

Review

Soil Moisture Prediction: A Review of Models, Principles, Applications and Future Needs

Duncan Kikoyo ^{1,*} , John Zhang ², Ann-Marie Fortuna ² , Patricia K. Smith ¹ , Sherry Hunt ², Paul Flanagan ² , Phillip Busted ² and Jaehak Jeong ³ 

¹ Department of Biological & Agricultural Engineering, Texas A&M University, College Station, TX 77843, USA; patricia.smith@ag.tamu.edu

² USDA-ARS Agroclimate & Hydraulic Engineering Research Unit, EL Reno, OK 73036, USA; john.zhang@usda.gov (J.Z.); ann-marie.fortuna@usda.gov (A.-M.F.); sherry.hunt@usda.gov (S.H.); paul.flanagan2@usda.gov (P.F.); phil.busted@usda.gov (P.B.)

³ Texas A&M AgriLife Research, Temple, TX 76502, USA; jaehak.jeong@brc.tamus.edu

* Correspondence: kikoyo@tamu.edu

Abstract

Soil moisture is a fundamental variable controlling hydrologic partitioning, land–atmosphere exchange, and biogeochemical cycling. Although widely characterized through observations, remote sensing, and data-driven approaches, the representation of soil water fluxes and subsurface processes in predictive models remains less systematically synthesized. Here, we present a structured review of widely used predictive models, focusing on their process formulations, spatial discretization, and treatment of soil water fluxes across scales. The synthesis reveals consistent trade-offs among physical realism, scalability, data intensity, and computational efficiency. Conceptual models based on tipping-bucket approaches simplify soil water movement as threshold-driven storage processes and underrepresent transient redistribution and deep soil moisture dynamics. Storage-routing models introduce flux-based redistribution but rely on empirical parameterization that dampen transient flux dynamics. Physically based models resolve hydraulic gradients and provide the highest process fidelity but require extensive data and computational resources. Across scales, the absence or simplification of preferential flow and lateral subsurface flow constitutes the dominant structural limitation, producing systematic smoothing of soil moisture variability. The review provides a comparative basis for model selection and highlights critical directions for improving the representation of subsurface hydrologic dynamics in predictive frameworks.

Keywords: soil moisture; predictive models; soil water fluxes; model evaluation



Academic Editor: Joaquim Esteves
Da Silva

Received: 29 June 2026

Revised: 26 July 2026

Accepted: 2 August 2026

Published: 5 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Soil moisture, the water stored within soil pore spaces, is a fundamental component of the terrestrial water cycle and a critical driver of ecological and biogeochemical processes. Hydrologically, it governs infiltration, runoff generation, and groundwater re-charge, while constraining evapotranspiration and influencing surface energy balance [1,2]. Through these interactions, soil moisture exerts strong control on climate feedback and ecosystem functioning. Soil water deficits or excesses influence plant water availability and crop productivity, making soil moisture a critical factor in agricultural resilience and global food security [3,4]. In addition, it regulates subsurface heat transfer and solute transport, thereby affecting contaminant mobility and other environmental processes [5]. Consequently,

robust characterization and prediction of soil moisture dynamics are indispensable for advancing hydrology, soil science, agronomy, and environmental management.

A range of approaches exist for estimating soil water content, including direct measurements, in situ sensor-based techniques, geophysical methods, remote sensing methods, predictive models, and data-driven machine learning. Direct measurements offer high accuracy yet lack spatial representativeness and scalability [6–11], while sensor-based observations, though continuous, remain affected by calibration requirements, soil heterogeneity, and site-specific variability [12]. Geophysical methods provide non-invasive spatial characterization of soil moisture variability but remain dependent on site-specific calibration and interpretation of indirect geophysical signals [13,14]. Remote sensing extends spatial coverage but is constrained by vegetation interference, surface roughness, atmospheric effects, and shallow sensing depth [2,4,15–17]. Collectively, these approaches quantify soil moisture conditions but provide limited insight into the internal redistribution of water within the soil profile and cannot resolve the subsurface fluxes that govern its dynamics. These limitations highlight the importance of predictive modeling approaches, which provide a framework to generalize across conditions, fill observational gaps, and integrate process understanding across scales. However, most predictive models have historically been developed to reproduce surface responses, particularly runoff generation. Consequently, many widely applied models are parameterized for surface processes, and rely on simplified or implicit assumptions and representations that inadequately resolve subsurface water redistribution. This challenge is compounded by the fragmented evolution of modeling approaches across hydrological, agricultural, and land surface disciplines. Machine learning methods have also emerged as alternatives to process-based models, with growing hybrid applications that combine the strengths of both approaches, particularly where data limitations or complex interactions challenge traditional approaches [18,19]. While these techniques can flexibly capture relationships without explicit physical representation, their predictive reliability is highly dependent on large, well-distributed training datasets and deteriorates under data scarcity or extrapolation [18]. Moreover, their predominantly black-box structure limits interpretability, constraining process understanding and scientific transferability [18,19].

Despite the central role of subsurface fluxes in determining soil moisture dynamics and advances in predictive modeling, systematic evaluation of predictive models in this context remains limited. Existing reviews of predictive models primarily focus on runoff, erosion, and nutrient transport, whereas reviews on soil water estimation methods have largely emphasized observational and estimation methods [8,11–13,16,20], remote sensing techniques [3,4,15,18], and machine learning applications [18,19,21]. As a result, the adequacy, consistency, and scalability of current approaches for representing soil water dynamics remain insufficiently resolved.

This study addresses the previously described gap by providing a structured synthesis of widely used predictive models for soil moisture and soil water flux simulation. In contrast to prior reviews, this synthesis examines modeling frameworks across hydrological, agricultural, and land surface domains, evaluating their representation of subsurface processes, spatial organization, computational structure, and data requirements. Through this comparative analysis, we identify key trade-offs governing model performance and applicability, establish a basis for consistent model comparison, and assess their capacity to represent the fluxes that control soil moisture dynamics. The synthesis provides a unifying perspective on existing modeling approaches, highlights persistent limitations in representing subsurface heterogeneity and process coupling, and outlines priorities for advancing predictive frameworks of soil water dynamics.

2. Selected Soil Water Predictive Models

A wide range of models exist for predicting soil water content and can be systematically categorized according to their representation of physical processes, treatment of spatial variability and scale of application [22–24]. From a process perspective, models span a continuum from conceptual formulations that approximate fluxes using empirical storage transfer relationships to physically based approaches that resolve water movement as a continuous function of soil hydraulic properties. In terms of spatial representation, models range from lumped to semi-distributed and fully distributed frameworks, increasingly resolving heterogeneity at the cost of greater data and computational demands. Lumped models treat the entire domain as a single homogeneous unit, simplifying structure and reducing data requirements but limiting representation of local processes. Distributed models discretize the domain into grid cells or elements with distinct properties, enabling detailed simulations but requiring high-resolution input data and substantial computational resources. Semi-distributed models partition the domain into subareas with similar characteristics, providing a practical balance between complexity and computational efficiency, though some fine-scale variability is lost. As applications extend from field to watershed and regional scales, simplifications in process representation are often introduced to maintain tractability, which can reduce simulation fidelity. These classifications are not mutually exclusive, and substantial overlap exists among categories, particularly in newer model versions that increasingly incorporate hybrid formulations to address identified limitations and to better meet emerging application and research needs. For consistency, models are classified according to their original theoretical foundations and intended scale of application as described in the foundational literature and model documentation, rather than subsequent modifications or expanded applications.

Accordingly, commonly applied soil water models used in hydrological and agricultural research (Figure 1) discussed hereafter are organized by their primary scale of application (field, watershed, and regional). Within each scale category, models are evaluated based on their representation of physical processes and treatment of spatial variability. Each model is examined with respect to its theoretical foundation, soil moisture prediction methodology, input data requirements, and output data. In addition, model performance is assessed through a discussion of reported predictive accuracy and inherent limitations, providing a comparative perspective to support informed model selection across diverse applications. This synthesis draws upon peer-reviewed literature documenting model development, theoretical underpinnings, evaluation, and application across a wide range of spatial scales, environmental conditions, and research and management contexts.

2.1. Field-Scale Models

2.1.1. APEX (Agricultural Policy/Environmental eXtender) Model Description

APEX is a process-based conceptual modeling framework designed to evaluate the impacts of agricultural management practices on soil, water, and environmental quality at field to watershed scales [25,26]. It integrates hydrology, crop growth, nutrient cycling, and management operations within a flexible framework, making it suitable for scenario analysis and decision support in agricultural systems. The model typically operates on a daily time step, aggregating outputs to monthly or annual scales, and is primarily employed to evaluate water balance components, nutrient transport pathways, and crop productivity under diverse management regimes and climatic variability. Model implementation is supported through multiple interfaces, including native ASCII text-based configuration files, a Windows-based graphical user interface, and Excel-driven editors. Furthermore, APEX is

frequently integrated into GIS-based platforms, which facilitate spatial parameterization, routing, and visualization of hydrologic and pollutant fluxes [25,27,28].

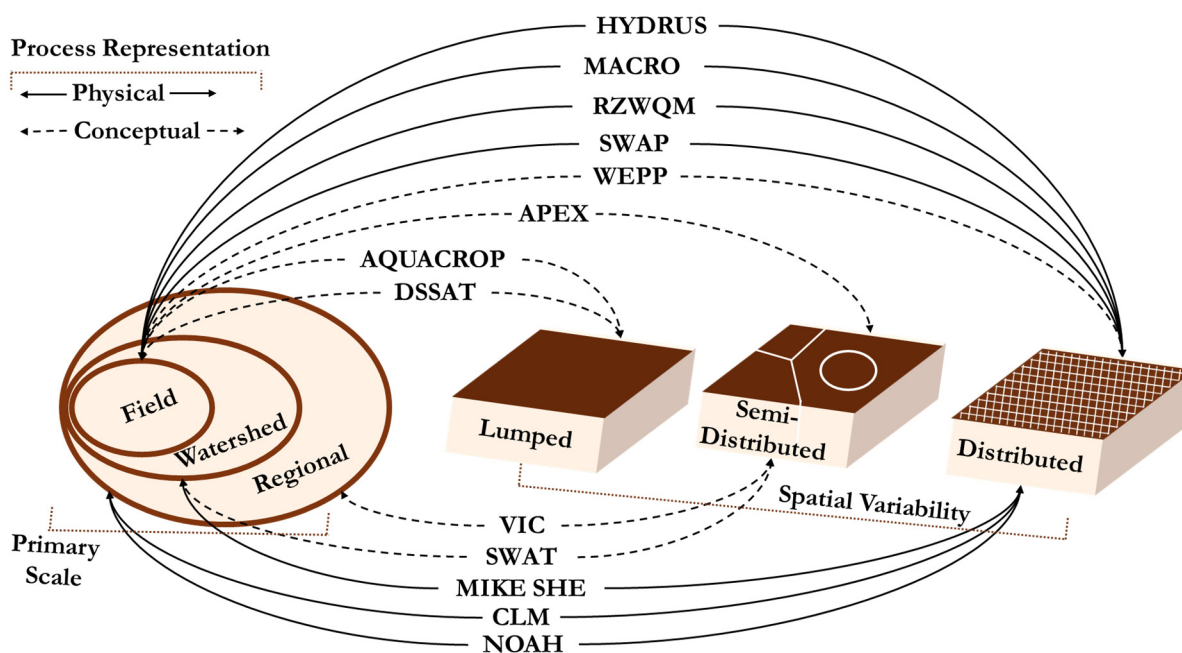


Figure 1. Classification of models by their soil water content simulation approach. The figure maps common soil water models by process representation (conceptual–physical), spatial structure (lumped, semi-distributed, distributed), and primary scale of application (field, watershed, regional). Solid arrows denote physically based models, and dotted arrows denote conceptual models. Arrows place each model within their spatial discretization and scale of application categories.

Soil Moisture Content Prediction

APEX predicts soil moisture content as part of the daily subarea water balance using a layered storage-routing formulation combined with empirical algorithms. Precipitation and irrigation inputs are partitioned into surface runoff and infiltration based on methods such as the SCS Curve Number or Green–Ampt approach [28]. Infiltrated water is routed through a multi-layer soil profile, where redistribution occurs according to soil hydraulic properties and evapotranspiration demand. Downward percolation takes place when the water content of a layer exceeds its field capacity. Lateral subsurface flow is simulated when excess soil water coincides with sloping terrain; this process is represented conceptually through an empirical relationship incorporating soil water surplus, lateral hydraulic conductivity, and slope gradient, with gravity-driven flow routed to adjacent subareas or channels [29]. Plant water uptake is allocated across layers according to root depth and density, while evapotranspiration is computed using approaches such as Penman–Monteith or Priestley–Taylor [25,29]. The change in soil water storage for each layer is calculated as infiltrated water minus losses from evapotranspiration, percolation, lateral flow, and plant uptake.

The model requires climate data (e.g., precipitation, temperature, solar radiation), soil properties (e.g., texture, hydraulic conductivity, porosity, field capacity), crop parameters (e.g., rooting depth, growth stages), and management practices (e.g., tillage, irrigation, fertilization). Initial conditions specify soil moisture in each layer. Outputs include soil moisture content by layer, infiltration and percolation rates, lateral subsurface flow, surface runoff, and evapotranspiration components.

Predictive Accuracy and Limitations

Although APEX is widely applied for simulating runoff, soil erosion, and nutrient transport, its application for soil moisture modeling remains limited. Available field-scale applications have shown good agreement with observed soil moisture after calibration of hydraulic properties [25,30,31]. Enhancements such as integrating a Richards-based solver have improved representation of unsaturated flow and root-zone redistribution [32]. However, like other models that rely on simplified empirical formulations for soil water fluxes, APEX may underperform under complex hydrological conditions involving preferential flow that form in swelling/cracking soils or highly heterogeneous soils. Overall, while current evidence is insufficient to confirm its robustness for soil moisture prediction at field and watershed scales, existing studies suggest APEX can reliably simulate other water balance components. Further research is needed to validate its performance for soil moisture modeling.

2.1.2. AquaCrop

Description

Developed by FAO's Land and Water Division, AquaCrop is a process-based crop model simulating yield response to water availability in herbaceous crops under varying soil, climate, and management scenarios [33–35]. It prioritizes water biomass relationships and balances simplicity, robustness, and accuracy by using a limited set of intuitive parameters [36,37]. Its principal spatial scale is the field level, although it can be extended to farm or regional scales through aggregation. Operating on a daily time step, the model integrates soil–water dynamics, crop phenology, canopy cover, and evapotranspiration within a multi-layer soil profile. AquaCrop is widely used for irrigation planning, drought impact assessment, and water productivity analysis in both research and practical applications. The model features a Windows-based graphical user interface (GUI) and is compatible with GIS-based spatial modules [36,37].

Soil Moisture Content Prediction

AquaCrop partitions precipitation and irrigation into infiltration, runoff, and deep percolation using simple soil hydraulic thresholds. The model predicts soil moisture using a tipping bucket approach, where water infiltrates into successive soil layers until storage capacity is reached, after which excess water percolates downward or contributes to drainage. It tracks daily soil moisture across multiple root-zone layers, maintaining a continuous water balance [33,37]. Evapotranspiration is calculated using the FAO Penman–Monteith method, adjusted by canopy cover and crop coefficients. Vertical fluxes, including percolation and capillary rise, and root-zone uptake are dynamically simulated. The model requires inputs such as daily weather, soil characteristics, and crop descriptors (e.g., rooting depth, canopy growth stages). Model outputs include daily soil water content by layer, infiltration and percolation rates, surface runoff, evapotranspiration components, crop water-stress indicators, water balance summaries, biomass accumulation, and yield predictions [33,34,38].

Predictive Accuracy and Limitations

Validation evidence indicates that AquaCrop can capture daily and seasonal soil moisture dynamics at both field and regional scales, with strong agreement in standard irrigation settings [38,39]. Performance declines under more complex hydro-pedological stressors. Deeper-profile SWC under moderate-to-severe deficit irrigation are less accurately simulated, consistent with sensitivities to root distribution and the model's simplified representation of preferential flow [40]. The model's main strength lies in its simplicity

and robustness. However, it simplifies several soil water flux processes, which can limit accuracy in complex conditions. It assumes uniform root distribution and does not model preferential flow or lateral subsurface movement, making deep soil moisture less reliable.

2.1.3. DSSAT (Decision Support System for Agrotechnology Transfer)

Description

DSSAT is a widely used, process-based modeling framework designed to simulate crop growth, soil water balance, and nutrient dynamics under varying management and environmental conditions. DSSAT integrates multiple crop models with soil and weather modules to evaluate agricultural productivity and resource use efficiency, and incorporates utilities for data management, economic evaluation, and uncertainty analysis [41]. It is primarily applied at the field scale, though it can be extended to watershed or regional scales through aggregation. Temporal resolution is typically daily, with simulations spanning from a single growing season to multiple decades for climate impact assessments. DSSAT is extensively applied in research and decision support, with interoperability through GIS platforms and external systems for spatial analysis.

Soil Moisture Content Prediction

DSSAT predicts soil moisture dynamics using a tipping bucket approach, a conceptual method that represents the soil profile as a series of discrete layers, each with a defined water-holding capacity. Water enters the system through precipitation or irrigation and infiltrates into the uppermost layer after accounting for surface runoff. Within each layer, soil water content is updated daily based on infiltration, evaporation, transpiration, and drainage. When the water content of a layer exceeds its field capacity, the surplus is assumed to drain instantaneously to the next layer or out of the profile, mimicking the behavior of a “bucket” tipping over when full. Plant water uptake is distributed across layers according to root depth and water availability, while evapotranspiration is computed using physically based methods such as Penman–Monteith or Priestley–Taylor. This approach simplifies unsaturated water flow by assuming that excess water moves rapidly between soil layers once field capacity is exceeded, rather than simulating gradual movement driven by matric potential gradients. As a result, it is computationally efficient and well suited for water balance assessments; however, it is less suitable for applications requiring detailed representation of preferential flow, macropore transport, or rapid water redistribution in heterogeneous soils. DSSAT requires comprehensive input data including daily weather variables (precipitation, temperature, solar radiation), soil profile properties (texture, depth, water retention, hydraulic conductivity), crop parameters (growth stages, rooting depth, water use efficiency), and management practices (planting dates, irrigation schedules, fertilization). Initial soil moisture and nutrient conditions must also be specified [41,42]. DSSAT provides outputs such as daily soil water content by layer, infiltration and percolation rates, surface runoff, and evapotranspiration components. Additional outputs include crop water stress indicators, water balance summaries, and yield predictions [41].

Predictive Accuracy and Limitations

DSSAT has demonstrated robust performance in simulating soil moisture and crop growth when properly parameterized. Field-scale studies report good agreement between simulated and observed soil moisture, particularly in the root zone. Integration of satellite-derived soil moisture products further enhances DSSAT’s predictive capability for root-zone moisture, improving its utility. Despite these strengths, DSSAT’s reliance on the tipping bucket approach introduces limitations. The method cannot represent gradual unsaturated flow or preferential pathways, which may reduce accuracy under complex hydrological conditions. Additionally, the model requires detailed soil hydraulic properties and crop

genotype-specific parameters for calibration, which can be resource-intensive. While computationally efficient, the conceptual approach sacrifices physical realism. Nevertheless, DSSAT remains a robust and widely adopted tool for simulating water balance and crop productivity, particularly when combined with calibration and data assimilation techniques.

2.1.4. HYDRUS

Description

HYDRUS is a physically based modeling framework designed to simulate water, heat, and solute transport in variably saturated soils [43,44]. It numerically solves Richards' equation using the finite element method and supports one-, two-, and three-dimensional domains [45]. A Windows-based graphical user interface enables intuitive specification of soil horizons, root uptake patterns, and boundary conditions, as well as mesh generation and visualization. The platform also provides access to soil hydraulic property catalogs and pedotransfer functions [46,47]. HYDRUS has been applied across a wide range of spatial and temporal scales, from laboratory experiments to field studies, with simulation periods ranging from minutes to millennia.

Soil Moisture Content Prediction

Soil moisture prediction in HYDRUS is achieved through the solution of the Richards equation using a finite element approach. The model accounts for infiltration, redistribution, and drainage within the soil profile, as well as evapotranspiration partitioned into soil evaporation and plant transpiration [43,46]. Root water uptake is simulated using stress response functions such as those proposed by Feddes or van Genuchten, which consider both water availability and salinity effects [45,47]. Soil hydraulic properties are parameterized using functions such as the van Genuchten–Mualem model, which describe water retention and hydraulic conductivity as continuous functions of matric potential [45]. To accomplish this, HYDRUS requires detailed input data describing soil hydraulic properties, initial and boundary conditions, root water uptake parameters, and domain geometry. Soil hydraulic properties include water retention and hydraulic conductivity functions. Initial conditions specify soil moisture or pressure head profiles, while boundary conditions encompass atmospheric fluxes, constant head or flux boundaries, and root distribution. Domain geometry and discretization define soil profile depth, layering, and mesh resolution for finite element calculations. These requirements are common to all physically based models derived from Richards' equation. HYDRUS produces high-resolution outputs, including volumetric water content profiles, pressure head distributions, vertical and lateral fluxes, evapotranspiration components, root zone water stress indicators, and cumulative water balance summaries [46,47].

Predictive Accuracy and Limitations

HYDRUS is widely regarded as one of the most accurate tools for simulating soil moisture dynamics because it employs physically based equations rather than empirical approximations. Numerous studies have demonstrated its robust performance in representing unsaturated flow and root-zone processes under a wide range of soil, crop, and climatic conditions [47]. However, the model requires extensive input data and careful parameterization, which can be challenging in data-scarce environments. Computational demands increase substantially for two- and three-dimensional simulations, and preferential flow processes are not inherently represented unless dual-porosity or dual-permeability options are activated. HYDRUS is most effective at plot and field scales, with limited feasibility for watershed or regional applications due to complexity and computational cost [46].

2.1.5. MACRO

Description

MACRO is a physically based, one-dimensional dual-permeability model developed to simulate water flow and solute transport in structured porous soils [48–50]. The model conceptualizes the soil pore space as two interacting domains: a matrix (micropore) domain (low conductivity–high porosity) and a macropore domain (high-conductivity–low porosity). In the micropore domain, water movement is governed by Richards’ equation. The macropore domain represents gravity-driven preferential flow, represented by the kinematic wave equation [50]. Mass exchange between the domains is approximated by first-order expressions [48]. At each model time step, vertical water and solute transport is first resolved within the soil matrix. The resulting updates to soil water storage are then used to identify excess water available for transfer to the macropore domain. Subsequently, macropore flow is computed, and corresponding solute concentrations are determined using a numerical elimination scheme. MACRO can simulate coupled unsaturated–saturated flow, perched water tables, and drainage to tile systems. Its dual-domain framework is particularly suited for analyzing soil moisture dynamics at event-to-seasonal scales, and spatially, at field scale. The latest version is distributed in both command-line and packaged formats, accompanied by programming tools for batch data processing and visualization.

Soil Moisture Content Prediction

The water balance in MACRO is resolved by simultaneously computing fluxes in the micropore and macropore domains and their interactions [49,50]. Precipitation and irrigation are prescribed as surface fluxes at hourly or daily resolution, with daily totals redistributed using a user-defined application intensity and optional solute concentrations. Water infiltration at the upper boundary is partitioned between matrix and macropore domains to prevent matrix oversaturation while allowing preferential flow. Soil moisture dynamics are simulated for a vertically discretized soil profile, with water contents computed independently for each soil layer in both pore domains based on layer-specific hydraulic properties and interdomain exchange. Free drainage is imposed at the lower boundary as a vertical flux under a unit hydraulic gradient. Atmospheric demand is represented by daily potential evaporation, and root water uptake is simulated using an empirical scheme in which plant demand is preferentially met from macropore storage, with any remaining demand supplied by the soil matrix. Practical applications typically require input datasets comprising of precipitation, temperature, radiation, potential evapotranspiration data, soil hydraulic, and structural parameters for both domains, crop development data such as rooting depth, and management practices. Common outputs include daily or sub-daily volumetric water content profiles, perched water table depth, drain flow hydrographs that reveal preferential flow events, and water balance summaries detailing infiltration, percolation, macropore versus matrix partitioning, and evapotranspiration.

Predictive Accuracy and Limitations

Field evaluations demonstrate that the MACRO dual-permeability model simulates layer-resolved soil moisture dynamics with generally good skill in structured soils, particularly during infiltration events that activate preferential flow. Comparisons between predicted and observed volumetric water contents across soil layers typically report moderate to strong correlations [48–50]. Predictive agreement is generally highest in near-surface soil layers and during wet periods when macropore flow dominates [48]. MACRO’s performance is constrained by parameter uncertainty and structural simplifications. Predictive skill is sensitive to soil hydraulic and macropore parameters, many of which are not directly measurable, often necessitating site-specific calibration and high-resolution flux observa-

tions. Model accuracy typically declines under dry conditions or in weakly structured soils where preferential pathways are less active. In addition, MACRO's one-dimensional vertical formulation neglects lateral water redistribution, limiting its applicability in heterogeneous landscapes, while numerical demands associated with explicit matrix flow solutions further restrict computational efficiency and flexibility.

2.1.6. WEPP (Water Erosion Prediction Project)

Description

The WEPP model is a process-based, continuous simulation model developed to predict soil erosion and sediment transport under diverse land management and climatic conditions [51,52]. It integrates hydrology, plant growth, residue decomposition, and erosion processes within a spatially distributed framework, making it suitable for field to watershed-scale applications. The model operates on a daily time step, simulating infiltration, runoff, soil detachment, and sediment delivery. The model is widely used for soil erosion and hydrological studies, including watershed management and sediment yield estimation. Recent research has confirmed its accuracy for runoff, sediment, and nutrient predictions across diverse land uses (e.g., [53–56]). Model implementation is supported through multiple interfaces, including command-line tools, a Windows-based graphical user interface, GIS, and web-based platforms [57].

Soil Moisture Content Prediction

The WEPP water balance component is, in principle, like the water balance component in the APEX model. Precipitation and irrigation inputs are partitioned into infiltration and surface runoff using the Green–Ampt infiltration equation, which accounts for soil hydraulic conductivity, suction head, and initial water content [52,58]. The model simulates soil water dynamics within its daily water balance framework using a multi-layer soil profile and a storage-routing approach. The water balance module maintains a continuous accounting of root-zone moisture, incorporating vertical redistribution through the Ritchie evapotranspiration algorithm [59] and percolation between layers via a storage-routing method [60]. The model computes root-zone soil water content and evapotranspiration losses by integrating climate, infiltration fluxes, and crop-growth state variables. Inputs typically include precipitation/temperature/radiation, infiltrated water volumes, and vegetation/residue descriptors such as leaf area index, rooting depth, and surface cover. Outputs include daily soil water content per layer, infiltration and percolation rates, surface runoff, and evapotranspiration components. Additional outputs include sediment yield, erosion rates, and water balance summaries [52,61].

Predictive Accuracy and Limitations

Although WEPP has been widely developed and applied for runoff and erosion prediction, direct validation of its soil water outputs, including volumetric soil moisture and/or root-zone water storage, is relatively sparse, and performance is site- and process-dependent. Ref. [62] found strong agreement for root-zone soil water on bare rangeland plots but weaker performance under herbaceous cover, indicating sensitivity to vegetation controls on infiltration and evapotranspiration. Ref. [51] leveraged multi-year datasets from instrumented watersheds to refine WEPP's water balance and crop growth routines, and demonstrated that the model could reproduce seasonal soil moisture trends in the upper 0.5 m. However, deeper profile dynamics were less accurately simulated, with WEPP tending to overestimate subsoil water availability. Ref. [63] reported low-to-negative efficiency when predicted profile soil water content was compared to long-term neutron-probe measurements. The limited available validation evidence suggests that WEPP can predict soil moisture dynamics reasonably well in some settings (e.g., bare plots) but

performance may degrade under vegetation and/or site-specific hydroclimatic conditions without careful parameterization of infiltration and evapotranspiration controls that drive the model's daily soil water balance. In heterogeneous environments, predictive accuracy may decline due to the model's simplified representation of preferential flow and limited mechanistic treatment of lateral subsurface redistribution.

2.1.7. RZWQM (Root Zone Water Quality Model)

Description

RZWQM is a process-based, physically grounded agrohydrological model designed to simulate water flow, solute transport, nutrient cycling, and crop growth within the soil–plant–atmosphere continuum at the field scale [64–66]. Its computational framework is based on vertical discretization of the soil profile into multiple layers, each governed by coupled equations describing water, heat, and chemical transport processes. The model operates at sub-daily time steps for water and solute fluxes, with daily updating of crop growth and management operations. Although the model adopts a primarily one-dimensional representation, it incorporates conceptual formulations for macropore flow and subsurface drainage, enabling simulation of preferential transport and tile–drain interactions in structured soils. RZWQM is widely applied to problems including irrigation management, nutrient leaching, pesticide transport, crop yield prediction, and assessment of conservation practices under varying climatic conditions.

Soil Moisture Content Prediction

Soil moisture dynamics within RZWQM are simulated using a one-dimensional variably saturated flow formulation based on the Richards equation [64,65]. Hydraulic behavior is represented through soil water retention and hydraulic conductivity functions, with infiltration and redistribution simulated using either Green–Ampt-type approximations or numerical solutions of the Richards equation. Evapotranspiration is partitioned into soil evaporation and plant transpiration, with root water uptake calculated as a function of root distribution, soil water potential, and plant stress response.

Preferential flow processes are represented using a macropore-based conceptual framework that partitions water between the soil matrix and rapid bypass pathways. These pathways become active under near-saturated or high-intensity rainfall conditions, facilitating rapid transmission of water and solutes to deeper layers or drainage systems. Exchange between matrix and macropore domains is parameterized through empirical coefficients, enabling representation of rapid transport while maintaining computational efficiency. Sub-surface drainage, including tile flow and water table interactions, is explicitly incorporated, linking soil moisture storage to lateral outflow processes. Standard model formulations neglect lateral unsaturated flow within the soil profile; however, quasi-two-dimensional representations of drainage and macropore connectivity allow limited simulation of lateral redistribution in structured soils. Simulation of soil water content requires specification of soil hydraulic properties, soil stratigraphy, vegetation parameters, and time-varying climatic and management inputs. Model outputs include temporally resolved profiles of volumetric water content, matric potential, infiltration, evapotranspiration, runoff, percolation, and drainage fluxes.

Predictive Accuracy and Limitations

The predictive accuracy of RZWQM soil moisture simulations is primarily governed by the quality of soil hydraulic parameters and the representation of management inputs. The Richards-equation framework provides a physically robust basis for modeling transient unsaturated flow; however, parameterization of soil hydraulic functions is often subject to uncertainty due to spatial heterogeneity and scale effects [64]. Representation of pref-

erential flow improves simulation of rapid infiltration and solute transport but remains approximate because macropore processes are described through parameterized domains rather than explicitly resolved pore networks. Consequently, model performance is sensitive to assumptions regarding macroporosity, hydraulic conductivity, and interdomain exchange coefficients [67]. RZWQM is data-intensive and requires careful calibration, often performed through component-wise adjustment of soil, crop, and management parameters. Despite these limitations, RZWQM has demonstrated strong predictive capability across a range of agricultural systems when supported by adequate data, calibration, and sensitivity analysis [68].

2.2. Watershed Models

2.2.1. MIKE SHE

Description

MIKE SHE is a fully distributed, physically based hydrological model designed to simulate the coupled interactions of surface water, unsaturated flow, groundwater, and channel processes across heterogeneous catchments [69–73]. Its computational architecture is based on spatial discretization into grid cells, each containing vertically resolved soil columns coupled to groundwater flow equations. The model typically operates at sub-daily time steps, allowing dynamic simulation of transient hydrologic processes, including infiltration pulses, groundwater recharge, and surface–subsurface interactions. The platform is delivered through a Windows-based MIKE Zero graphical user interface with GIS integration. MIKE SHE is widely applied to problems such as conjunctive surface groundwater management, wetlands, irrigation and crop water use, flood routing, and catchment-scale water balance assessments.

Soil Moisture Content Prediction

Vertical soil moisture dynamics in the unsaturated zone are represented using a one-dimensional formulation for each grid cell, with full hydraulic coupling to the saturated zone to ensure physically consistent exchanges across a transient water table [69,74]. Water flow can be simulated using either the Richards equation or simpler water-balance approaches, depending on the desired balance between physical detail and computational efficiency. Under the Richards formulation, volumetric water content is obtained directly from the soil water retention and unsaturated hydraulic-conductivity functions at each time step, with preferential flow represented implicitly through dual-domain or enhanced-conductivity parameterizations that capture rapid near-saturated transmission. The gravity-flow option updates layer water content by routing infiltration downward under a unit hydraulic gradient while accounting for evapotranspiration losses, providing an efficient representation of recharge when capillarity is secondary. The two-layer water-balance scheme updates the root zone and the overlying layer above the water table using storage accounting controlled by evapotranspiration and percolation, offering a suitable approximation in shallow water-table settings where root-zone processes dominate recharge dynamics. Redistribution within the soil profile is simulated as continuous flow governed by hydraulic gradients, capturing capillary movement, drainage, and interaction with groundwater systems. Lateral flow is explicitly resolved through coupling with the saturated zone, using Darcy-based groundwater flow equations. In the standard MIKE SHE framework, unsaturated flow is represented primarily as a vertical process within each grid cell, whereas lateral subsurface redistribution is resolved through coupling with the saturated groundwater system. When the 3D groundwater module is used, subsurface water can move laterally between grid cells according to hydraulic gradients. Consequently, lateral flow occurring within the unsaturated zone itself is not explicitly represented and may

be important in landscapes where hillslope-scale redistribution contributes substantially to soil water movement.

Simulation of soil water content requires specification of soil hydraulic properties together with soil stratigraphy, vegetation characteristics, and time-varying climatic inputs. When macropore processes are represented, additional dual-domain or near-saturated hydraulic parameters describing preferential-flow fractions, exchange coefficients, or structural porosity must also be defined. MIKE-SHE produces spatially and temporally resolved outputs including volumetric water content, matric potential, infiltration, percolation, capillary rise, recharge, and evapotranspiration fluxes; when activated, preferential-flow contributions are also reported, enabling separation of matrix and bypass pathways.

Predictive Accuracy and Limitations

The predictive accuracy of MIKE SHE's unsaturated-zone simulations is governed primarily by the fidelity of soil hydraulic parameters and the suitability of the selected flow formulation. The Richards equation typically provides the most accurate representation of transient moisture dynamics but requires well-constrained hydraulic functions, which are often non-unique and sensitive to measurement scale. Simplified gravity-flow and water-balance approaches reduce computational load but introduce assumptions, such as neglect of capillary gradients or vertical heterogeneity [22]. Representation of macropore flow remains approximate because preferential pathways are emulated through parameterized dual-domain or conductivity enhancement schemes rather than explicitly resolved pore networks [75]. In addition, the one-dimensional representation of unsaturated flow may be less suitable in steep, heterogeneous, or shallow-soil environments where lateral unsaturated flow contributes appreciably to moisture redistribution. Despite these limitations, MIKE SHE has demonstrated robust predictive skill across diverse hydroclimatic settings when supported by adequate data, calibration, and sensitivity analysis [76].

2.2.2. SWAP (Soil-Water-Atmosphere-Plant)

Description

SWAP is a physically based model designed to simulate water movement and soil–plant–atmosphere interactions within vertically resolved soil profiles, often applied at field scale but extended to watershed analysis through spatial generalization [77,78]. Its computational architecture relies on numerical solutions of flow equations at daily or sub-daily time steps. The model is delivered through a structured, text-based modeling system with dedicated input modules for soils, crops, and meteorological forcing, and provides post-processing routines for water-balance diagnostics and profile-scale simulations. Unlike fully distributed models, SWAP remains fundamentally one-dimensional, with spatial variability addressed through multiple independent simulations rather than explicit lateral coupling.

Soil Moisture Content Prediction

Soil moisture dynamics in SWAP are simulated using a one-dimensional vertical formulation that solves the Richards equation for variably saturated flow, fully coupled to an energy-based representation of soil–plant–atmosphere exchanges [77,78]. The model computes changes in volumetric water content by integrating the soil water retention curve and unsaturated hydraulic-conductivity function within a finite-difference framework, enabling detailed tracking of wetting-front propagation and root-zone storage under transient climatic forcing. Root water uptake is represented through a sink term distributed across the root zone, commonly parameterized using stress response functions that account for matric, osmotic, aeration, and salinity constraints on plant transpiration [79]). Preferential or macropore flow can be simulated through an optional dual-domain or bypass-flow

module, in which a fraction of infiltrating water is routed rapidly downward under near-saturated conditions [78]. Lateral flow is not explicitly modeled, and subsurface water movement is restricted to vertical fluxes within each soil profile.

Simulation of soil water content requires specification of soil hydraulic parameters, porosity, bulk density, residual water content, and soil layering, together with atmospheric inputs. Boundary conditions include irrigation or rainfall at the surface and groundwater levels or free drainage at depth, while vegetation inputs define rooting depth, root-length density, phenology, and transpiration demand. Outputs relevant to soil moisture prediction include volumetric water content, matric potential, soil water storage, infiltration, drainage, percolation, capillary rise, evaporation, transpiration, and actual evapotranspiration.

Predictive Accuracy and Limitations

SWAP has demonstrated robust performance in agricultural, ecohydrological, and groundwater-recharge applications when supported by high-quality soil characterization, reliable meteorological forcing, and rigorous calibration and sensitivity analysis [77]. Its predictive accuracy, however, depends strongly on the fidelity of soil hydraulic parameters, root-zone representation, and climate inputs. Because SWAP is driven by Richards' equation, realistic simulation of transient soil moisture dynamics requires well-parameterized soil water retention and hydraulic-conductivity functions, which are often non-unique and may vary with soil structure, compaction, and hysteresis [75]. Uncertainties in root-zone properties, particularly rooting depth, root-length density distribution, and plant stress-response functions, can propagate into evapotranspiration estimates and root-zone water availability. Representation of preferential flow remains approximate, as macropore networks are not explicitly resolved but simulated through parameterized bypass-flow fractions that can be difficult to constrain [78]. In addition, the inherent assumption of strictly vertical, one-dimensional flow limits the model's applicability on steep slopes, in layered hillslopes, or in shallow soils over bedrock where lateral unsaturated flow contributes significantly to moisture redistribution.

2.2.3. SWAT (Soil & Water Assessment Tool)

Description

SWAT is a semi-distributed, process-based, continuous model developed by USDA-ARS and Texas A&M to quantify the effects of land management, climate, and watershed characteristics on water quantity and quality from small watersheds to large river-basin scales [80,81]. SWAT partitions watersheds into sub-basins and further into hydrologic response units (HRUs) representing unique combinations of soil, land use, and slope. SWAT+, the next-generation version of SWAT, introduces a flexible, object-oriented architecture that enhances spatial representation and connectivity [82]. It introduces landscape units to explicitly route flows and constituents among uplands, floodplains, channels, reservoirs, wetlands, and point sources. Both SWAT and SWAT+ operate at watershed to regional scales and are typically applied at daily temporal resolutions. Model setup and execution are supported through multiple interfaces, including GIS-based tools, text editors, and command-line utilities, providing users with options for flexible and detailed configuration.

Soil Moisture Content Prediction

SWAT and SWAT+ predict soil moisture using a storage-routing approach within each HRU. Precipitation and irrigation inputs are partitioned into surface runoff and infiltration using methods such as the USDA curve number method. Infiltrated water is stored in a multi-layer soil profile and redistributed vertically based on storage thresholds and percolation rates. Evapotranspiration is computed using methods such as Penman–Monteith, Priestley–Taylor, or Hargreaves, constrained by soil moisture availability and crop demand.

SWAT requires extensive input data, including daily climate variables, soil properties, land use and crop parameters, and management practices. Spatial datasets such as digital elevation models, soil maps, and land cover data are essential for watershed delineation, HRU and landscape unit definition. SWAT provides outputs such as daily soil water content by layer for each HRU, infiltration and percolation rates, lateral subsurface flow, surface runoff, and evapotranspiration components. Additional outputs include water balance summaries, crop water stress indicators, and groundwater recharge estimates, supporting integrated assessments of hydrology, water quality, and agricultural productivity [80,82].

Predictive Accuracy and Limitations

Although SWAT is widely applied for simulating land surface processes such as streamflow and water quality, studies focusing on soil water content (SWC) remain limited. Evaluation across diverse environments has produced mixed results for SWAT SWC simulations. While several studies have reported successful reproduction of seasonal soil moisture dynamics, others have found that strong streamflow calibration does not necessarily translate into equally accurate representation of internal soil moisture states. At sites in Indiana, Texas, and Colorado, SWAT showed limited SWC accuracy under both dryland and irrigated conditions, even with successful streamflow and evapotranspiration calibration [83]. In Saskatchewan, SWAT captured seasonal trends but correlated only moderately with observations and underestimated early-season moisture [84]. Incorporating hydropedology into SWAT+ improved SWC accuracy in South Africa but performance still remained suboptimal [85]. Reported discrepancies in SWC simulations have been attributed, in part, to structural characteristics of the model, including the semi-distributed HRU framework, which does not explicitly represent lateral unsaturated flow within HRUs, as well as simplified treatment of preferential or macropore flow processes. However, the influence of these factors varies among watersheds, climatic regimes, management conditions, and calibration strategies. SWAT+, however, addresses some issues by routing flows among landscape units and improving connectivity. Furthermore, reliance on streamflow-only calibration in most studies may lead to equifinality—accurate discharge but misrepresented internal states—underscoring the need for multi-objective calibration using soil moisture, groundwater, and solute data to better constrain water storage and fluxes.

2.3. Regional Models

2.3.1. CLM (Community Land Model)

Description

CLM constitutes the terrestrial land surface component of the Community Earth System Model (CESM) [86,87]. It is a widely adopted, process-based land surface modeling framework that explicitly represents the coupled exchanges of water, energy, carbon, and momentum between the terrestrial system and the atmosphere across spatial scales ranging from regional to global [87]. In its current generation, CLM5, the model formalizes sub-grid heterogeneity by partitioning each grid cell into land units and plant functional types and advances hydrologic and eco-physiological realism through new parameterizations for soil hydrology, snow, plant hydraulics, and land management. The model employs a hierarchical sub-grid structure that partitions each atmospheric grid cell into land units, columns, and patches to represent heterogeneity in land cover, hydrology, and vegetation [87]. CLM5 has been employed for climate–land coupling, hydrologic assessment, carbon–nitrogen cycle studies, and human impacts (e.g., crops, irrigation), reflecting its role as a comprehensive platform for Earth system research [87]. CLM is executed as a command line model code within the CESM framework or, less commonly, in a land-only configuration.

Soil Moisture Content Prediction

CLM represents soil moisture using a one-dimensional, multi-layer soil column that resolves vertical water storage and transport in the unsaturated zone. Precipitation is partitioned into rainfall and snowfall, with snow accumulation and melt governed by an explicit multi-layer snow model that resolves energy balance, compaction, and phase change. Liquid soil water movement is governed by Richards' equation, with hydraulic properties prescribed from soil texture, enabling simulations of infiltration, percolation, capillary rise, and drainage under variably saturated conditions [87]. Soil moisture is coupled to vegetation through root water uptake and moisture-stress functions that regulate transpiration and stomatal conductance. The scheme further accounts for soil freeze–thaw processes by partitioning water into liquid and ice phases, which modifies hydraulic conductivity and runoff generation. To account for spatial variation in soil thickness and columnar water holding capacity, different soil thicknesses (by default ranging from 0.4 to 8.5 m depth) can be applied for each soil column [87]. The model's expanded hydrologic suite in CLM5 includes a dry-surface layer affecting vapor fluxes, revised canopy interception and canopy snow processes, an updated groundwater scheme, and optional representation of lateral subsurface flow through a hillslope configuration that redistributes saturated water downslope within a grid cell.

Operationally, CLM soil moisture simulation requires temporally resolved atmospheric forcing (e.g., precipitation, temperature, humidity, radiation, wind, and surface pressure) together with static datasets describing soil hydraulic properties, land cover, and vegetation characteristics. Soil texture-based parameters control water storage and vertical transport, while plant functional type and rooting distributions regulate evapotranspiration and soil water uptake. Realistic soil moisture states are typically achieved through model spin-up from prescribed initial conditions. Optional datasets describing topography, groundwater, and land management are required when these processes are enabled, allowing CLM to represent soil moisture dynamics and land–atmosphere coupling across spatial scales. The model returns time series of vertically resolved soil moisture and temperature, canopy and ground heat fluxes, evapotranspiration components (transpiration, soil evaporation, canopy interception loss), infiltration and runoff partitioning, subsurface drainage and water table diagnostics, snow properties, and, when enabled, carbon and nitrogen fluxes and pools.

Predictive Accuracy and Limitations

Independent evaluations using in situ observations, satellite products, and reanalysis datasets demonstrate that the CLM reproduces the observed seasonal cycle and interannual variability of soil moisture across a wide range of climatic regimes, indicating general good agreement with observed soil moisture at seasonal to interannual timescales [88,89]. However, these studies also highlight systematic limitations that constrain predictive accuracy in specific contexts. CLM's soil moisture simulations remain strongly dependent on the quality of meteorological forcing and land-surface input data; biases in precipitation, radiation, vegetation phenology, and snow processes—particularly in coarse or globally gridded datasets—can propagate directly into soil moisture errors. In addition, soil hydraulic parameters derived from pedotransfer functions introduce substantial uncertainty at regional to continental scales, with numerous evaluations showing high sensitivity of simulated soil moisture to these parameters and a frequent need for site- or region-specific calibration to achieve consistency with in situ observations. Finally, CLM's default vertical one-dimensional hydrologic formulation neglects lateral water redistribution, limiting realism in complex terrain unless augmented with the hillslope configuration or external lateral routing schemes.

2.3.2. NOAH-LSM (NOAH Land Surface Models)

Description

The NOAH family of land surface models provides physically based frameworks for simulating land–atmosphere exchanges in weather, climate, and hydrologic systems. The original NOAH LSM integrates surface energy balance, multi-layer soil moisture and temperature, snowpack, and vegetation processes. It is widely used in operational forecasting systems and research applications such as drought monitoring and hydrological prediction [90,91]. NOAH-MP (NOAH with Multi-Parameterization Options) extends NOAH LSM by introducing multiple physics options for infiltration, runoff, evapotranspiration, snow, and vegetation phenology, as well as groundwater interactions [92]. This modular design enables improved realism and flexibility for diverse hydroclimatic conditions. The model operates at sub-daily time steps and is often coupled with atmospheric models or integrated into large-scale hydrologic forecasting systems [92,93].

Soil Moisture Content Prediction

NOAH represents soil moisture using a multi-layer column (typically a four-layer column extending to approximately 2 m depth) and computes vertical water movement via Richards' equation [90,92]. Infiltration is represented using modified Green–Ampt or infiltration-capacity-based formulations. Redistribution within the soil profile is computed using continuous hydraulic relationships driven by soil moisture gradients, though these formulations are simplified relative to fully physically based models. Evapotranspiration is calculated using energy balance methods, with strong coupling to vegetation processes and atmospheric forcing. NOAH-MP enhances soil moisture simulation through dynamic vegetation phenology, alternative stomatal resistance schemes, and multiple runoff/groundwater options. Lateral flow in NOAH-based models is generally not explicitly represented within individual grid cells, and subsurface interactions are treated independently across the domain. While some implementations include groundwater coupling or runoff-routing schemes, subsurface lateral redistribution remains simplified and does not resolve hillslope processes. Inputs include meteorological, soil texture/hydraulic parameters, and vegetation descriptors. Spatially distributed datasets such as land cover maps and soil texture grids are essential for large-scale applications. Outputs include layer-wise soil moisture, infiltration and drainage rates, evapotranspiration components, runoff/baseflow, soil temperature, and surface energy fluxes [92–95].

Predictive Accuracy and Limitations

NOAH LSM has been extensively validated at regional to continental scales, particularly through NLDAS and global reanalysis products. Ref. [91] evaluated NOAH soil moisture outputs within NLDAS, showing reasonable agreement for near-surface layers but reduced accuracy for deeper profiles. NOAH-MP generally outperforms NOAH LSM in heterogeneous landscapes and complex terrain, especially when groundwater options and dynamic vegetation are enabled. However, NOAH-MP's increased complexity requires careful physics selection and parameter calibration. Both models remain sensitive to soil hydraulic parameterization and forcing data quality; performance declines in deeper layers and under freeze–thaw or snow-dominated regimes without targeted improvements [94,95]. In practice, NOAH models perform well in capturing near-surface soil moisture variability and seasonal trends but show reduced accuracy in deeper soil layers. Compared to CLM, NOAH-MP offers greater flexibility and parameter customization but introduces increased sensitivity to parameter uncertainty. Compared to VIC, NOAH provides more physically consistent vertical flux representation.

2.3.3. VIC (Variable Infiltration Capacity) Model

Description

VIC is a semi-distributed macroscale hydrologic model designed to simulate water and energy balances across large spatial domains, with a focus on capturing sub-grid variability in hydrologic processes [96,97]. The model's computational architecture is based on grid cells that operate independently, with each cell containing a layered soil column and parameterized vegetation components. It typically operates at daily or sub-daily time steps and is widely used in regional hydrologic assessments and climate impact studies. VIC has been applied from basin to global scales for hydrologic dataset construction, trend analyses of fluxes and states, data evaluation and assimilation, forecasting, coupled climate modeling, and climate-change impact assessments [97–99]. The model is open-source, and the current release (VIC-5) features a modular C core accessed through command-line environments.

Soil Moisture Content Prediction

Infiltration in VIC is represented using the Variable Infiltration Capacity scheme, which accounts for spatial heterogeneity in infiltration rates by dividing the grid cell into fractions with different infiltration capacities [96]. This approach provides a conceptual but effective way to represent sub-grid variability in runoff generation without explicitly resolving soil physics. Redistribution is driven primarily by gravity-based relationships within the soil profile, with evapotranspiration computed using energy balance formulations. While these formulations allow efficient simulation of large-scale water balance, they do not explicitly resolve hydraulic gradients or capillary processes [96,100]. Lateral flow in VIC is not directly simulated within grid cells, and interactions between cells are handled through separate routing models. This approach simplifies computation but neglects subsurface connectivity and hillslope processes, resulting in limited representation of lateral soil moisture redistribution. Baseflow is typically parameterized using nonlinear reservoir functions, further emphasizing the conceptual nature of subsurface flux representation [96,100]. VIC requires gridded meteorological forcing, soil parameter datasets, and vegetation information, with moderate to high data requirements depending on resolution [97]. The output provides time series of soil moisture by layer. Streamflow is obtained by coupling to an external routing model.

Predictive Accuracy and Limitations

Several studies have applied the VIC model to evaluate soil moisture dynamics across different spatial scales. Ref. [98] demonstrated VIC's ability to capture global seasonal and interannual variability in soil moisture, though absolute values were biased, overestimated in arid regions and underestimated in humid areas, primarily due to forcing data uncertainties. At the continental scale, [99] showed that soil moisture predictions were sensitive to modeling time step and energy balance assumptions, requiring parameter adjustments for consistency. Basin-scale evaluations, such as [101], found that VIC overpredicted soil moisture because of underestimated evapotranspiration and omission of human water use. Common limitations across these studies include VIC's independent grid-cell assumption (minimal lateral flow), reliance on a statistical infiltration curve and conceptual baseflow, and strong parameter sensitivity necessitating region-specific calibration. Compared to CLM and NOAH, VIC relies more heavily on conceptual parameterizations and provides less detailed process representation, but it offers greater computational efficiency and robustness for large-scale applications.

3. Current Application and Implications for Soil Water Prediction

3.1. Cross-Scale Trade-Offs in Model Structure and Performance

Soil moisture modeling has evolved from early storage-based formulations to a multi-scale modeling hierarchy capable of representing vadose-zone processes from field to global scales. Early tipping-bucket models represented soil water as discrete storage compartments, capturing bulk soil water balance but neglecting internal hydraulic gradients and transient redistribution. The development of Richards' equation-based models introduced a mechanistic framework for simulating infiltration, redistribution, evapotranspiration, and root water uptake under dynamic boundary conditions, enabling realistic representation of unsaturated flow. Despite this progression, all models reflect fundamental structural trade-offs related to process representation, scale, intended application, and computational feasibility that give rise to several characteristic strengths and limitations. The reviewed literature indicates several recurring constraints (Table 1), including simplifications in soil water physics; incomplete representation of lateral or preferential flow (e.g., macropores, dual-domain exchange); calibration challenges related to equifinality and high-dimensional parameter spaces; and substantial computational costs for models using fine spatial discretization or complex numerical solvers. These categories reflect broad trends rather than exhaustive or definitive assessments.

Table 1. Overview of key limitations and strengths of widely used soil moisture models.

Model	Key Limitations	Key Strengths
HYDRUS	Computationally intensive (2D/3D); limited scalability	Detailed physics; high resolution soil water dynamics
SWAP	Limited to 1D vertical flow; simplified macropore representation	Strong soil–crop–atmosphere coupling
MACRO	Uncertain macropore parameterization; 1D structure; simplified chemistry	Designed for preferential flow; effective for rapid transport events
DSSAT	Simplified soil physics; coarse soil layering; limited macropore representation	Robust crop growth simulation; links soil water to yield response
WEPP	Simplified subsurface hydrology; weak deep soil and groundwater representation	Strong infiltration–runoff dynamics; effective for hillslope-scale erosion processes
AQUACROP	Simplified soil profile; does not represent preferential/macropore flow	Computational efficiency; low data requirements; robust yield–water relationships
APEX	Simplified subsurface hydrology; limited explicit macropore representation; parameter sensitivity at larger scales	Field-to-watershed integration; strong for management, conservation practices, and scenario analysis
SWAT	HRU-based aggregation; simplified infiltration; simplified vertical soil water processes	Widely applied model; effective for long-term, large-scale simulations
MIKE-SHE	High data requirements; long run times; computationally demanding calibration	Fully integrated surface–soil–groundwater modeling; strong spatial representation
RZWQM	High parameterization complexity; data intensive macropore setup; time consuming calibration	Detailed root-zone processes; strong coupling of water, nutrient, and preferential flow dynamics
VIC	Simplified infiltration; limited vertical soil resolution; grid cell averaging; region-specific calibration	Robust large-scale hydrology; effective for soil moisture variability and data assimilation
CLM	High model complexity; long spin-up periods; parameter equifinality	Detailed multi-layer soil physics; strong land atmosphere coupling at regional to global scales
NOAH	Limited deep soil and groundwater representation; coarse spatial resolution	Computational efficiency; robust real-time land surface and soil moisture simulations with data assimilation

Across all model classes, soil moisture prediction is governed by how infiltration and redistribution are conceptualized, and how lateral flow is incorporated or omitted. These differences produce systematic, mechanism-driven variations in model behavior. In tipping-bucket models, infiltration is typically represented as a storage-filling process or empirical partitioning between runoff and infiltration. This approach neglects infiltration capacity limitations and hydraulic gradient effects. Redistribution is treated as instantaneous once field capacity is exceeded, resulting in systematic overestimation of percolation and underestimation of soil moisture persistence, particularly in fine-textured or layered soils [39,40].

Storage-routing models partially address these limitations by introducing flux-based redistribution and moisture-dependent conductivity functions. However, these fluxes are governed by empirical relationships rather than explicit hydraulic gradients, resulting in attenuated infiltration–redistribution coupling and simplified vertical flux dynamics. In SWAT, for example, infiltration partitioning using the Curve Number method dampens rainfall variability, which propagates into reduced variability in soil moisture storage and runoff generation [102]. In contrast, physically based models simulate infiltration and redistribution as continuous processes governed by hydraulic gradients. This allows a realistic representation of infiltration fronts, capillary flow, and delayed drainage [44].

3.2. Role of Spatial Scale and Lateral Connectivity

Across spatial scales, models generally achieve scalability through aggregation and simplification of subsurface processes. However, this introduces equifinality, where calibration against streamflow can produce acceptable surface flux predictions while masking errors in internal soil moisture states. In SWAT, for example, HRU aggregation smooths spatial variability [103], while in VIC, NOAH and CLM, simplified vertical and lateral processes lead to systematic biases in soil moisture magnitude under different climatic regimes [94,95,97,99].

The representation of lateral subsurface flow constitutes the most significant structural limitation in soil moisture modeling. Fully distributed models such as MIKE SHE demonstrate that accurate representation of lateral connectivity is essential for simulating spatial soil moisture patterns and subsurface flow pathways. In regional models such as CLM and VIC, the absence of explicit lateral flow results in independent soil column behavior, which suppresses spatial variability and limits the ability to simulate realistic moisture redistribution across landscapes. Similarly, infiltration formulations become increasingly simplified with scale. While models such as HYDRUS resolve infiltration dynamically using hydraulic conductivity functions, large-scale models rely on approaches that decouple rainfall intensity from infiltration dynamics. In regional models, infiltration is further influenced by canopy interception, snowmelt, and frozen soil conditions, which are parameterized rather than explicitly resolved, introducing additional uncertainty in surface–subsurface interactions.

3.3. Implications for Model Selection and Future Development

A central conclusion of this analysis is that soil moisture models operate along a continuum defined by trade-offs between process fidelity, scalability, data requirements, and computational cost, with no single framework achieving optimal performance across all dimensions. Physically based models resolve vertical and lateral processes but are constrained by parameter uncertainty and computational cost. Conceptual and semi-distributed models achieve scalability but simplify or omit key processes such as preferential flow and lateral redistribution. Regional models maintain consistency across large domains but treat soil moisture as a simplified state variable, limiting their ability to represent dynamic

subsurface processes. This fundamental constraint explains the observed pattern across all models: as spatial scale increases, process fidelity is systematically reduced, particularly for lateral flow and transient infiltration dynamics. As a result, soil moisture predictions become increasingly uncertain not due to random error but due to structural simplifications inherent in model design.

The review underscores the necessity of scale- and process-aware model selection. Models such as HYDRUS should be used when accurate representation of infiltration and redistribution is required, particularly in experimental or field-scale studies. Models such as DSSAT and AquaCrop are appropriate for agricultural applications where coupling between soil moisture and crop growth is critical but detailed subsurface processes are secondary. At larger scales, CLM and VIC are suitable for integrated hydrologic or climate analyses, but their soil moisture outputs must be interpreted with recognition of underlying structural limitations.

Future model development may benefit from addressing several key challenges. First, improved representation of lateral subsurface flow and spatial connectivity is required, particularly in watershed and regional models. This will likely require hybrid approaches that incorporate physically consistent lateral fluxes without incurring prohibitive computational cost. Second, improved treatment of preferential flow and soil heterogeneity is necessary to capture rapid redistribution processes observed in structured soils. In addition, integration of remote sensing and data assimilation techniques is essential to constrain model states and reduce uncertainty, particularly at regional scales where direct observations are sparse. Advancing soil moisture modeling therefore requires not only improvements in process representation but also development of frameworks that balance physical realism with scalability. Without such advances, structural limitations will continue to constrain the predictive capability of soil water models from field to watershed and regional applications.

4. Conclusions

This review provides a comprehensive, process-focused evaluation of predictive soil moisture models across field, watershed, and regional scales, emphasizing how subsurface fluxes are represented and how these structural choices control predictive behavior. The analysis demonstrates that differences in soil moisture prediction arise primarily from fundamental assumptions about infiltration, redistribution, and subsurface connectivity, rather than from calibration alone. Across all model classes, the absence or simplification of lateral subsurface flow constitutes the primary cross-scale limitation in soil moisture modeling, particularly at watershed and regional scales, where models that neglect or approximate this process systematically underrepresent hillslope connectivity and spatial moisture gradients. Future progress in soil moisture modeling requires improved representation of lateral subsurface flow and spatial connectivity, more physically consistent treatment of infiltration, and the development of hybrid modeling approaches that combine physically based process representation with scalable computational structures. Addressing these limitations, particularly the coupled representation of infiltration dynamics and lateral subsurface flow, will be essential for improving predictive consistency of soil moisture and advancing its role in hydrology, soil science, agriculture, and Earth system science.

Author Contributions: Conceptualization, D.K., A.-M.F. and J.Z.; methodology, D.K., A.-M.F. and J.Z.; writing—original draft preparation, D.K.; writing—review and editing, D.K., A.-M.F., P.K.S., S.H., J.Z., P.F., P.B. and J.J.; funding acquisition, P.K.S. and S.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by USDA-ARS OCPARC AHERU through agreement 58-3070-4-051 in support of project number: 3070-13000-154-00D. This research contributes to the Natural

Resources Conservation Services, Conservation Effects Assessment (CEAP) Project and is a contribution of the USDA ARS Southern Plains Long-Term Agroecosystem Research (LTAR) Site. Mention of trade names or commercial products in this publication is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the US Department of Agriculture. USDA is an equal opportunity provider, employer, and lender.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

APEX	Agricultural Policy Environmental eXtender
ARCAPEX	Agricultural Research Center–Agricultural Policy Environmental eXtender
ARS	Agricultural Research Service
ASCII	American Standard Code for Information Interchange
CEAP	Conservation Effects Assessment Project
CESM	Community Earth System Model
CLM	Community Land Model
DSSAT	Decision Support System for Agrotechnology Transfer
EPIC	Environmental Policy Integrated Climate
FAO	Food and Agriculture Organization
GIS	Geographic Information System
GUI	Graphical User Interface
HRU	Hydrologic Response Unit
LSM	Land Surface Model
MACRO	Model for Agricultural Chemicals in the Root Zone
NLDAS	North American Land Data Assimilation System
RUSLE	Revised Universal Soil Loss Equation
RZWQM	Root Zone Water Quality Model
SWAP	Soil-Water-Atmosphere-Plant Model
SWAT	Soil and Water Assessment Tool
SWC	Soil Water Content
USDA	United States Department of Agriculture
VIC	Variable Infiltration Capacity Model
WEPP	Water Erosion Prediction Project
WRF	Weather Research and Forecasting Model

References

1. Brocca, L.; Ciabatta, L.; Massari, C.; Camici, S.; Tarpanelli, A. Soil Moisture for Hydrological Applications: Open Questions and New Opportunities. *Water* **2017**, *9*, 140. [\[CrossRef\]](#)
2. Huang, J.; Sehgal, V.; Alvarez, L.V.; Brocca, L.; Cai, S.; Cheng, R.; Cheng, X.; Du, J.; El Masri, B.; Endsley, K.; et al. Remotely Sensed High-Resolution Soil Moisture and Evapotranspiration: Bridging the Gap Between Science and Society. *Water Resour. Res.* **2025**, *61*, e2024WR037929. [\[CrossRef\]](#)
3. Teixeira, A.C.; Bakon, M.; Lopes, D.; Cunha, A.; Sousa, J.J. A Systematic Review on Soil Moisture Estimation Using Remote Sensing Data for Agricultural Applications. *Sci. Remote Sens.* **2025**, *12*, 100328. [\[CrossRef\]](#)
4. Abbes, A.; Jarray, N.; Farah, I. Advances in Remote Sensing Based Soil Moisture Retrieval: Applications, Techniques, Scales and Challenges for Combining Machine Learning and Physical Models. *Artif. Intell. Rev.* **2024**, *57*, 224. [\[CrossRef\]](#)
5. Wang, Y.; Li, H.; Li, Y.; Zheng, A.; Dang, W. Current Research Status and Development Trends in Soil Moisture–Heat Coupled Migration Mechanisms: A Review. *Plant Soil* **2025**, *515*, 1107–1133. [\[CrossRef\]](#)
6. Yao, Y.; Fan, J.; Li, J. A Review of Advanced Soil Moisture Monitoring Techniques for Slope Stability Assessment. *Water* **2025**, *17*, 390. [\[CrossRef\]](#)

7. Liu, Y.; Yang, Y. Advances in the Quality of Global Soil Moisture Products: A Review. *Remote Sens.* **2022**, *14*, 3741. [\[CrossRef\]](#)
8. Susha Lekshmi, S.U.; Singh, D.N.; Shojaei Baghini, M. A Critical Review of Soil Moisture Measurement. *Measurement* **2014**, *54*, 92–105. [\[CrossRef\]](#)
9. Dobriyal, P.; Qureshi, A.; Badola, R.; Hussain, S.A. A Review of the Methods Available for Estimating Soil Moisture and Its Implications for Water Resource Management. *J. Hydrol.* **2012**, *458–459*, 110–117. [\[CrossRef\]](#)
10. Reynolds, S.G. The Gravimetric Method of Soil Moisture Determination Part I A Study of Equipment, and Methodological Problems. *J. Hydrol.* **1970**, *11*, 258–273. [\[CrossRef\]](#)
11. Schmugge, T.J.; Jackson, T.J.; McKim, H.L. Survey of Methods for Soil Moisture Determination. *Water Resour. Res.* **1980**, *16*, 961–979. [\[CrossRef\]](#)
12. Hardie, M. Review of Novel and Emerging Proximal Soil Moisture Sensors for Use in Agriculture. *Sensors* **2020**, *20*, 6934. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Romero-Ruiz, A.; Linde, N.; Keller, T.; Or, D. A review of geophysical methods for soil structure characterization. *Rev. Geophys.* **2018**, *56*, 672–697. [\[CrossRef\]](#)
14. Terry, N.; Day-Lewis, F.; Lane, J.; Johnson, C.; Werkema, D. Field evaluation of semi-automated moisture estimation from geophysics using machine learning. *Vadose Zone J.* **2023**, *22*, e20246. [\[CrossRef\]](#) [\[PubMed\]](#)
15. Petropoulos, G.P.; Ireland, G.; Barrett, B. Surface Soil Moisture Retrievals from Remote Sensing: Current Status, Products & Future Trends. *Phys. Chem. Earth* **2015**, *83–84*, 36–56. [\[CrossRef\]](#)
16. Babaeian, E.; Sadeghi, M.; Jones, S.B.; Montzka, C.; Vereecken, H.; Tuller, M. Ground, Proximal, and Satellite Remote Sensing of Soil Moisture. *Rev. Geophys.* **2019**, *57*, 530–616. [\[CrossRef\]](#)
17. Verstraeten, W.W.; Veroustraete, F.; Feyen, J. Assessment of Evapotranspiration and Soil Moisture Content across Different Scales of Observation. *Sensors* **2008**, *8*, 70–117. [\[CrossRef\]](#) [\[PubMed\]](#)
18. Lamichhane, M.; Mehan, S.; Mankin, K.R. Soil Moisture Prediction Using Remote Sensing and Machine Learning Algorithms: A Review on Progress, Challenges, and Opportunities. *Remote Sens.* **2025**, *17*, 2397. [\[CrossRef\]](#)
19. Taheri, M.; Bigdeli, M.; Imanian, H.; Mohammadian, A. An Overview of Machine-Learning Methods for Soil Moisture Estimation. *Water* **2025**, *17*, 1638. [\[CrossRef\]](#)
20. Rasheed, M.W.; Tang, J.; Sarwar, A.; Shah, S.; Saddique, N.; Khan, M.U.; Imran Khan, M.; Nawaz, S.; Shamshiri, R.R.; Aziz, M.; et al. Soil Moisture Measuring Techniques and Factors Affecting the Moisture Dynamics: A Comprehensive Review. *Sustainability* **2022**, *14*, 11538. [\[CrossRef\]](#)
21. Wang, Y.; Shi, L.; Hu, Y.; Hu, X.; Song, W.; Wang, L. A Comprehensive Study of Deep Learning for Soil Moisture Prediction. *Hydrol. Earth Syst. Sci.* **2024**, *28*, 917–943. [\[CrossRef\]](#)
22. Refsgaard, J.C. *Terminology, Modelling Protocol And Classification of Hydrological Model Codes*; Springer: Dordrecht, The Netherlands, 1990.
23. Refsgaard, J.C.; Knudsen, J. Operational Validation and Intercomparison of Different Types of Hydrological Models. *Water Resour. Res.* **1996**, *32*, 2189–2202. [\[CrossRef\]](#)
24. Beven, K. *Rainfall-Runoff Modelling: The Primer*, 2nd ed.; John Wiley & Sons: Hoboken, NJ, USA, 2012.
25. Wang, X.; Williams, J.R.; Gassman, P.W.; Baffaut, C.; Izaurralde, R.C.; Jeong, J.; Kiniry, J.R. EPIC and APEX: Model Use, Calibration, and Validation. *Trans. ASABE* **2012**, *55*, 1447–1462. [\[CrossRef\]](#)
26. Gassman, P.; Williams, J.; Wang, X.; Saleh, A.; Osei, E.; Hauck, L.M.; Izaurralde, R.C.; Flowers, J. The Agricultural Policy Environmental Extender (APEX) Model: An Emerging Tool for Landscape and Watershed Environmental Analyses. *Trans. ASABE* **2010**, *53*, 711–740. [\[CrossRef\]](#)
27. Tuppad, P.; Winchell, M.F.; Wang, X.; Srinivasan, R.; Williams, J.R. ARCAPEX: Arcgis Interface for Agricultural Policy Environmental Extender (APEX) Hydrology/Water Quality Model. *Int. Agric. Eng. J.* **2009**, *18*, 59–71.
28. Williams, J.; Izaurralde, R. The APEX Model. In *Watershed Models*; Singh, V.P., Frevert, D.K., Eds.; CRC Press, Taylor and Francis Group: Boca Raton, FL, USA, 2006; pp. 437–482.
29. Wang, X.; Kemanian, A.R.; Williams, J.R. Special Features of the EPIC and APEX Modeling Package and Procedures for Parameterization, Calibration, Validation, and Applications. In *Methods of Introducing System Models into Agricultural Research*; Ahuja, L., Ma, L., Eds.; John Wiley & Sons: Hoboken, NJ, USA, 2011; pp. 177–208.
30. Berihun, M.L.; Awoke, G.W.W.; Teshome, F.T.; Hailegnaw, N.S.; Assefa, T.T.; Waqas, M.S.; Bayabil, H.K. Modeling Soil Moisture and Evapotranspiration Dynamics from Variably Irrigated Vegetable Fields. *Model. Earth Syst. Environ.* **2026**, *12*, 21. [\[CrossRef\]](#)
31. Zhao, J.; Zhang, X.; Yang, Y.; Zang, H.; Yan, P.; Meki, M.N.; Doro, L.; Sui, P.; Jeong, J.; Zeng, Z. Alternative Cropping Systems for Groundwater Irrigation Sustainability in the North China Plain. *Agric. Water Manag.* **2021**, *250*, 106867. [\[CrossRef\]](#)
32. Jones, C.D.; Reddy, A.D.; Jeong, J.; Williams, J.R.; Hamilton, S.K.; Hussain, M.Z.; Bandaru, V.; Izaurralde, R.C. Improved Hydrological Modeling with APEX and EPIC: Model Description, Testing, and Assessment of Bioenergy Producing Landscape Scenarios. *Environ. Model. Softw.* **2021**, *143*, 105111. [\[CrossRef\]](#)

33. Steduto, P.; Hsiao, T.C.; Raes, D.; Fereres, E. Aquacrop—the FAO Crop Model to Simulate Yield Response to Water: I. Concepts and Underlying Principles. *Agron. J.* **2009**, *101*, 426–437. [\[CrossRef\]](#)
34. Raes, D.; Steduto, P.; Hsiao, T.C.; Fereres, E. Aquacrop—The FAO Crop Model to Simulate Yield Response to Water: II. Main Algorithms and Software Description. *Agron. J.* **2009**, *101*, 438–447. [\[CrossRef\]](#)
35. Hsiao, T.C.; Heng, L.; Steduto, P.; Rojas-Lara, B.; Raes, D.; Fereres, E. Aquacrop—The FAO Crop Model to Simulate Yield Response to Water: III. Parameterization and Testing for Maize. *Agron. J.* **2009**, *101*, 448–459. [\[CrossRef\]](#)
36. Foster, T.; Brozović, N.; Butler, A.P.; Neale, C.M.U.; Raes, D.; Steduto, P.; Fereres, E.; Hsiao, T.C. AquaCrop-OS: An Open Source Version of FAO’s Crop Water Productivity Model. *Agric. Water Manag.* **2017**, *181*, 18–22. [\[CrossRef\]](#)
37. Steduto, P.; Raes, D.; Hsiao, T.C.; Fereres, E.; Heng, L.K.; Howell, T.A.; Evett, S.R.; Rojas-Lara, B.A.; Farahani, H.J.; Izzi, G.; et al. Concepts and Applications of AquaCrop: The FAO Crop Water Productivity Model. In *Crop Modeling and Decision Support*; Springer: Berlin/Heidelberg, Germany, 2009.
38. De Roos, S.; De Lannoy, G.J.M.; Raes, D. Performance Analysis of Regional AquaCrop (v6.1) Biomass and Surface Soil Moisture Simulations Using Satellite and in Situ Observations. *Geosci. Model Dev.* **2021**, *14*, 7309–7328. [\[CrossRef\]](#)
39. Busschaert, L.; De Roos, S.; Thiery, W.; Raes, D.; De Lannoy, G.J.M. Net Irrigation Requirement under Different Climate Scenarios Using AquaCrop over Europe. *Hydrol. Earth Syst. Sci.* **2022**, *26*, 3731–3752. [\[CrossRef\]](#)
40. Ahmadi, S.H.; Mosallaepour, E.; Kamgar-Haghighi, A.A.; Sepaskhah, A.R. Modeling Maize Yield and Soil Water Content with AquaCrop Under Full and Deficit Irrigation Managements. *Water Resour. Manag.* **2015**, *29*, 2837–2853. [\[CrossRef\]](#)
41. Jones, J.; Hoogenboom, G.; Porter, C.; Boote, K.; Batchelor, W.; Hunt, L.; Ritchie, J. The DSSAT Cropping System Model. *Eur. J. Agron.* **2003**, *18*, 235–265. [\[CrossRef\]](#)
42. Shelia, V.; Šimunek, J.; Boote, K.; Hoogenboom, G. Coupling DSSAT and HYDRUS-1D for Simulations of Soil Water Dynamics in the Soil-Plant-Atmosphere System. *J. Hydrol. Hydromech.* **2018**, *66*, 232–245. [\[CrossRef\]](#)
43. Šimunek, J.; Brunetti, G.; Jacques, D.; van Genuchten, M.T.; Šejna, M. Developments and Applications of the HYDRUS Computer Software Packages since 2016. *Vadose Zone J.* **2024**, *23*, e20310. [\[CrossRef\]](#)
44. Šimunek, J.; van Genuchten, M.T. Modeling Nonequilibrium Flow and Transport Processes Using HYDRUS. *Vadose Zone J.* **2008**, *7*, 782–797. [\[CrossRef\]](#)
45. Šimunek, J.; van Genuchten, M.T.; Šejna, M. Recent Developments and Applications of the HYDRUS Computer Software Packages. *Vadose Zone J.* **2016**, *15*, 1–25. [\[CrossRef\]](#)
46. Šimunek, J.; van Genuchten, M.T.; Šejna, M. Development and Applications of the HYDRUS and STANMOD Software Packages and Related Codes. *Vadose Zone J.* **2008**, *7*, 587–600. [\[CrossRef\]](#)
47. Šimunek, J.; Van Genuchten, M.T.; Šejna, M. Hydrus: Model Use, Calibration, and Validation. *Trans. ASABE* **2012**, *55*, 1263–1276. [\[CrossRef\]](#)
48. Larsbo, M.; Roulier, S.; Stenemo, F.; Kasteel, R.; Jarvis, N. An Improved Dual-Permeability Model of Water Flow and Solute Transport in the Vadose Zone. *Vadose Zone J.* **2005**, *4*, 398–406. [\[CrossRef\]](#)
49. Jarvis, N.J.; Jansson, P.-E.; Dik, P.E.; Messing, I. Modelling Water and Solute Transport in Macroporous Soil. I. Model Description and Sensitivity Analysis. *J. Soil Sci.* **1991**, *42*, 59–70. [\[CrossRef\]](#)
50. Jarvis, N.; Larsbo, M. MACRO (V5.2): Model Use, Calibration, and Validation. *Trans. ASABE* **2012**, *55*, 1413–1423. [\[CrossRef\]](#)
51. Zhang, X.C. Calibration, Refinement, and Application of the WEPP Model for Simulating Climatic Impact on Wheat Production. *Trans. Am. Soc. Agric. Eng.* **2004**, *47*, 1075–1085. [\[CrossRef\]](#)
52. Laflen, J.M.; Lane, L.J.; Foster, G.R. WEPP: A New Generation of Erosion Prediction Technology. *J. Soil Water Conserv.* **1991**, *46*, 34–38. [\[CrossRef\]](#)
53. East, A.E.; Logan, J.B.; Dow, H.W.; Smith, D.P.; Iampietro, P.; Warrick, J.A.; Lorenson, T.D.; Hallas, L.; Kozłowicz, B. Post-Fire Sediment Yield From a Central California Watershed: Field Measurements and Validation of the WEPP Model. *Earth Space Sci.* **2024**, *11*, e2024EA003575. [\[CrossRef\]](#)
54. Wells, R.R.; Flanagan, D.C.; Langendoen, E.J.; McGehee, R.P.; Bingner, R.L.; Frankenberger, J.R.; Locke, M.A.; Momm, H.G.; Renschler, C.S.; Srivastava, A.; et al. Cropland Water Erosion Estimates Simulated by RUSLE2 and WEPP: Results from Two Initial Studies. *J. Soil Water Conserv.* **2024**, *79*, 215–232. [\[CrossRef\]](#)
55. Basso, M.; Brooks, E.; Srivastava, A.; Keizer, J.; Robichaud, R.P. Evaluating Watershed Response Using WEPPcloud—EU for Wildfire Burned Areas in Portugal. *Hydrol. Process.* **2025**, *39*, e70182. [\[CrossRef\]](#)
56. Licciardello, F.; Taguas, E.V.; Barbagallo, S.; Gómez, J.A. Application of the Water Erosion Prediction Project (WEPP) in Olive Orchards on Vertic Soil with Different Management Conditions. *Trans. ASABE* **2013**, *56*, 951–961. [\[CrossRef\]](#)
57. Flanagan, D.C.; Gilley, J.E.; Franti, T.G. Water Erosion Prediction Project (WEPP): Development History, Model Capabilities, and Future Enhancements. *Trans. ASABE* **2007**, *50*, 1603–1612. [\[CrossRef\]](#)
58. Chu, S.T. Infiltration during an Unsteady Rain. *Water Resour. Res.* **1978**, *14*, 461–466. [\[CrossRef\]](#)
59. Ritchie, J.T. Model for Predicting Evaporation from a Row Crop with Incomplete Cover. *Water Resour. Res.* **1972**, *8*, 1204–1213. [\[CrossRef\]](#)

60. Williams, J.R.; Jones, C.A.; Dyke, P.T. A Modelling Approach to Determining the Relationship between Erosion and Soil Productivity. *Trans.-Am. Soc. Agric. Eng.* **1984**, *27*, 129–144. [\[CrossRef\]](#)
61. Flanagan, D.; Nearing, M. *USDA Water Erosion Prediction Project: Hillslope Profile and Watershed Model Documentation*; NSERL Rep. 10; Agricultural Research Service: West Lafayette, IN, USA, 1995.
62. Savabi, M.R.; Rawls, W.J.; Knight, R.W. Water Erosion Prediction Project (WEPP) Rangeland Hydrology Component Evaluation on a Texas Range Site. *J. Range Manag.* **1995**, *48*, 535. [\[CrossRef\]](#)
63. Blanco, C.N.; Pérez, M.; Bentancur, O. WEPP Model Prediction Evaluation of Soil Water Content in Northeast Uruguay. *Agrociencia* **2020**, *24*, e63. [\[CrossRef\]](#)
64. Ma, L.; Ahuja, L.R.; Nolan, B.T.; Malone, R.W.; Trout, T.J.; Qi, Z. Root Zone Water Quality Model (RZWQM2): Model Use, Calibration, and Validation. *Trans. ASABE* **2012**, *55*, 1425–1446. [\[CrossRef\]](#)
65. Ahuja, L.R.; Rojas, K.W.; Hanson, J.D.; Shaffer, M.J. *Root Zone Water Quality Model: Modelling Management Effects on Water Quality and Crop Production*; Water Resources Publication: Highlands Ranch, CO, USA, 2000.
66. Flerchinger, G.N.; Aiken, R.M.; Rojas, K.W.; Ahuja, L.R. Development of the Root Zone Water Quality Model (RZWQM) for over-Winter Conditions. *Trans. Am. Soc. Agric. Eng.* **2000**, *43*, 59–68. [\[CrossRef\]](#)
67. Ahuja, L.R.; Decoursey, D.G.; Barnes, B.B.; Rojas, K.W. Characteristics of Macropore Transport Studied with the ARS Root Zone Water Quality Model. *Trans.-Am. Soc. Agric. Eng. Gen. Ed.* **1993**, *36*, 369–380. [\[CrossRef\]](#)
68. Zhang, H.; Ma, L.; Hanson, J.D.; Qi, Z. The USDA Root Zone Water Quality Model. In *Current Crop Models: State-of-the-Art and Future Developments*; Hoogenboom, G., Ed.; Burleigh Dodds Science Publishing Limited: Cambridge, UK, 2025; pp. 273–325.
69. Jaber, F.H.; Shukla, S. MIKE SHE: Model Use, Calibration, and Validation. *Trans. ASABE* **2012**, *55*, 1479–1489. [\[CrossRef\]](#)
70. Rujner, H.; Leonhardt, G.; Marsalek, J.; Viklander, M. High-Resolution Modelling of the Grass Swale Response to Runoff Inflows with Mike SHE. *J. Hydrol.* **2018**, *562*, 411–422. [\[CrossRef\]](#)
71. Li, D.; Liang, Z.; Li, B.; Lei, X.; Zhou, Y. Multi-Objective Calibration of MIKE SHE with SMAP Soil Moisture Datasets. *Hydrol. Res.* **2019**, *50*, 644–654. [\[CrossRef\]](#)
72. Islam, N.; Wallender, W.W.; Mitchell, J.P.; Wicks, S.; Howitt, R.E. Performance Evaluation of Methods for the Estimation of Soil Hydraulic Parameters and Their Suitability in a Hydrologic Model. *Geoderma* **2006**, *134*, 135–151. [\[CrossRef\]](#)
73. Xia, L.; Bi, R.T.; Song, X.Y.; Hu, W.; Lyu, C.J.; Xi, X.; Li, H.Y. Soil Moisture Response to Land Use and Topography across a Semi-Arid Watershed: Implications for Vegetation Restoration on the Chinese Loess Plateau. *J. Mt. Sci.* **2022**, *19*, 103–120. [\[CrossRef\]](#)
74. Graham, D.N.; Butts, M.B. Flexible Integrated Watershed Modeling with MIKE SHE. In *Watershed Models*; CRC Press: Boca Raton, FL, USA, 2005.
75. Šimůnek, J.; Jarvis, N.J.; Van Genuchten, M.T.; Gärdenäs, A. Review and Comparison of Models for Describing Non-Equilibrium and Preferential Flow and Transport in the Vadose Zone. *J. Hydrol.* **2003**, *272*, 14–35. [\[CrossRef\]](#)
76. Refsgaard, J.C. Parameterisation, Calibration and Validation of Distributed Hydrological Models. *J. Hydrol.* **1997**, *198*, 69–97. [\[CrossRef\]](#)
77. Kroes, J.G.; van Dam, J.C.; Bartholomeus, R.P.; Groenendijk, P.; Heinen, M.; Hendriks, R.F.A.; Mulder, H.M.; Supit, I.; van Walsum, P.E.V. *SWAP Version 4: Theory Description and User Manual*; Wageningen Environmental Research: Wageningen, The Netherlands, 2017.
78. van Dam, J.C.; Groenendijk, P.; Hendriks, R.F.A.; Kroes, J.G. Advances of Modeling Water Flow in Variably Saturated Soils with SWAP. *Vadose Zone J.* **2008**, *7*, 640–653. [\[CrossRef\]](#)
79. Feddes, R.A.; Kowalik, P.; Kolinska-Malinka, K.; Zaradny, H. Simulation of Field Water Uptake by Plants Using a Soil Water Dependent Root Extraction Function. *J. Hydrol.* **1976**, *31*, 13–26. [\[CrossRef\]](#)
80. Arnold, J.G.; Moriasi, D.N.; Gassman, P.W.; Abbaspour, K.C.; White, M.J.; Srinivasan, R.; Santhi, C.; Harmel, R.D.; van Griensven, A.; Van Liew, M.W.; et al. SWAT: Model Use, Calibration, and Validation. *Trans. ASABE* **2012**, *55*, 1491–1508. [\[CrossRef\]](#)
81. Gassman, P.W.; Reyes, M.R.; Green, C.H.; Arnold, J.G. The Soil and Water Assessment Tool: Historical Development, Applications, and Future Research Directions. *Trans. ASABE* **2007**, *50*, 1211–1250. [\[CrossRef\]](#)
82. Bieger, K.; Arnold, J.G.; Rathjens, H.; White, M.J.; Bosch, D.D.; Allen, P.M.; Volk, M.; Srinivasan, R. Introduction to SWAT+, A Completely Restructured Version of the Soil and Water Assessment Tool. *J. Am. Water Resour. Assoc.* **2017**, *53*, 115–130. [\[CrossRef\]](#)
83. Hashem, A.A.; Engel, B.A.; Marek, G.W.; Moorhead, J.E.; Flanagan, D.C.; Rashad, M.; Radwan, S.; Bralts, V.F.; Gowda, P.H. Evaluation of Swat Soil Water Estimation Accuracy Using Data from Indiana, Colorado, and Texas. *Trans. ASABE* **2020**, *63*, 1827–1843. [\[CrossRef\]](#)
84. Zare, M.; Azam, S.; Sauchyn, D. Evaluation of Soil Water Content Using SWAT for Southern Saskatchewan, Canada. *Water* **2022**, *14*, 249. [\[CrossRef\]](#)
85. van Tol, J.; Bieger, K.; Arnold, J.G. A Hydropedological Approach to Simulate Streamflow and Soil Water Contents with SWAT+. *Hydrol. Process.* **2021**, *35*, e14242. [\[CrossRef\]](#)

86. Danabasoglu, G.; Lamarque, J.F.; Bacmeister, J.; Bailey, D.A.; DuVivier, A.K.; Edwards, J.; Emmons, L.K.; Fasullo, J.; Garcia, R.; Gettelman, A.; et al. The Community Earth System Model Version 2 (CESM2). *J. Adv. Model. Earth Syst.* **2020**, *12*, e2019MS001916. [\[CrossRef\]](#)
87. Lawrence, D.M.; Fisher, R.A.; Koven, C.D.; Oleson, K.W.; Swenson, S.C.; Bonan, G.; Collier, N.; Ghimire, B.; van Kampenhout, L.; Kennedy, D.; et al. The Community Land Model Version 5: Description of New Features, Benchmarking, and Impact of Forcing Uncertainty. *J. Adv. Model. Earth Syst.* **2019**, *11*, 4245–4287. [\[CrossRef\]](#)
88. Lawrence, D.M.; Oleson, K.W.; Flanner, M.G.; Thornton, P.E.; Swenson, S.C.; Lawrence, P.J.; Zeng, X.; Yang, Z.-L.; Levis, S.; Sakaguchi, K.; et al. Parameterization Improvements and Functional and Structural Advances in Version 4 of the Community Land Model. *J. Adv. Model. Earth Syst.* **2011**, *3*, M03001. [\[CrossRef\]](#)
89. Ou, M.; Zhang, S. Evaluation and Comparison of the Common Land Model and the Community Land Model by Using In Situ Soil Moisture Observations from the Soil Climate Analysis Network. *Land* **2022**, *11*, 126. [\[CrossRef\]](#)
90. Ek, M.B.; Mitchell, K.E.; Lin, Y.; Rogers, E.; Grunmann, P.; Koren, V.; Gayno, G.; Tarpley, J.D. Implementation of Noah Land Surface Model Advances in the National Centers for Environmental Prediction Operational Mesoscale Eta Model. *J. Geophys. Res. Atmos.* **2003**, *108*, 8851. [\[CrossRef\]](#)
91. Mitchell, K.E.; Lohmann, D.; Houser, P.R.; Wood, E.F.; Schaake, J.C.; Robock, A.; Cosgrove, B.A.; Sheffield, J.; Duan, Q.; Luo, L.; et al. The Multi-Institution North American Land Data Assimilation System (NLDAS): Utilizing Multiple GCIP Products and Partners in a Continental Distributed Hydrological Modeling System. *J. Geophys. Res. Atmos.* **2004**, *109*, D07S90. [\[CrossRef\]](#)
92. Niu, G.Y.; Yang, Z.L.; Mitchell, K.E.; Chen, F.; Ek, M.B.; Barlage, M.; Kumar, A.; Manning, K.; Niyogi, D.; Rosero, E.; et al. The Community Noah Land Surface Model with Multiparameterization Options (Noah-MP): 1. Model Description and Evaluation with Local-Scale Measurements. *J. Geophys. Res. Atmos.* **2011**, *116*, D12109. [\[CrossRef\]](#)
93. Yang, Z.L.; Niu, G.Y.; Mitchell, K.E.; Chen, F.; Ek, M.B.; Barlage, M.; Longuevergne, L.; Manning, K.; Niyogi, D.; Tewari, M.; et al. The Community Noah Land Surface Model with Multiparameterization Options (Noah-MP): 2. Evaluation over Global River Basins. *J. Geophys. Res. Atmos.* **2011**, *116*, D12110. [\[CrossRef\]](#)
94. Zhuo, L.; Dai, Q.; Han, D.; Chen, N.; Zhao, B. Assessment of Simulated Soil Moisture from WRF Noah, Noah-MP, and CLM Land Surface Schemes for Landslide Hazard Application. *Hydrol. Earth Syst. Sci.* **2019**, *23*, 4199–4218. [\[CrossRef\]](#)
95. Arsenaault, K.R.; Nearing, G.S.; Wang, S.; Yatheendradas, S.; Peters-Lidard, C.D. Parameter Sensitivity of the Noah-MP Land Surface Model with Dynamic Vegetation. *J. Hydrometeorol.* **2018**, *19*, 815–830. [\[CrossRef\]](#)
96. Liang, X.; Lettenmaier, D.P.; Wood, E.F.; Burges, S.J. A Simple Hydrologically Based Model of Land Surface Water and Energy Fluxes for General Circulation Models. *J. Geophys. Res.* **1994**, *99*, 14415–14428. [\[CrossRef\]](#)
97. Hamman, J.J.; Nijssen, B.; Bohn, T.J.; Gergel, D.R.; Mao, Y. The Variable Infiltration Capacity Model Version 5 (VIC-5): Infrastructure Improvements for New Applications and Reproducibility. *Geosci. Model Dev.* **2018**, *11*, 3481–3496. [\[CrossRef\]](#)
98. Nijssen, B.; Schnur, R.; Lettenmaier, D.P. Global Retrospective Estimation of Soil Moisture Using the Variable Infiltration Capacity Land Surface Model, 1980–93. *J. Clim.* **2001**, *14*, 1790–1808. [\[CrossRef\]](#)
99. Haddeland, I.; Lettenmaier, D.P.; Skaugen, T. Reconciling Simulated Moisture Fluxes Resulting from Alternate Hydrologic Model Time Steps and Energy Budget Closure Assumptions. *J. Hydrometeorol.* **2006**, *7*, 355–370. [\[CrossRef\]](#)
100. Franchini, M.; Pacciani, M. Comparative Analysis of Several Conceptual Rainfall-Runoff Models. *J. Hydrol.* **1991**, *122*, 161–219. [\[CrossRef\]](#)
101. Tang, Q.; Gao, H.; Yeh, P.; Oki, T.; Su, F.; Lettenmaier, D.P. Dynamics of Terrestrial Water Storage Change from Satellite and Surface Observations and Modeling. *J. Hydrometeorol.* **2010**, *11*, 156–170. [\[CrossRef\]](#)
102. King, K.W.; Arnold, J.G.; Bingner, R.L. Comparison of Green-Ampt and Curve Number Methods on Goodwin Creek Watershed Using SWAT. *Trans. Am. Soc. Agric. Eng.* **1999**, *42*, 919–926. [\[CrossRef\]](#)
103. Kikoyo, D.; Oker, T. Comparative Evaluation of the Performance of SWAT, SWAT+, and APEX Models in Simulating Edge of Field Hydrological Processes. *Open J. Model. Simul.* **2023**, *11*, 37–49. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.