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Soil Moisture Frameworks for Irrigation Decision Support Systems

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Abstract

Advances in soil sensors, remote sensing, and forecasting technologies have expanded the data types and integration options for irrigation optimization. This data includes *in-situ* measurements, satellite-derived products, weather forecasts, hydrological, and machine learning models. However, there is still limited operational guidance on translating soil moisture data into actionable decisions. This paper reviews recent literature and discusses advancements in soil moisture-driven irrigation systems, focusing on how soil moisture information is translated and embedded in decision-support frameworks. Studies show that irrigation efficiency depends on how crop root zones are defined, how moisture is converted into crop-relevant indicators, and how information from multiple depths is synthesized. However, the approaches to this vary widely. Fixed-depth, dynamic, and root-weighted root-zone representations coexist, each balancing accuracy with practical constraints. Similarly, irrigation frameworks range from reactive, sensor-based systems to forecast-informed and hybrid architectures. Each framework reflects different trade-offs between complexity and reliability. The review showed that increasing data integration alone does not necessarily guarantee better information for irrigation decisions. However, improving irrigation support systems requires shifting the emphasis from precision in soil moisture estimation to the transparency and interpretability of irrigation decision logic.

Keywords

Irrigation Decision-Support Systems, Irrigation Management, Precision Irrigation, Agricultural Water Management, Soil Moisture

1. Introduction

Efficient irrigation management increasingly depends on a thorough understanding of the interactions between soil, plants, and the atmosphere. The need for this understanding has increased due to climate variability and the demand for sustainable agricultural production. Soil moisture is at the core of this challenge. It regulates plant water availability and interacts with atmospheric demand, soil properties, and irrigation inputs. Recent advances in sensing technologies, satellite platforms, and modeling tools have increased access to soil moisture information. However, converting this wealth of data into reliable, actionable irrigation decisions remains challenging. Early Earth observation efforts primarily concentrated on estimating crop water requirements using evapotranspiration (ET) modeling. For instance, [1] demonstrated that integrating satellite-derived ET with agrometeorological observations could provide location-specific irrigation recommendations. While farmers found these tools helpful, many struggled to interpret the technical units involved. This highlighted broader usability issues.

Similar trends emerge in broader reviews of remote sensing for crop water management. Methods such as the Penman-Monteith equation, reflectance-based crop coefficients, and surface energy balance models have all matured. However, they often fall short of directly prescribing irrigation amounts without additional modeling or decision rules [2] [3].

Alongside these ET approaches, remote sensing has also been used to infer soil moisture and irrigation activity at different spatial scales. Microwave and optical satellite missions now enable mapping of soil moisture and irrigation patterns. Studies using Sentinel-1 and Sentinel-2 in semi-arid zones have demonstrated this capability [4]. Even so, limitations remain. These include low revisit frequency, unclear depth-resolved information, and mismatches between spatial scale and field-level needs.

Despite improvements in retrieval accuracy, many soil moisture products still face challenges with resolution, continuity, and integration [5] [6]. *In-situ* sensing has become more common in response. Modern systems offer continuous monitoring at multiple depths using both invasive and non-invasive techniques [7]. However, field results have shown that commonly used irrigation triggers are not always reliable. According to [8], profile storage and depletion metrics offer a better basis for scheduling, especially in layered or variable soils. These insights, however, suggest that direct measurements must also be carefully interpreted.

To overcome observational limits, model-based and forecast-guided irrigation frameworks have emerged. These systems link soil moisture estimates with crop simulations, hydrological models, and weather forecasts. Research by [9] demonstrated that integrating forecast data with hydrological modeling and remote sensing can improve irrigation scheduling. Other studies have emphasized the value of coupling simulation models with emerging technologies, such as machine learning, IoT networks, and remote sensing tools [10]. These combined approaches can improve efficiency and yields. However, they introduce new risks related to model accuracy, calibration, and data access. Machine learning has added new tools to this space. Algorithms such as ensemble methods, regression models, and AutoML have achieved strong predictive results when trained on multisource data

[11] [12]. Still, these models often struggle to transfer across regions or growing seasons. High accuracy does not always lead to actionable decisions. Reviews of IoT-based systems note that automation improves labor and efficiency only when decision logic is well-integrated [13].

Across all these developments, irrigation decision-support systems (DSS) have become more complex. Many now utilize GIS platforms, cloud-based tools, and analytics to combine data from soil, weather, and crops [14] [15]. This boosts analytical power but raises new questions. How is soil moisture used in these systems? How is it interpreted or combined with other indicators? Indices such as the Soil Water Deficit Index (SWDI) aim to formalize these translations [16]. Their success, however, depends on assumptions about root zone depth and crop behavior. Despite years of progress, a gap still exists between estimating soil moisture and turning that into irrigation decisions. Satellite products offer spatial context but rarely provide direct advice. Sensors deliver precision but are costly and difficult to scale up. Forecast models can look ahead, but they come with uncertainties. Many reviews agree: the challenge now is not technical capacity, but translating technical capabilities into user-friendly, reliable tools [2] [3].

In this context, the objective of this review is to examine how soil moisture information derived from *in-situ* sensing, remote sensing, and predictive modeling approaches is operationalized within irrigation decision-support systems. Attention is given to how soil moisture is translated into relevant indicators, incorporated into decision logic, and fused with other data streams. By identifying where uncertainty enters the irrigation decision chain, this review seeks to identify key considerations for improving irrigation tools that are both reliable and interpretable.

2. Methodology

This review employs a narrative synthesis approach, focusing on irrigation decision-support systems that leverage soil moisture data. Rather than comparing the predictive accuracy of soil moisture estimation algorithms in isolation, the goal is to understand how various data sources and modeling strategies are assimilated, combined, and translated in irrigation contexts. The emphasis lies in examining how decision frameworks are structured, how they incorporate soil moisture, and how they translate it into actionable terms. Particular attention is given to integration methods and the structure of decision logic across different systems. This synthesis allows recurring patterns, translation mechanisms, and operational limitations in different studies.

2.1. Scope and Inclusion Criteria

The scope of the review was defined around peer-reviewed journal articles that connect soil moisture information to irrigation management actions. Studies were included when they satisfied at least one of the following conditions, the: (i) use of *in-situ*, remotely sensed, forecast-derived, or simulated soil moisture data to guide irrigation scheduling (ii) combination of soil moisture with complementary inputs such as meteorological observations or crop modeling outputs (iii) implementation of predictive irrigation frameworks in which soil moisture functions as a primary or supporting system variable. Priority was given to literature published between 2015 and 2026 to capture developments associated with modern sensing platforms, remote sensing products, forecast systems, machine learning approaches, and decision-support technologies relevant to contemporary irrigation management. Both field-scale and regional-scale applications were considered, provided irrigation decision-making remained a central objective. Methodological studies dedicated to soil moisture retrieval accuracy, sensor calibration, or algorithmic development were excluded from the primary synthesis unless they demonstrated direct implications for irrigation decisions. Selected review articles were consulted to strengthen contextual grounding where appropriate.

2.2. Literature Identification and Thematic Classification

Literature was identified through targeted keyword searches conducted using Google Scholar and ScienceDirect. The query words focused on capturing the intersection between soil moisture information and irrigation frameworks. Search expressions included combinations such as: "soil moisture sensor irrigation", "remote sensing irrigation", irrigation decision support", "root-zone soil moisture management", "integrated irrigation frameworks". Retrieved studies were organized thematically according to the functional role soil moisture plays within irrigation systems. As detailed in Sections 3 through 5, five primary groupings emerged: (i) *in-situ* soil moisture sensing applied to irrigation control, (ii) remote sensing products used within irrigation decision contexts (iii) model-driven or forecast-informed soil moisture scheduling approaches (iv) translation methods linking soil moisture to root-zone availability or crop stress indicators and (v) integrated frameworks combining multiple information streams within unified decision-support architectures. This structure enabled comparison of diverse studies while maintaining focus on irrigation relevance. This structure analyzed diverse studies while keeping the focus on irrigation decision-making. The synthesis prioritized identifying recurring decision strategies and the tradeoffs embedded in different system architectures. Within each thematic group, attention was given to how soil moisture data are represented, how they interact with other information sources, and how they ultimately inform irrigation actions.

The literature search was conducted between January and February 2026, during which relevant studies were identified through the targeted keyword searches described above. Titles and abstracts were first screened for relevance, followed by full-text assessment based on the inclusion criteria. In total, approximately 130 studies were initially identified, of which about 70 were retained for the final synthesis. A limited number of additional studies were also incorporated in April 2026 to strengthen key themes within the synthesis. This synthesis was intentionally qualitative rather than meta-analytic due to the diversity of the different study objectives. Several limitations should be considered when interpreting the findings. Although the selected databases provide broad coverage, some relevant studies indexed elsewhere may not have been fully captured. In addition, the focus on system-level insights rather than quantitative performance comparisons also limits its direct evaluation across studies. In addition, the inclusion criteria emphasize studies that explicitly link soil moisture to irrigation decision-making, which may be perceived as biased with a specific focus. These considerations indicate that the findings should be interpreted as a conceptual synthesis rather than a fully systematic assessment.

3. Data sources and Inputs in Irrigation Systems

Sections 3.1-3.3 differentiate soil moisture data sources and predictive approaches, while subsequent sections examine how these inputs are translated and integrated within decision-support frameworks.

3.1. *In-Situ* Soil Moisture Sensors in Irrigation Management

Integrating *in-situ* soil moisture sensors into irrigation systems has been a major step forward in precision water management. These sensors provide real-time data that helps guide irrigation decisions based on actual field conditions. In the literature, three key themes consistently emerge: (i) threshold-based decision logic, (ii) depth-specific interpretation of root-zone moisture, and (iii) operational limits that affect how widely and effectively these systems can be used.

A dominant trend is the use of threshold-based control. Irrigation is triggered when soil moisture or matric potential crosses a set limit. These thresholds are often based on agronomic indicators such as plant-available water or crop-specific stress points [17] [18]. For instance, [19] recommends applying irrigation when average soil moisture drops below the lower limit defined by field capacity and allowable depletion. Even simpler setups, such as maintaining moisture at 90% - 100% of field capacity using just one 10 cm sensor, have shown yield and economic benefits [20]. Calibration methods vary, but the threshold logic is the most common way to turn sensor readings into irrigation actions.

Another critical design choice is sensor depth. Multi-depth configurations are common. They capture how water moves vertically through the soil profile, especially in relation to the crop's root zone. Most systems install two to four sensors at different depths, starting near the surface (0 - 15 cm) and extending to deeper (60 - 120 cm). This setup tracks moisture patterns throughout the crop's root zone. One study used a four-sensor layout at 15, 30, 61, and 91 cm to monitor soil response to irrigation or rainfall [17]. Another used three sensors (15, 30, and 60 cm) and triggered irrigation when any layer dropped below a set threshold [18]. Some studies, however, emphasized simplicity. Some rely on a single sensor placed at 10 cm [20]. Others divide the soil into segments such as shallow (0 -10 cm), mid (11 - 40 cm), and deep zones (41 - 60 cm) [21].

These choices often come down to trade-offs: accuracy vs. cost, crop type vs.

root depth, or uniformity vs. variability across the field, which makes scaling challenging. Sensor accuracy can vary with soil texture or salinity [21] [22]. Determining optimal sensor placement is also necessary [23]. On larger farms, wireless networks face communication limits and computational strain [24]. And then there is the cost of deploying enough sensors to cover large, diverse fields, which is expensive [17]. Some studies offer ways to work around these barriers. For example, placing sensors only in key zones or clustering them within smaller management areas can keep costs manageable [25]. Studies also illustrate the shift towards full automation. In these setups, real-time soil moisture data feed directly into irrigation controllers, opening valves or gates without human input, reducing labor demands [23] [25]. However, it still hinges on good sensor placement and stable data transmission networks [24].

More recently, there has been a shift toward making sensor use proactive rather than reactive. A growing number of studies now combine total soil water estimation with short-term forecasting to predict irrigation needs before deficits occur [22]. A few systems even pair sensors with machine-learning forecasts to estimate weekly irrigation demand [26]. Others propose low-cost sensor platforms that could eventually support forecast-informed irrigation schedules at scale [21]. In summary, *in-situ* sensors continue to play an important role in irrigation management. They offer depth-aware, real-time insight into moisture availability. However, their scalability is still shaped by technical limits, infrastructure constraints, and the costs of widespread deployment.

3.2. Remote Sensing Products in Irrigation Decision Management

To overcome the spatial limitations of *in-situ* sensors, many irrigation frameworks now include remote sensing data and products. These biophysical products provide indirect information on crop water status and support spatially distributed decision-making. However, across the literature, remote sensing rarely acts as a direct trigger for irrigation. Instead, it plays a supporting role, providing spatial context, improving estimates of water balance, and guiding broader optimization strategies.

One common pattern is the use of remote sensing as an indirect proxy for soil moisture or plant water stress. Coarse-resolution microwave products from platforms like SMAP are often used to detect irrigation needs. They help flag discrepancies between observed soil moisture patterns and modeled simulations that exclude irrigation [27]-[30]. At the same time, multispectral vegetation indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Moisture Stress Index (MSI), and Normalized Difference Moisture Index (NDMI) are widely used to explain plant water conditions [31]-[33]. Even when soil moisture is not directly measured, these indices, along with crop coefficients (Kc or Kcb), are central to estimating water demand. They often feed into evapotranspiration models or soil water balance models to refine irrigation recommendations.

Only a few studies have pushed remote sensing closer to real-time decision-making. [28] used satellite-based moisture data to detect specific irrigation events and estimate the volumes of water applied. Research by [34] integrated land surface temperature into a hydrological framework to forecast irrigation needs based on plant stress thresholds. These examples reflect a shift from retrospective analysis toward operational scheduling. Still, in most cases, remote sensing provides valuable inputs while leaving the final decision to other data sources or to the farmer's judgment [33] [35]-[37].

Several factors continue to limit its real-time utility. Spatial resolution is a major problem. Coarse microwave sensors cannot resolve small fields or detect localized irrigation, and even high-resolution optical imagery struggles in fragmented landscapes [27] [38]. Temporal limitations are also common. Long revisit intervals, cloud interference, or unfavorable overpass timing often result in missed or incomplete irrigation detection [29]. In many cases, remote sensing is not used alone. It is integrated into larger modeling systems such as AquaCrop, FAO-56 methods, or soil water balance models. These require careful calibration to match vegetation indices with local crop types, growth stages, and assumed rooting depths [32] [36] [37]. Errors in those assumptions, especially regarding root depth or soil properties, can result in misleading estimates of soil moisture depletion. This makes validation with field data essential [31] [34].

Across the reviewed work, a clear distinction emerges. Studies that focus on estimating irrigation use at broad scales are often for water accounting or policy [27] [30]. Others aim to assist on-farm management by supporting variable-rate irrigation, stress detection, and delineation of management zones [31] [33] [38]. Even in these cases where it is applied, remote sensing tends to support rather than drive irrigation choices. Overall, remote sensing improves irrigation management by expanding spatial insight and enhancing model-driven water planning. However, its impact depends on how well satellite-based soil moisture measures and indicators are translated into root-zone conditions that actually matter for crop health and timing.

3.3. Model and Forecast-Driven Soil Moisture in Irrigation Management

Model and forecast-based systems imply a shift from reactive to proactive irrigation approaches. Rather than waiting for moisture deficits to appear, these approaches aim to anticipate crop water needs and plan irrigation accordingly. The reviewed studies show a wide range of techniques for predicting soil moisture. Some rely on physical process-based models, while others use data-driven methods like machine learning. Both are, however, widely used to support irrigation scheduling.

A key difference lies in how soil moisture is represented. In many process-based models, soil moisture is simulated as a vertically layered profile. This allows for detailed tracking of water movement across the root zone, a critical factor for timing irrigation [39]-[41]. Other systems simplify the process. Model Predictive Control (MPC) frameworks, for example, often rely on bulk or averaged moisture states. This helps reduce computation time and improves real-time performance [42]. Machine learning models improve this performance, as algorithms like Long Short-Term Memory (LSTM) networks [43] and XGBoost [44] do not require full physical modeling. Instead, they learn patterns directly from past data. These approaches are useful in places where detailed soil and crop parameters are hard to obtain.

Across these modeling strategies, soil moisture forecast functions as a decision variable. They are important for triggering, delaying, or adjusting future irrigation events. Predictive soil moisture and evapotranspiration information are now commonly integrated into decision-support systems that automate irrigation based on predefined stress or depletion thresholds [45] [46]. Other studies project soil water balance forward in time to assess whether moisture levels are expected to fall below critical thresholds [39] [47]. Additionally, many of these predictive approaches embed soil moisture forecasts into broader crop or water balance models. Such models include Agricultural Production Systems Simulator (APSIM), Root Zone Water Quality Model (RZWQM2), and AquaCrop. The models allow soil moisture dynamics to be interpreted according to crop growth stage and atmospheric demand [41] [48] [49].

Forecast horizon is another central design consideration. Short-term lead times of approximately 1-5 days are most commonly adopted and are generally regarded as operationally feasible for irrigation scheduling [41] [45]. These horizons reflect both meteorological predictability and the timescales over which soil moisture deficits translate into crop stress. Some studies extend predictive horizons to support more strategic planning, which includes 9-day rolling simulations [48] and forecasts up to 15 days [39]. However, forecast reliability declines with increasing lead time. This was demonstrated in evaluations of the Global Ensemble Forecast System (GEFS) inputs, where correlations between forecast and observed rainfall decrease with increasing horizon length [40]. As a result, longer-horizon approaches typically require frequent updates to manage growing uncertainty as irrigation decisions approach [50].

Managing uncertainty and ensuring decision reliability, therefore, remain recurring concerns. Studies commonly quantify predictive skill using statistical performance metrics [40] [41] [44] and emphasize calibration and site-specific parameter adjustment to maintain accuracy [49] [51]. Additionally, ensemble simulations, continuous model updating, and adaptive thresholding based on anticipated rainfall are frequently employed to mitigate forecast uncertainty [34] [44] [50]. Machine learning approaches also introduce additional challenges. There is a limitation related to model generalization, prompting recommendations for crop- or site-specific retraining under changing conditions [43].

One clear advantage of forecast-driven irrigation systems is their ability to bring together multiple sources of information. Many hybrid decision-support tools do this by combining modeled soil moisture with real-time sensor data, weather forecasts, and crop condition indicators. The goal is to make irrigation scheduling more reliable, even under changing field or climate conditions. Several studies, however, point out that these models do not always account for the effects of irrigation itself. In other words, unless irrigation events are explicitly included in the model, soil moisture estimates may miss key variability introduced by the irrigation process [39] [46].

Despite demonstrated advances, practical limitations remain. Forecast-based irrigation systems are highly sensitive to the quality of meteorological inputs, particularly precipitation forecasts [45] [51]. There is also spatial variability in soil properties, root distribution, and management practices, which complicates model transferability. Infrastructure requirements for data acquisition, processing, and communication add to constrain adoption in resource-limited settings [42]. At the same time, these issues highlight the trade-offs between predictive complexity and operational feasibility [40] [49]. Model-driven systems represent an important pathway to advancing irrigation management toward risk-aware decision-making.

4. Root-Zone Representation and Translation of Soil Moisture for Irrigation Decisions

Effective irrigation management requires more than accurate soil moisture measurement in a system. Understanding how that data is translated into meaningful insights that align with a crop's actual water needs also matters. In most frameworks, the root zone is the key interpretive layer for making this translation. However, there is considerable variation across studies in how that zone is defined, how moisture readings are processed, and what assumptions are built into the logic that drives irrigation actions.

Root-zone representation differs widely. Several studies adopt fixed-depth representations grounded in empirical observations or standard agronomic practice [52] [53], allowing straightforward implementation across fields and crops. Other approaches introduce dynamic root-zone definitions that evolve with crop development. For example, [54] simulated linear root growth from 0.1 to 1.0 m over the growing season, aligning root-zone representation with phenological stages. Still more detailed methods incorporate vertical root density distributions. This treats the root zone as a weighted domain of water uptake, which adds biological realism to decision logic but also increases data demands [55]-[57]. In contrast, fixed-depth models are easier to apply, though less physiologically precise.

Once the root zone is defined, soil moisture becomes actionable by being transformed into variables that reflect crop water status. A dominant approach relies on deficit-based metrics, where soil water depletion relative to field capacity or maximum allowable depletion thresholds triggers irrigation [52] [54]. Other studies rely on stress-oriented indicators. They integrate soil hydraulic properties and plant responses more, which includes the Plant Water Deficit Index (PWDI), the

Soil Water Deficit Index (SWDI), and water stress factors derived from plant-available water [16] [53] [55]-[57]. These indicators go beyond just tracking volumetric moisture. They aim to reflect a crop's sensitivity to water loss, based on both soil and plant behavior. Some frameworks further refine this logic using multi-level decision rules or stage-dependent criteria [54]. These tend to improve timing but often require detailed, site-specific data.

How moisture data is combined across depths also varies. One method is to average moisture values across the root zone, either arithmetically or using depth-weighted averaging. This typically excludes soil layers that the roots have not reached [54] [58] [59]. It aligns well with standard sensor setups and keeps the method simple. Another option is root-weighted aggregation, which emphasizes layers with the most active uptake [55]-[57]. A third approach uses surface soil moisture as a proxy for the whole root zone, especially common with satellite data [16], which provides broader coverage but risks missing important rootzone changes.

Even with all these techniques, every method relies on simplifying assumptions. Many assume uniform soil conditions across depth, whether in water retention [59] or sensor performance [22]. However, in reality, soil variability can be substantial even within a single field. Remote sensing can add further mismatch, since surface reflectance signals do not always reflect what is happening in the soil [16]. Limited data availability also leads to compromises: simulated root growth curves, generalized retention functions, and fixed crop parameters are all common [54] [59]. Even well-calibrated indices like PWDI still depend on assumptions about root structure or crop-stress response factors that are difficult to measure and may not apply to all conditions [55] [57]. In the end, these root-zone representations and moisture translation methods form the foundation of irrigation decision-making. However, for these methods to be useful, they must be embedded in comprehensive decision-support systems that also account for timing, scale, and farmer interaction.

5. Integrated Irrigation Decision-Support Frameworks

The evolution of irrigation decision-support frameworks increasingly reflects a convergence of diverse data streams, including *in-situ* observations, weather stations, remote sensing products, simulation models, and machine learning outputs within adaptive or predictive systems. To inform irrigation decisions, translated representations of soil water status are coupled with complementary information. This section synthesizes how integrated irrigation frameworks combine these heterogeneous inputs and address practical limitations. The studies discussed in this section span conceptual frameworks, prototype systems, and field-implemented tools, reflecting different stages of development and validation.

5.1. Data Integration Architectures in Irrigation Systems

This subsection primarily describes conceptual and prototype-level architectures that define how data streams are structured and integrated within irrigation decision-support systems. A key feature of current irrigation decision-support systems is their ability to combine multiple data streams into unified structures that help users in making informed irrigation decisions. Most frameworks combine soil moisture information from field sensors, remote sensing products (e.g., SMAP, MODIS, Landsat), or the High-Resolution Land Data Assimilation System (HRLDAS). They are combined with meteorological inputs derived from local weather stations or numerical weather prediction products. Together, they establish temporal context and enable anticipatory scheduling. Systems such as WaterSmart-GIS [46] and the decision-support framework developed by [60] offer concrete examples of integrated irrigation platforms. These systems combine soil moisture, meteorological, and crop-specific data into unified decision environments. Beyond direct sensing, many architectures also incorporate soil or crop simulation models. These models rely on real-time or forecasted environmental inputs to estimate soil water movement and crop water requirements [49] [61]-[63]. Their inclusion enables anticipatory irrigation scheduling that responds to both current field conditions and short-term changes in atmospheric demand. Machine-learning-based approaches help extend this integration capacity. They extract irrigation-relevant patterns from historical and real-time data streams to enable prediction of soil moisture or irrigation demand in data-sparse environments [31] [64] [65].

Additional data layers are frequently used to contextualize soil moisture within broader water-balance and crop response frameworks. These include vegetation indices such as Leaf Area Index (LAI), energy-balance indicators, evapotranspiration estimates, and water deficit metrics [46] [61]. Some systems even integrate high-frequency groundwater observations to infer irrigation activity indirectly [66]. Together, these inputs allow integrated frameworks to move beyond static threshold-based decisions. Instead, they support more dynamic representations of water availability and crop demand.

Most systems are also built on a modular foundation. They take in raw environmental data, clean it, and convert it into structured recommendations. Many also include ways for users to adjust parameters or provide feedback, bringing human insight into the decision-making process [60] [67]. This kind of interaction matters for decision-making. It allows farmers' experience and agronomic judgment to guide system behavior, rather than treating the model as a black box. Crop2Cloud [68] and the AI-driven platform developed by [69], for example, utilize cloud computing, IoT networks, fuzzy logic, and deep learning. These frameworks are designed to process multiple types of data automatically with minimal manual input. This shows that soil moisture is no longer used in isolation. Instead, it is part of a larger, evolving system that combines multiple inputs to guide smarter irrigation.

5.2. Decision Logic and Operational Constraints

The systems discussed here represent a combination of prototype implementations, in which decision logic and operational constraints are evaluated at varying levels. In many integrated systems, soil moisture plays a central role in irrigation decision-making. Real-time irrigation scheduling tool (RTIST), HRLDAS-based platforms, and energy-water balance models use either measured or modeled soil moisture as a direct proxy for plant-available water [41] [61] [63]. These values then drive irrigation frequency and volume. Even in machine-learning-based systems, soil moisture is often the main predictor or target variable in forecasting models [68] [70]. How soil moisture data is used varies across systems. Some calculate daily irrigation volumes [62] [63]. Others focus on weekly totals [70] or set irrigation duration for each management unit [71].

In many cases, soil moisture is combined with evapotranspiration or water deficit estimates to determine net irrigation requirements [41] [65]. A growing number of systems also introduce flexible scheduling and adaptive responses. These help systems to adjust when field conditions change, whether due to heat stress or unexpected rainfall [60] [69]. Additionally, not every tool puts soil moisture at the center. In some systems, it is just one of several indicators. For instance, Wei and Xu (2025) [66] use soil moisture along with other hydrological variables to infer irrigation needs. Similarly, [64] used soil water depletion as the main metric and used soil moisture primarily as a supporting measure. These differences show how varied the design philosophies behind these systems can be. Another important factor is how systems handle time. Reactive frameworks respond to present conditions. Predictive tools, on the other hand, incorporate forecast data to anticipate future irrigation needs. Many recent platforms include short-term forecasts for precipitation, temperature, or evapotranspiration. These are used to fine-tune irrigation schedules, especially to avoid overwatering during expected rainfall or heatwaves [41] [62] [69].

For instance, Jamal *et al.* (2023) [63] use three-day probabilistic forecasts to optimize irrigation decisions daily. Madhukumar *et al.* (2024) [65] combine weather projections with transformer-based models to estimate root-zone moisture and support proactive scheduling. However, not all systems rely on forecasts. Some fall back to real-time monitoring when data quality drops or uncertainty is too high [68] [71]. Others mimic agronomist-derived rules using weekly prediction models that require no forecasts at all [70]. Despite these innovations, integrated systems still face real-world constraints. Data quality and spatial resolution remain top concerns. Satellite products provide wide coverage but limited depth resolution [65]. Modeled soil moisture often underestimates conditions in the root zone, especially during irrigation events [46]. Systems like FEST-EWB may require manual calibration to function well [61]. While calibration improves accuracy, it makes scaling more difficult.

There are other limitations with these models, too. Labeling irrigation events in ML datasets is often coarse. Cloud cover can disrupt satellite vegetation indices. Field-scale variability may go undetected by point-based sensors [63] [64] [66]. Some systems still use simplified water balance models. These often skip over important processes such as runoff, lateral flow, and local soil and crop differences [67]. Infrastructure challenges can also limit performance. Systems may suffer from power outages, weak communication signals, or faulty sensor hardware [68]. And then there is the human side, which is something no algorithm fully captures. Farmer behavior, policy constraints, and how irrigation systems are built all affect outcomes. These human factors remain difficult to translate into automated decision rules, even in the most advanced frameworks [67] [71].

5.3. Implementations and System-Level Examples

This subsection focuses primarily on field-validated systems and applied implementations to highlight ongoing developments in irrigation decision-support systems. Over the past few years, researchers have explored how irrigation decision-support systems work in the field across different crops, weather conditions, and management goals. Many of these tools skip dense sensor networks and instead rely on model-based soil water balance methods to estimate what is happening underground. One example is Irrigation-Advisor (IA), developed by [72]. It models soil water dynamics within a 60 cm root-zone and separates evaporation from crop transpiration. The system also pulls in weather forecasts to anticipate when irrigation might be needed. Interestingly, it avoids using crop coefficients or frequent field visits. However, even without on-site sensors, it closely matched farmers' actual irrigation patterns. However, IA still depends on weekly crop growth observations to estimate transpiration, which can be challenging to maintain consistently.

Other Sensor-based or hybrid platform systems fuse real-time soil moisture readings with weather data, water-use logs, and predictive models. DSSPIM, for instance, combines soil moisture sensors, water meters, historical climate data, and short-term forecasts to guide irrigation in horticulture [73]. Reported results showed water savings of up to 20%. The Smart & Green framework [74] goes even further. It links IoT devices to preprocessing routines and machine-learning models that predict soil moisture or matric potential based on weather, crop conditions, and irrigation input. This setup works well even in areas with limited sensor infrastructure. Still, both DSSPIM and Smart & Green face a familiar issue: the quality of the decision depends on the quality of the input data. Errors can creep in, and uncertainty spreads quickly when combining different sources.

In perennial cropping systems such as vineyards and orchards, soil moisture often informs stress-based or deficit-oriented irrigation rules. King and Shellie (2023) [75] built an IoT system for wine grapes that integrates soil moisture, canopy temperature, weather conditions, and past irrigation data. The tool calculates a Crop Water Stress Index and triggers irrigation based on how the plant is responding, not just how dry the soil appears. Similarly, [76] used artificial neural networks to predict weekly soil moisture, helping vineyards implement regulated deficit irrigation. However, in both cases, system performance dipped under heavy rainfall. This shows that smart systems can have limitations.

Ease of use is also becoming more important for irrigation-based decision support systems. The idCROP tool [77] embeds soil water dynamics into a simulation engine. It connects DSSAT outputs with both real-time and forecasted weather to create irrigation schedules and economic projections. The system does most of the work in the background, requiring little user input. [78] followed a similar path. They built a simplified irrigation support tool for olive orchards that uses reference evapotranspiration and soil moisture from capacitive sensors. The reported result showed an 11% reduction in irrigation without yield loss.

More recent tools increasingly use AI not just for predictions but also for reasoning. For example, [79] blends soil sensors, weather APIs, retrieval-augmented generation, and autonomous logic to give field-specific advice tailored to each farm. Others, such as IrrigaSys [80] and earlier fuzzy-logic systems [81], mix water balance models with forecasts and NDVI satellite products. These platforms offer digital recommendations, but there are deviations between recommended and actual farmer actions. That gap shows that real-world decisions depend on more than just data, behavior, and infrastructure. A more adaptive approach was proposed by [82]. Their framework uses machine learning to translate diverse data streams into irrigation timing decisions. However, they admit that turning all that information into a single clear decision path remains a tough challenge. This implies that no single model or dataset is enough on its own [83]. What works best are systems that combine soil moisture with other inputs, whether it is human insight, process models, or both, which ensures real robustness.

6. Discussion

6.1. Data Integration and Decision Making

The literature synthesized in Sections 3-5 demonstrates a clear trend. A lack of environmental data no longer constrains contemporary irrigation management. *In-situ* sensors, satellite products, weather forecasts, and simulation models are now widely available and increasingly integrated within irrigation decision-support systems. However, despite this expansion in data availability and system complexity, irrigation decisions remain highly sensitive to uncertainty and context. This marks a shift in the nature of the problem. The central challenge is not acquiring data, but ensuring stability and reliability in the decision logic itself.

As irrigation frameworks incorporate more heterogeneous inputs, uncertainty accumulates across the decision chain. Measurement error, temporal mismatch, spatial aggregation, and forecast uncertainty do not operate independently. They interact and propagate through translation and decision rules. As a result, increased data does not necessarily yield more robust irrigation recommendations. This pattern is reflected in the reviewed studies. For example, a simplified irrigation advisory tool produced farmers' irrigation strategies using limited inputs while still achieving water savings [72]. Similarly, a highly integrated decision-support system was shown to closely match crop water requirements and observed farmer practices [73]. Yet differences persisted when factors such as crop management decisions or field-specific conditions were not fully captured within the system.

In another case, irrigation outcomes were found to depend strongly on how soil moisture data were processed before use [74]. This also highlights how even differences in data handling can influence irrigation decisions. When considered within integrated systems, this sensitivity becomes more pronounced.

Rather than resolving uncertainties, richer information ecosystems expose the assumptions embedded within root-zone representation, aggregation strategies, and threshold selection. This helps explain why, even in highly instrumented systems, irrigation decisions often remain conservative or partially reactive.

One key insight stands out from this synthesis. The reliability of irrigation decisions depends less on the accuracy of soil moisture observations but more on how those observations are interpreted within the root zone. As discussed in Section 4, the root zone is not a fixed or universally defined construct. It is a design choice shaped by operational goals, data availability, and agronomic assumptions. Fixed-depth profiles, dynamically evolving root zones, and root-weighted aggregation schemes are all distinct interpretations of how crops access water.

These choices directly influence estimates of water stress, depletion, and irrigation timing. Two systems could use the same soil moisture inputs yet recommend different irrigation actions. This is simply because they adopt different methods. In this sense, divergence in irrigation outcomes across frameworks does not necessarily indicate disagreement in soil moisture measurement, but rather reflects differences in how soil moisture is operationalized as a decision variable. This translation layer, therefore, represents a structural source of decision fragility, summarized in **Table 1**.

Table 1. Translation stages where uncertainty propagates into irrigation decisions.

Translation Stage	Dominant Assumption	Implementation	Sources of Uncertainty	Potential Impact on Irrigation Decisions
Root-zone definition	Root depth adequately represents crop water uptake	Static depth thresholds; stage-based rooting depth estimates	Variation in rooting depth across crops, soils, and growth phases	Misrepresentation of available water leading to premature or delayed irrigation
Vertical aggregation	Moisture across depths can be combined into a single representative state	Depth-weighted averaging; root-weighted aggregation	Non-uniform moisture profiles; sensor placement variability	Underestimation or overestimation of soil water storage
Indicator construction	Selected metric captures crop water stress reliably	Depletion thresholds; stress indices; plant-available water thresholds	Dependence on soil hydraulic parameters and crop sensitivity assumptions	Inconsistent stress detection across sites or seasons
Threshold selection	Fixed or stage-based thresholds generalize across conditions	Maximum allowable depletion; stage-dependent trigger levels	Sensitivity to soil texture, climate, and management practices	Results in inefficient irrigation timing or excessive conservation
Temporal factor	Present or forecasted moisture aligns with crop demand windows	Real-time monitoring; short-term forecast integration	Forecast uncertainty; timing mismatch between observation and uptake	Increases the risk of missing peak stress periods or unnecessary watering
Spatial generalization	Single-point or surface data represent field-scale behavior	Point-based sensors; satellite soil moisture proxies	Spatial heterogeneity; scaling mismatch	Inefficient irrigation distribution across heterogeneous fields

6.2. Reactive, Predictive, and Hybrid Decision Frameworks

The move from reactive to predictive irrigation systems, as shown in Table 2, reflects not just improved technology, but also evolving strategies for managing risk. Reactive tools that rely on real-time soil moisture data are still common. This does not mean they are outdated; rather, it means they are dependable. When forecasts fail, or data are missing, reactive systems still offer something farmers can trust: a direct response to actual field conditions.

Predictive frameworks offer something different. They enable scheduling irrigation in advance, reducing water waste and improving overall efficiency. However, their success depends heavily on the accuracy of the forecasts and the calibration of the models. As the forecast horizon increases, uncertainty increases. This is where predictive systems often lose traction simply because they need constant updates to stay useful. Hybrid systems have therefore emerged as a practical compromise. They combine real-time measurements with short-term forecasts and flexible rules. They do not rely on just one approach and are often more resilient as a result.

Irrigation decision-support performance also varies across crop types and operational contexts. Systems applied to annual and vegetable crops tend to effectively reproduce irrigation strategies across short growth cycles. However, deviations still occur when certain management practices are not captured [72] [73]. In contrast, perennial systems such as vineyards and olive orchards rely more on adaptive or stress-based decision logic. They provide stable control over longer periods but often require specific calibration and greater system complexity [75] [76] [78]. Differences in irrigation scheduling approaches, including deficit, full, or model-based strategies, further influence how soil moisture information is translated into decisions [73] [80].

Table 2. Conceptual trade-offs among irrigation decision-support frameworks.

Decision Frameworks	Primary Data Dependence	Decision Strength	Key Vulnerability	Typical Use Context
Reactive (sensor-driven)	Direct *in-situ* soil moisture measurements	Transparent decision logic	Limited foresight; does not scale easily across variable soils	Small to medium fields; high-value crops
Predictive (model-driven)	Weather forecasts and simulated or predicted soil moisture	Enables proactive irrigation scheduling; enhances efficiency	Dependent on forecast skill and model calibration	Strategic irrigation planning
Hybrid (sensor + forecast)	Combination of field sensors and forecast data	Offers adaptive flexibility; balances real-time response with forward planning	Requires careful integration; system complexity increases	Operational farm-scale systems under variable climate conditions
Spatially informed (remote sensing)	Satellite-derived vegetation indices or soil moisture proxies	Supports field prioritization and spatial irrigation zoning	Limited temporal resolution; root-zone signal often indirect	Regional-scale irrigation planning or large heterogeneous fields

Performance also varies across irrigation methods. For example, in the study by [84], greater efficiency gains are typically observed in drip systems due to precise control of water application, while sprinkler systems show more moderate improvements. Surface systems exhibit higher variability due to physical constraints, such as infiltration and water-advance time. Overall, these findings indicate that irrigation decision-support systems cannot be evaluated independently of their agronomic or operational context. The performance also depends on the interaction between crop characteristics and irrigation strategy.

Across the studies reviewed, it is clear that what matters most is not perfect soil moisture estimation. What matters is decision logic that works reliably, is understandable, and even holds up when conditions change. Soil moisture must be treated not merely as a measured variable, but as a decision state. This state should be shaped by root-zone interpretation, temporal context, and acceptable risk. Frameworks that explicitly acknowledge uncertainty, accommodate spatial and temporal variability, and link irrigation actions to sufficiency rather than precision are likely to be more reliable in practice.

This perspective also underscores the importance of transparency and interpretability. As these tools become more automated and data-heavy, the choices they make, like how to combine different layers of data or set thresholds, need to be visible. Systems that allow these assumptions to be adjusted or examined by agronomic judgment are likely to achieve greater user trust and adoption. Additionally, the reviewed literature indicates that diverse soil moisture estimation and modeling approaches should be viewed as complementary rather than competing. Each approach provides distinct strengths in spatial coverage, temporal resolution, or predictive capability. The effectiveness of future systems would not depend on only data integration. It is turning their outputs into clear, usable guidance for irrigation.

Emerging work further reinforces the need to consider how uncertainty and user interaction are handled within decision logic. Adaptive control-based systems that incorporate both predictive modeling and human intervention demonstrate this claim. Embedding user preferences with the decision loop can enhance the practicality of irrigation recommendations [60]. At the same time, uncertainty in data reliability and model outputs remains a critical barrier to adoption. Decision-makers must interpret irrigation guidance in light of varying levels of risk associated with digital tools [85]. Broader assessments of precision irrigation systems further show that model uncertainty, data limitations, and user participation jointly influence the performance of decision-support frameworks [86].

Field-based evaluations also indicate that stakeholder involvement can significantly shape irrigation outcomes. This reinforced the continued role of human judgment alongside automated recommendations [84]. Together, these findings highlight that decision support systems must move beyond purely data-driven optimization. Frameworks must explicitly account for uncertainty, maintain interpretability, and support user engagement in decision-making.

7. Conclusions

This review synthesized recent advances in soil moisture-based irrigation decision-support systems. It spans *in-situ* sensing, remote sensing, and both model- and forecast-driven approaches. Beyond tracking technical progress, the review emphasizes a critical shift: future systems must focus on how environmental information is translated into decisions farmers can act on. As more data streams feed into irrigation frameworks, transparency becomes vital. Farmers need to understand how soil moisture is aggregated with crop water demand and how that combination translates into actionable guidance. Without this, trust and usability may decline.

The reviewed studies show a wide range of strategies: reactive, predictive, and hybrid systems, each tailored to specific constraints and uncertainty levels. Forecast-based tools add anticipatory power but also inject uncertainty. That tradeoff must be acknowledged and addressed. Decision-support systems should move toward adaptive, uncertainty-aware logic. They should go beyond simply offering data; they must interpret irrigation sufficiency and risk. Importantly, system success cannot be measured solely by accuracy. Future evaluations must consider decision outcomes and user interaction. In summary, progress in irrigation management depends on flexibility and clarity, not allegiance to a single technology. This review argues for a new framing: soil moisture is not just a metric. It is a decision state.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this research paper.

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