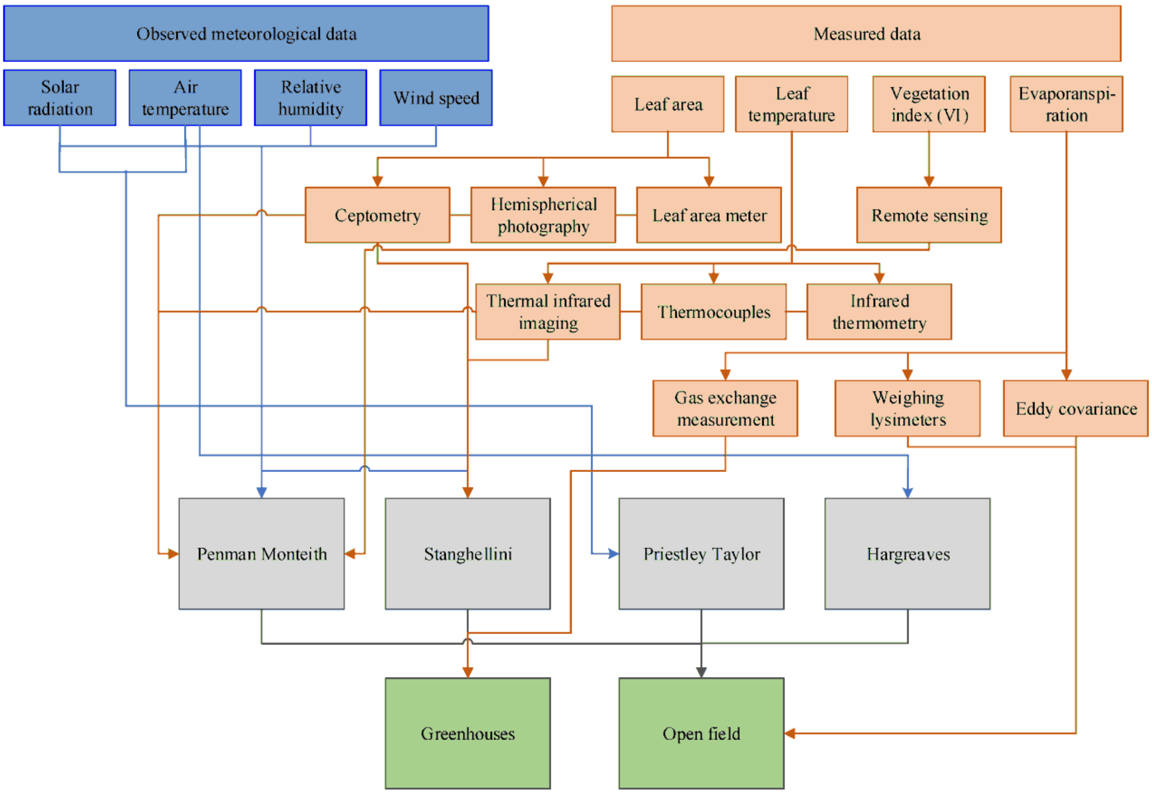

Fig. 5 Development Trends in ET measurement technique and models.

5. The Role of ET Measurement in Optimizing WEF Nexus

The rapidly growing population and rising economic activity create significant challenges in meeting increasing energy, water, and food demands. The interdependencies among the energy, water, and food sectors underscore the need for a holistic nexus approach to address these challenges effectively. Water plays a crucial role within the EWF nexus, supporting energy production (e.g., hydropower), water supply, and food production (e.g., agricultural irrigation). Consequently, accurate assessment and forecasting of water availability in these sectors are essential (Kan et al. 2018). The agricultural sector, responsible for 3.5% to 4.8% of total energy consumption and 70% of global freshwater withdrawals, is projected to require a 50% increase in irrigation water by 2050 to meet the anticipated 60% rise in food demand, highlighting the importance of improved irrigation practices for food security (Bazilian et al., 2011). Irrigation water requirements are a key point of interaction in the EWF nexus, with water and energy systems closely linked through the direct energy needed for pumping and desalinating water for irrigation. Inaccurate measurement of irrigation needs can lead to inefficient energy use (FAO, 2017). Agriculture also consumes indirect energy via fertilizers, creating a vital energy-food nexus (Lahlou et al., 2020). For instance, spikes in fertilizer and fuel costs have contributed to increased food prices. Proper assessment and management of fertilizer type and quantity are essential since nutrient uptake by plants varies with soil moisture and transpiration rates. Overestimating ET can result in excessive irrigation, leading to nutrient leaching into groundwater.

Nutrient and water interactions are directly tied to plant growth, with outcomes dependent on their balance. Optimal irrigation enhances nutrient availability and supports their transformation into bioavailable forms. For example, the mineralization of soil or fertilizer-derived nitrogen is highly influenced by soil moisture levels. Ammonium nitrification increases with sufficient moisture but is vulnerable to leaching under excessive irrigation. Adequate soil moisture ensures nitrification, while too much or too little inhibits the process (Li et al., 2009). Low soil moisture reduces nutrient uptake of elements like sodium, potassium, calcium, magnesium, and zinc, which can lower the overall dry weight of avocado leaves, stems, and fruits (Slowik et al., 1979). Conversely, excessive soil moisture can also negatively impact plants, such as reducing iron and zinc concentrations in avocado leaves. Similar effects have been observed in citrus plants, where excess moisture limits the intake of calcium, magnesium, and iron in seedlings (Labanauskas et al, 1965). This close link between water and nutrient efficiency makes it vital to determine nutrient ratios and irrigation requirements carefully and monitor their supply to optimize plant health and growth. Calcium deficiency is another issue affected by water availability and transpiration rates. Calcium moves through the plant's xylem, driven primarily by transpiration, and high fruit surface-to-volume ratios promote transpiration and calcium uptake. As fruits grow and wax accumulates, transpiration slows, reducing calcium flow. Research shows that enhancing plant transpiration is more effective for addressing calcium deficiencies than adding calcium to the substrate. Climate factors, such as low solar radiation and high humidity, have also been linked to calcium deficiencies in tomatoes, which manifest as leaf damage and yield reduction. These climate parameters influence ET rates, so assessing them helps to anticipate and manage climate impacts on crop growth and yield. For tomatoes, lowering humidity to counterbalance high solar intensity can increase transpiration and help regulate calcium flow in plants [28]. Similarly, excessive transpiration can cause calcium deficiencies in low-transpiring crops like cauliflower, lettuce, and cabbage by diverting calcium predominantly to outer leaves, leaving inner leaves undernourished. Advances in agricultural systems often come with increased water and energy demands. Greenhouses exemplify yield-improvement systems that provide a controlled microclimate, but regulating parameters like temperature and humidity requires substantial energy input for heating, cooling, and ventilation systems. These parameters influence ET rates and, consequently, irrigation needs. CO_2 enrichment is another strategy to boost yields and reduce water use in greenhouses, typically achieved through commercial or industrial CO_2 or gas burners, which add energy costs. Elevated CO_2 levels reduce ET by causing stomata to partially close, impacting gas exchange (water vapor and CO_2) and necessitating adjustments in ET estimates and irrigation requirements. Failing to adjust ET calculations for new microclimate settings can lead to inefficient resource use and unnecessary energy and water consumption in greenhouses.

6. Conclusions and Recommendations

ET is essential in maintaining water balance, as it consumes water from plant interception, surface water, and soil moisture. In humid areas, ET accounts for approximately 50% of annual precipitation, while in arid regions, it can represent up to 90%. However, direct observation of actual ET is challenging and sensitive to external factors, making indirect estimation methods more common. Estimating actual ET through hydrological cycle simulations is crucial for adaptive water resource management, especially under changing environmental conditions. Numerous ET estimation methods exist within hydrological models, which are broadly classified into two main types: classification gathering methods and integrated converting methods. Classification gathering methods estimate various forms of ET individually before aggregating them to determine basin-wide ET based on land use patterns. In contrast, integrated converting methods estimate potential ET and adjust it to actual ET based on soil moisture content, with variations across methods in how they calculate potential ET and model soil moisture extraction. This review summarizes the most potential ET estimation methods and several soil moisture extraction functions, providing a comprehensive overview of the different approaches. However, uncertainties remain in model input, output, and structure, particularly for the physically based Penman-Monteith method, which requires extensive data. These uncertainties can impact the accuracy of hydrological simulations, underscoring the need for careful selection of ET estimation equations and soil moisture functions that align with each hydrological model's requirements to minimize inaccuracies. Moving forward, two main development trends are anticipated: first, an increase in the complexity of ET estimation methods within hydrological models to capture a broader range of conditions, and second, a simplification driven by research to enhance their practical usability for a wider range of applications.

Declaration (*Competing interest)*

The authors declare that they have no competing interests.

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