Crop Evapotranspiration Modeling Through Remote Sensing and GIS Integration: A Review

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Received: 07 Jun 2023
Revised: 29 Jun 2023
Accepted: 17 Jul 2023
Published: 07 Aug 2023

E-ISSN: 2989-5359
DOI: https://doi.org/10.54660/ejsa.2023.3.2.74-82

ABSTRACT
Background: Accurate crop evapotranspiration (ETc) measurement is crucial for sustainable water irrigation management, food safety, and hydrological planning due to the impact of rising climatic variability and water scarcity. Traditional Penman-Monteith method and lysimeter methods results in only point-source results and do not assess the crop's water consumption type across the region. The combination of remote sensing (RS) technology and Geographic Information Systems (GIS) stands out and has become the leading technique in spatial evapotranspiration measurement during recent decades.
Aim: The aim of this review is to gather issues researched by people in the field of RS combined with GIS methods and compare the surface energy balance, vegetation index, and machine learning methods, as well as highlight what questions are still not answered and what the latest achievements are.
Sources: 1, 842 records were found through a thorough search in Scopus, Web of Science, PubMed, ScienceDirect, and Google Scholar, of which 108 studies fulfilled the eligibility criteria and 34 studies were selected for corresponding thematic and comparative synthesis based on PRISMA selection.
Results: Energy balance modelling methods (SEBAL, METRIC, SSEBop, SEBS, TSEB) are amongst the most widely tested methods with deviations ranging from 10% to 20% compared to measured data from eddy covariance and Bowen ratio methods. However, machine learning and hybrid physics-informed modelling methods have started to show similar or even better results compared to classical energy balance methods, as well as a reduced need for meteorological data. GIS provides the necessary spatial framework for interpolation of values, zoning, and delivery of decision support, but there is still a lack of compatibility between the raster-based ET data and vector-based irrigation data.
Gap in research: Existing gaps are still there; including repeated thermal sensor visitation and cloudy conditions, subjective hot/cold pixel identification, lack of validation in smallholder and diverse cropping system in the southern hemisphere, and limited use of WebGIS-based decision support tools.
Conclusion: Although the integration of RS and GIS has developed into a workable framework for crop water accounting, success in the future relies on high-resolution thermal satellite networks, physics-based machine learning, cloud computing for geoprocessing and improved validation systems in areas with limited data.

Keywords: Crop evapotranspiration; Remote sensing; Geographic Information System (GIS); Surface energy balance; Irrigation scheduling; SEBAL/METRIC; Machine learning; Precision agriculture

1. Introduction
1.1. Background
Evapotranspiration (ET), which is the combined water loss from soil evaporation and plant transpiration, is the primary term in agricultural water consumption and may account for over 70-90% of irrigation water in arid farming systems [1, 2]. After the combination theory for relating the three parameters: net radiation, aerodynamic resistance, and canopy conductivity was proposed by Monteith, it was established that ET serves as the physical connection between soil-plant-atmosphere continuum and regional water resource management [1]. Standardization of reference ET (ET0) and crop coefficient (Kc) processes by FAO in FAO Irrigation and Drainage Paper 56 established the applicable methods for these processes worldwide [2].
Despite traditional ET calculation being reliant on point meteorological stations, lysimeters or eddy covariance and Bowen ratio energy balance (BREB) systems, which require expensive installation and maintenance, they fail to account for spatial variability of ET due to soil variability and differences in topography, crop phenology and irrigation uniformity in large agricultural environments [3, 4]. This problem has led to decades of innovations in the methodology for calculating ET with remote sensors (RS), such as SEBAL on the late 1990s [5, 6], METRIC [7], SEBS [8], SSEBop [9], and two-source energy balance/ALEXI-TSEB models [10, 11].

1.2. Importance of the Subject
Actual evapotranspiration (ETa) maps of different locations can be produced through satellite thermal, optical, and microwave observations. This makes it possible for water managers to use ETa maps and enhance water accounting directly in the field by using specially designed coefficients [12]. When this retrieval information collects and is put into a Geographic Information System (GIS), the ET information can be combined with digital elevation models, soil maps, land cover data, and information regarding irrigation systems used in the area to produce useful outputs for decision making, like irrigation scheduling, controlling water use rights, making drought prediction, and groundwater extraction calculations [13, 14]. Proper application of remote-sensing and GIS technology allows producing important practical results like FAO's WaPOR service, national evapotranspiration datasets provided by the USGS/USDA, and NASA's ECOSTRESS and OpenET applications that provide governments with means of realizing and maintaining Sustainable Development Goal (SDG) monitoring indicator 6.4.1 concerning water use efficiency [9, 13].

1.3. Current Global Scenario
The agriculture sector globally utilizes about 70% of the freshwater withdrawals, while climate change expectations show that combined weather shifts will bring about more demand for evaporation and rainfall variability in the major agricultural zones [12, 14]. At the same time, the data from satellites is no longer the same due to Landsat and Copernicus Sentinel programs being free and available on the market, the emergence of cloud-computing platforms such as Google Earth Engine, as well as unmanned aerial vehicle (UAV)-based thermal imaging, all contributing to making ET mapping cost- and technology-wise more achievable [15, 16]. With the help of machine learning (ML) and deep learning (DL) techniques, the range of methods has expanded due to the emergence of alternatives or options that can supplement the traditional approaches based on surface energy balance (SEB) models, especially where in-situ meteorological stations are not available [17-20].

1.4. Need for the Review
Though RS-GIS-based ET studies have emerged quite rapidly, the existing literature is still found to be fragmented across scientific domains, including hydrology, agronomy, remote sensing as well as geoinformatics. The current literature suffers from inconsistent validation protocols, heterogeneous spatial and temporal scales, as well as a lack of comparison between a physically-based as well as data-driven approaches. Several previous reviews have focused individually on the SEB model families or the utilization of machine learning in ET estimation, yet there is little literature synthesizing information with the emphasis on the GIS component of the ET calculation; this is the main topic of our review.

1.5. Objectives of the Review
This review aims to: (i) compile the theoretical framework and development of RS-based crop evapotranspiration models; (ii) analyze the application of GIS technologies in spatial integration, interpolation, and usage of RS-derived crop ET products; (iii) comparatively analyze the characteristics such as accuracy, data usage, and transferability of three groups of approaches (energy-balance, vegetation index, and machine learning approaches); (iv) highlight gaps in research methodology and geographic research; and (v) describe technological developments that are likely to influence the area over the next ten years.

1.6. Scope of the Review
The literature examined provides an overview of scholarly work predominantly published through peer-reviewed outlets between 2015 and 2025, along with some significant studies that have been influential in the methodology of research on the subject of this literature review. The paper specifically emphasizes crop and irrigated-agriculture-based applications of "RS-GIS-integrated ET modeling, " which include not only optical but also thermal infrared and microwave remote sensing using technologies such as Landsat, Sentinel-2 and 3, MODIS, VIIRS, and UAV sensors, surface energy balance and vegetation index modeling approaches, etc. The references will include studies on the natural ecosystem ET studies (not concerned with agricultural applications), pure meteorological forecasting of ET0 without spatial RS-GIS elements, and relying exclusively on conference abstracts.

2. Methodology of Literature Review
This review followed a structured, PRISMA-informed approach to literature identification, screening, and synthesis, adapted for a narrative-thematic review rather than a full systematic review with meta-analysis.

2.1. Literature Search Strategy
A systematic search was conducted across five databases - Scopus, Web of Science (WoS), PubMed, ScienceDirect, and Google Scholar - covering the period January 2015 to June 2025, with selected landmark publications from earlier decades retained for historical and theoretical grounding. Boolean search strings combined the terms ("evapotranspiration" OR "ET" OR "crop water requirement") AND ("remote sensing" OR "satellite" OR "Landsat" OR "MODIS" OR "Sentinel") AND ("GIS" OR "geographic information system" OR "spatial analysis" OR "irrigation scheduling"). Table 1 summarizes the search strategy applied across databases.

Table 1: Literature Search Strategy

Database	Search String (core terms)	Filters Applied	Search Period
Scopus	evapotranspiration AND remote sensing AND GIS	Article/Review; English	2015-2025
Web of Science	ET AND satellite AND irrigation scheduling	Peer-reviewed; English	2015-2025
PubMed	evapotranspiration AND remote sensing	Journal article	2015-2025
ScienceDirect	crop water requirement AND GIS AND satellite	Research/Review articles	2015-2025
Google Scholar	crop evapotranspiration remote sensing GIS review	Citation cross-check	2000-2025 (landmark studies)

2.2. Inclusion and Exclusion Criteria
Studies were included if they were peer-reviewed journal articles or authoritative institutional/organizational reports published in English, explicitly addressed crop or agricultural evapotranspiration, and involved a remote sensing component with either explicit or implicit GIS-based spatial integration. Studies were excluded if they were duplicate records, non-peer-reviewed grey literature (excluding major institutional

reports such as FAO/USGS technical documents), addressed only natural/forest ecosystem ET without an agricultural component, or lacked any spatial or satellite-derived data component. Table 2 details the inclusion and exclusion criteria.

Table 2: Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Peer-reviewed journal articles and major institutional reports (FAO, USGS, NASA)	Duplicate records across databases
English-language publications	Non-English publications without translation
Published 2015-2025 (landmark earlier studies retained)	Conference abstracts and non-peer-reviewed grey literature
Explicit crop/agricultural evapotranspiration focus	Natural/forest ecosystem ET without agricultural relevance
Remote sensing component with GIS-based spatial integration	Studies lacking any satellite/spatial data component

2.3. Study Selection Process (PRISMA-style)

Following removal of duplicates, titles and abstracts were screened for topical relevance, and full texts of potentially eligible articles were assessed against the inclusion criteria. A subset of 34 studies - selected for methodological diversity across energy-balance, vegetation-index, and machine-learning approaches, geographic spread, and citation impact - was retained for detailed thematic and comparative tabulation, while the broader set of 108 eligible studies informed the narrative synthesis throughout the review. The complete selection pathway is illustrated in Figure 1, and the annual distribution of retrieved publications is shown in Figure 2, which indicates a marked increase in RS-GIS integrated ET research since approximately 2019, coinciding with the operational maturation of Sentinel-2 data streams and cloud-based geoprocessing platforms.

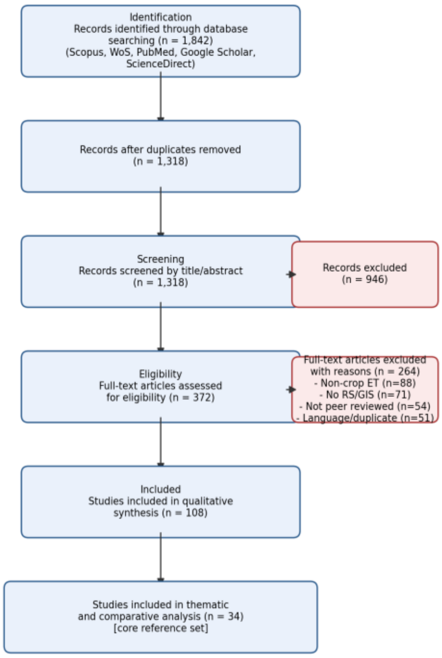

Fig 1: PRISMA Flow Diagram of the Literature Selection Process

3. Literature Review and Thematic Analysis

summarizes the thematic distribution of the 34 core reference studies, with surface energy balance models and machine-learning approaches representing the two largest thematic clusters, followed by vegetation-index/crop-coefficient methods, GIS-based irrigation decision-support systems, multi-sensor/UAV data fusion, and ground-truth validation studies.

3.1. Surface Energy Balance (SEB) Models

Surface energy balance models estimate actual evapotranspiration (ETa) as the residual of the surface energy balance equation, in which net radiation (Rn) is partitioned into soil heat flux (G), sensible heat flux (H), and latent heat flux (LE), with LE subsequently converted to ETa [5, 6]. SEBAL, introduced by Bastiaanssen and colleagues, pioneered the use of "hot" and "cold" anchor pixels within a satellite scene to internally calibrate the sensible heat flux without requiring extensive ground meteorological input, making it attractive for data-scarce regions [5, 6]. METRIC extended this internal-calibration logic with reference ET0-based anchoring and slope-corrected aerodynamic resistance, improving performance in mountainous and heterogeneous terrain [7].

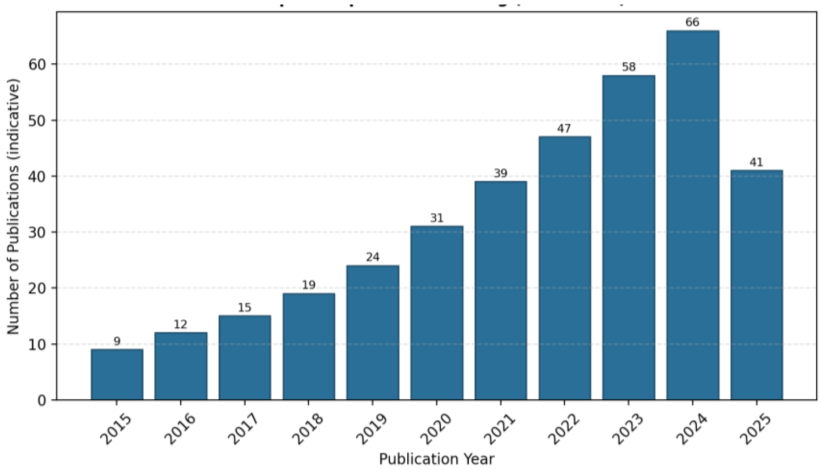

Figure 2: Publication Trend on Remote Sensing-GIS Based Crop Evapotranspiration Modeling (2015-2025)

Comparative evaluations consistently show that SEBAL, METRIC, SEBS, and SSEBop capture the broad spatial and temporal variation of cropland ET reasonably well, though their absolute accuracy diverges under extreme conditions. A comprehensive review by Derardja *et al*. found that S-SEBI, SEBAL, and SEBS performed more consistently than METRIC and SSEBop across a range of validation studies, while all SEB families tended to overestimate ET under very dry conditions and underestimate sensible heat flux [21]. In an four-model intercomparison over Midwestern U.S. cropland sites, METRIC, SEBAL, SEBS, and SSEBop each reasonably reproduced observed ET variability, though absolute magnitudes differed by model [21]. In Indian conditions, SSEBop showed good agreement with Bowen-ratio energy-balance references for a maize-wheat cropping system (R2 = 0.76, RMSE = 0.48 mm/day), albeit with a tendency to slightly overestimate crop ET [22].

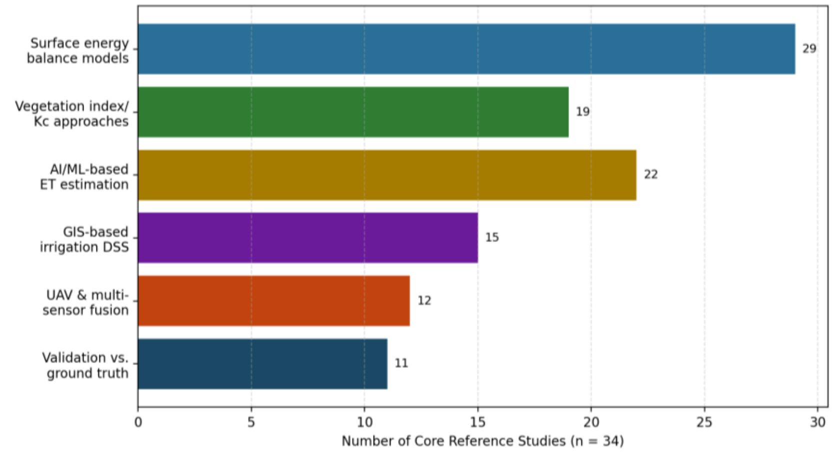

Fig 3: Thematic Classification of Reviewed Studies

Two-source energy balance (TSEB) and its thermal-image-driven regional extension ALEXI/DisALEXI explicitly separate soil and canopy energy fluxes, which improves performance over partially vegetated and heterogeneous fields relative to single-source models [10, 11]. A recent high-resolution UAV-based comparison over almond orchards found TSEB achieved the highest accuracy (R2 = 0.89 for latent heat flux) relative to eddy covariance, outperforming METRIC and SEBAL, which nonetheless remained within an acceptable error margin (RMSE within 58 W/m2) [23]. These findings collectively suggest that model choice should be guided by canopy structure and cover fraction: single-source SEBAL/METRIC/SSEBop formulations are computationally efficient and well suited to relatively homogeneous row-crop fields, whereas two-source TSEB/ALEXI frameworks offer superior performance in sparse, mixed, or orchard-type canopies at the cost of greater data and computational demand. A persistent methodological weakness across the SEB literature is the subjectivity involved in selecting hot and cold anchor pixels, which directly affects sensible heat flux calibration and can introduce operator-dependent bias, particularly in automated or large-area applications [6, 21]. Sensitivity analyses of SSEBop have shown particular sensitivity to land surface temperature (LST) inputs, reference ET0, and model parameters such as the differential temperature (dT) and maximum ET scalar (Kmax); subsequent refinements incorporating the Forcing and Normalizing Operation (FANO) algorithm have reduced bias in grassland and cropland applications and improved cross-platform implementation on Google Earth Engine and USGS EROS computing infrastructure [21].

3.2. Vegetation Index and Crop Coefficient (Kc) Based Approaches

An alternative and computationally simpler approach links satellite-derived vegetation indices - most commonly the Normalized Difference Vegetation Index (NDVI) - to crop coefficients through empirical or semi-empirical regression, avoiding the need for thermal-band surface temperature retrieval altogether [24]. This approach has been widely adopted for near-real-time irrigation advisory services because it can exploit the higher revisit frequency and finer spatial resolution of optical-only sensors such as Sentinel-2, without waiting for cloud-free thermal acquisitions [24].

Comparative studies, however, reveal important limitations. Salgado and Mateos found that energy-balance-derived crop coefficients (via METRIC) diverged from FAO-56 vegetation-index-based Kc estimates when satellite revisit intervals exceeded one week and under mild water-deficit conditions, with the vegetation-index approach systematically overestimating ET during water-stressed periods because NDVI is relatively insensitive to stomatal closure that precedes visible canopy stress [24]. This is a critical caveat for water-scarce irrigation districts, where the vegetation-index method may under-detect early-stage crop water stress precisely when accurate ET information is most operationally valuable.

GIS-based irrigation planning platforms frequently embed the FAO Penman-Monteith reference ET0 model spatially, coupling gridded meteorological surfaces with crop-specific Kc curves assigned by land-use/land-cover classification to generate spatially explicit crop water requirement maps [13]. Multiple studies (e.g., applications reviewed by Yimam and colleagues covering the Elnashar, Fares, Ramirez-Cuesta, Tessema Roba, and Garrido-Rubio study lines) have used this GIS-embedded Penman-Monteith-Kc approach for irrigation scheduling, land suitability assessment, and irrigation performance evaluation across diverse agro-climatic settings [13]. While computationally lightweight and easily scaled across large irrigation command areas, this approach remains dependent on the accuracy of generic Kc curves, which may not adequately represent cultivar-specific or locally adapted crop water use behavior.

3.3. GIS Integration and Spatial Decision-Support Frameworks

The distinguishing contribution of GIS to crop ET modeling lies not in flux estimation itself but in the spatial integration, interpolation, and operational delivery of ET information alongside ancillary geospatial layers - digital elevation models, soil maps, land-use/land-cover classifications, and irrigation network topology - to support water allocation decisions [13, 14]. GIS-based decision-support systems (DSS) for irrigation management typically ingest RS-derived ETa or ET0 rasters, combine them with crop coefficient and soil-water-balance modules, and output zonal or field-level irrigation scheduling recommendations [13].

Illustrative examples include the GISAREG model, which coupled the ISAREG irrigation scheduling simulation model with a GIS framework to represent spatially distributed agro-hydrological processes across the Yingke Irrigation District in China, revealing substantial spatial variation in water productivity and identifying that improved water conveyance and scheduling could reduce deep percolation losses by roughly 30% [25]. Similarly, GIS-based groundwater-irrigated cropping system frameworks have integrated RS-derived ET, vegetation indices, soil moisture, and groundwater storage anomalies to support climate-resilient decision-making for aquifer sustainability [26].

A recurring theme across this literature is the use of GIS not merely as a mapping tool but as an integrative platform reconciling raster-based RS outputs with vector-based cadastral, administrative, and infrastructure datasets - a step essential for translating pixel-level ET estimates into farm- or scheme-level water allocation decisions [13, 14, 27]. Nonetheless, interoperability between different raster ET products (varying in resolution, projection, and temporal compositing) and vector infrastructure layers remains inconsistently documented, and few studies report on the robustness of their spatial interpolation or zonal statistics methods, representing an underexplored methodological dimension of the RS-GIS integration literature.

3.4. Machine Learning and Artificial Intelligence Approaches

Over the past decade, machine learning (ML) and deep learning (DL) techniques have been increasingly applied to ET estimation, either as standalone data-driven predictors or as hybrid emulators of physically based SEB models [17-20]. A comprehensive review of ML models for ET estimation identified random forest, artificial neural networks, and support vector machines as the most frequently applied algorithms, noting that combining RS imagery with ML substantially reduces meteorological data requirements relative to FAO-56 Penman-Monteith while achieving comparable or superior accuracy in several studies [17].

Recent work has demonstrated that reference ET0 can be estimated from simple satellite-derived variables (land surface temperature, leaf area index, NDVI, water vapor) using ML models with reported R2 values approaching 0.99 in some validation settings, though spatially distributed application remains constrained by continued reliance on point-based training data [18]. Deep neural network (DNN) ensembles trained on large eddy-covariance flux-tower networks have also been used to merge multi-satellite ET products; one recent VIIRS-based DNN ensemble trained on 278 flux towers achieved R2 = 0.71 and Kling-Gupta Efficiency of 0.83, outperforming random forest and Bayesian model-averaging alternatives, and has been positioned as a successor product line to the long-standing MODIS MOD16 *et al*gorithm as the Terra/Aqua missions approach end-of-life [20].

A further methodological innovation involves eliminating thermal-band dependence altogether: Costa *et al.* used Sentinel-2 spectral bands and vegetation indices with machine learning algorithms to estimate the evapotranspiration fraction and actual ET for center-pivot-irrigated crops, demonstrating that reasonably accurate ET estimation is feasible using only optical (non-thermal) data, which substantially increases the effective temporal frequency of usable satellite observations given cloud-cover constraints on thermal sensors [28]. Coupled thermal-infrared and passive-microwave machine learning approaches (e.g., regression-tree-based all-weather land surface temperature estimation) have similarly been used to overcome cloud-contamination gaps in geostationary thermal ET products [29].

Collectively, the ML/DL literature suggests a clear trend toward hybrid or "physics-informed" approaches that retain the physical interpretability of SEB models while exploiting the pattern-recognition strength of data-driven algorithms to reduce input data burden and improve gap-filling under cloud cover - though cross-study comparability remains limited by heterogeneous training datasets, feature sets, and validation protocols [17, 19, 20].

3.5. Multi-Sensor and UAV-Based Data Fusion

The spatial and temporal resolution trade-off inherent to any single satellite platform - coarse-resolution, high-frequency sensors (MODIS, VIIRS) versus fine-resolution, lowfrequency sensors (Landsat) - has motivated growing interest in multi-sensor data fusion and UAV-satellite integration for field-scale ET mapping [15, 23]. UAV-borne thermal imaging, in particular, offers sub-meter spatial resolution unattainable from satellite platforms, enabling detailed within-field ET variability assessment for precision irrigation management, as demonstrated in the almond-orchard TSEB/METRIC/SEBAL comparison discussed in Section 3.1 [23].

Cloud-computing platforms such as Google Earth Engine have substantially lowered the computational barrier to processing large multi-temporal satellite archives, enabling operational implementation of SSEBop and related models at national and continental scales [21]. The advent of CubeSat and SmallSat constellations promises further improvement in thermal revisit frequency, directly addressing one of the most persistent limitations of thermal-based ET retrieval - infrequent cloud-free overpasses - though their radiometric calibration and long-term consistency for operational ET products are still being established [30].

3.6. Validation Against Ground-Based References

Across the reviewed literature, eddy covariance and Bowen ratio energy balance towers remain the principal ground-truth references for RS-derived ET, though both methods carry known limitations, including energy-balance closure errors and limited spatial footprint representativeness relative to satellite pixel scales [3, 22]. Validation studies report considerable variation in accuracy depending on land cover homogeneity, climate regime, and model choice, with RMSE values for daily ET typically ranging from approximately 0.4 to 1.5 mm/day across the SEB and ML literature reviewed [21, 22, 28].

A recurring critique is the geographic concentration of validation studies in well-instrumented regions of North America, Europe, and China, with comparatively few flux-tower-validated studies from smallholder-dominated agricultural systems in South Asia, sub-Saharan Africa, and parts of Latin America [21, 26]. This validation imbalance constrains confidence in model transferability precisely in the regions where operational RS-GIS ET tools could deliver the greatest food-security and water-management benefit.

Figure 3 synthesizes the thematic findings of Section 3 into a unified conceptual framework, illustrating how satellite, meteorological, and ancillary GIS data streams feed into either physically based surface-energy-balance/vegetation-index models or machine-learning emulators, both of which are spatially integrated within a GIS environment to generate operational irrigation and water-management outputs.

4. Comparative Analysis of Previous Studies

Table 3 and Table 4 present a comparative synthesis of representative studies selected from the core reference set, summarizing study location, methodological approach, and principal findings and limitations. The comparison highlights that while energy-balance approaches dominate the earlier literature (pre-2020), machine-learning and hybrid approaches have become increasingly prominent in studies published after 2021, generally coinciding with wider availability of cloud-computing infrastructure and larger flux-tower training datasets.

Table 3: Comparative Analysis of Modeling Approaches

Approach	Typical Accuracy (vs ground truth)	Data Requirements	Spatial Transferability	Operational Maturity
SEBAL / METRIC	10-20% deviation; site-dependent	Thermal + optical imagery, met. data	Moderate (needs local calibration)	High (widely operational)
SSEBop	R2 ~0.7-0.8 vs BREB	LST, ET0, minimal met. data	High (designed for large-area use)	High (USGS/FAO operational products)
TSEB / ALEXI	R2 up to 0.89 (UAV-scale)	Thermal imagery, canopy structure data	Moderate-High	Medium (research to operational transition)
Vegetation Index / Kc	Overestimates under water stress	Optical imagery only	High (simple, scalable)	High (widely used for advisories)
Machine Learning / DL	R2 0.71-0.99 (context-dependent)	Training data-dependent; flux towers preferred	Variable (training-domain dependent)	Emerging (rapid growth since 2020)

5. Research Gaps and Emerging Trends

Synthesis of the reviewed literature reveals several unresolved issues and methodological limitations that constrain the operational maturity of RS-GIS integrated crop ET modeling First, thermal-infrared sensors central to SEB models remain constrained by cloud cover and infrequent satellite revisit (16 days for Landsat, longer under persistent cloud), creating temporal gaps that are particularly problematic during peak irrigation decision windows [21, 29]. Second, the subjective selection of hot/cold anchor pixels in SEBAL/METRIC-family models introduce operator-dependent variability that limits automation and cross-study reproducibility, despite refinements such as the FANO algorithm for SSEBop [6, 21]. Third, validation networks remain geographically skewed toward well-resourced regions, leaving model transferability to smallholder, heterogeneous cropping systems in the Global South inadequately tested [21, 26].

Fourth, GIS integration practices are inconsistently documented: few studies report explicit methods for reconciling raster ET products of differing resolution and temporal compositing with vector-based irrigation infrastructure and cadastral datasets, and open, interoperable WebGIS-based decision-support tools remain limited in operational deployment beyond a handful of national platforms (e.g., FAO WaPOR) [13, 14, 27]. Fifth, machine-learning ET models, while promising, are frequently trained and validated on limited or geographically narrow flux-tower datasets, raising concerns about overfitting and limited generalizability when applied outside their training domain [17, 19, 20].

Emerging trends that are likely to address several of these gaps include: the deployment of CubeSat/SmallSat thermal constellations offering higher revisit frequency [30]; physics-informed machine learning that embeds energy-balance constraints within data-driven architectures to improve extrapolation beyond training conditions [17, 20]; expanded cloud-based geoprocessing (Google Earth Engine, open data cubes) that facilitates large-scale, reproducible ET mapping

[21]; UAV-satellite multi-scale data fusion for field-scale precision irrigation [23]; and policy-linked operational water-accounting products such as FAO's WaPOR portal that directly support SDG indicator 6.4.1 monitoring [9, 13]. Figure 5 maps these gaps against the modeling pipeline stages, and Figure 6 summarizes the corresponding emerging research directions.

The synthesis presented in this review indicates that RS-GIS integrated crop evapotranspiration modeling has progressed from largely experimental, single-site validation studies in the early 2000s toward increasingly operational, multi-scale water-accounting systems capable of supporting national and transboundary water governance [9, 13, 21]. The convergence of three methodological streams - surface energy balance physics, vegetation-index/crop-coefficient empiricism, and machine-learning data-driven inference - reflects a broader maturation in which no single approach is universally superior; rather, model selection increasingly depends on canopy structure, data availability, and the operational time-scale required (near-real-time advisory versus retrospective water accounting) [10, 17, 21, 23].

A notable pattern across the literature is the persistent trade-off between physical interpretability and data efficiency: SEB models such as SEBAL, METRIC, and TSEB retain strong physical grounding and are broadly transferable across climates without extensive retraining, but require thermal-band imagery, careful pixel calibration, and are vulnerable to cloud contamination; ML/DL approaches reduce meteorological data burden and can exploit optical-only or fused data streams but depend heavily on the representativeness of their training datasets and often function as "black boxes" with limited physical interpretability [17, 21]. The growing interest in hybrid, physics-informed ML architectures represents a logical response to this trade-off, and the reviewed evidence suggests this is likely to become the dominant methodological direction over the next decade [20].

The role of GIS within this landscape is best understood not as a competing modeling approach but as the essential spatial integration and translation layer that converts pixel-level ET estimates into field-, scheme-, and basin-level decision-relevant information [13, 14]. The comparative weakness identified in this review - inconsistent documentation of GIS-based spatial integration methods relative to the extensive methodological detail typically provided for the underlying RS-ET algorithm - suggests that the GIS component of RS-GIS integration has received comparatively less critical methodological scrutiny than the remote sensing component itself, an imbalance that future research and reporting standards should address.

From a practical standpoint, the operational products already in use (WaPOR, OpenET, national SSEBop-based datasets) demonstrate that RS-GIS integrated ET information can meaningfully support irrigation advisory services, drought early warning, and water-rights accounting at scale [9, 13]. However, the geographic concentration of validation evidence in data-rich regions raises legitimate concerns about the reliability of these tools when transferred, often with minimal local calibration, to data-scarce smallholder systems where the food-security stakes of accurate water accounting may be highest [21, 26]. Bridging this evidence gap should be considered a priority for both the research community and international development and donor agencies funding agricultural water management programs.

7. Conclusion

This analysis provides an overview of peer-reviewed literature regarding remote sensing and Geographic Information Systems use in modeling crop evapotranspiration on the basis of 108 separate studies and 34 primary studies with detailed thematic and comparative analysis undertaken. The findings indicate that surface energy balance models (such as SEBAL, METRIC, SSEBop, SEBS, TSEB/ALEXI) stay in the top-rated list of methods for the estimation of actual ET in spatial terms. In addition, vegetation index/crop coefficient techniques are shown to have advantages in terms of cost and speed of use although they have limitations when being applied to water-stressed environments. Furthermore, machine learning technologies are emerging as a new area in terms of complementing conventional techniques in effective modeling and minimizing data needed for estimation.

The crucial point of this synthesis rests in showing that RS-GIS-based ET modeling has progressed from the experimental level into a usable means for managing water resources around the world but at the same time pointed that this progress is unevenly achieved since it mainly happens in areas with a developed technical base such as North America, Europe, and China, while the gaps in validation and implementation still exist in agriculture characterized by a prevalence of smallholders.

As for the researchers, the following recommendations can be made in terms of (i) increasing transparency and standardization in the methodologies and procedures of GIS-based spatial integration with RS-ET algorithms; (ii) broadening the coverage of flux-tower and ground-truth validation networks, especially in the agriculture of the Global South; (iii) continuing the development of hybrid physics-informed ML models combining the advantages of the energy balance physics approach and data-driven techniques; and (iv) making benchmarking across different studies systematic through the establishment of harmonized validation protocols. In the recommendation outlined in the study, policymakers and practitioners are advised to ensure investment on the functionality of open and interoperable decision support platforms based on WebGIS which can use information derived from RS technology on ET for irrigation scheduling and accounting for water rights in developing countries challenged by water shortages. Instead of creating independent and non-interoperable systems, the existing successful products must be used for implementation.

Future research should address the utilization of the CubeSat/SmallSat thermal constellations in the context of increased frequency of ET monitoring, development of UAV-Satellite multi-scale data fusion for the purpose of precise irrigation, improvement of the cloud-based geoprocessing framework intended for reproducible mapping of ET on large areas, and establishment of relationship between RS-GIS ET based products and international water accounting. All these aspects show the connection between new tendency toward more effective management of water resources in agriculture.

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