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Integrated crop and hydraulic modeling for precision irrigation: parameter estimation and sensitivity analysis (a review)

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ABSTRACT

Sustainable agriculture demands innovative strategies to optimize water use amid growing climatic uncertainties, resource limitations, and to bolster the resilience of farming systems worldwide in the face of climate change. This review provides a critical synthesis of state-of-the-art modeling approaches that integrate crop growth dynamics with soil hydraulic processes to support precision irrigation management. Emphasizing the vadose zone's central role as the critical interface governing soil-plant-water interactions, the paper examines a suite of widely used, process-based crop models (e.g., WOFOST, CERES, AquaCrop, DSSAT, APSIM) alongside specialized hydrological models (e.g., HYDRUS, SWAP, SWAT). It highlights their synergistic capability to simulate the complex, nonlinear feedback between root water uptake, soil moisture dynamics, evapotranspiration, and solute transport, which is fundamental for predicting crop water requirements and responses to irrigation. The primary challenge for this approach is the accurate determination of often unknown or highly variable soil hydraulic and crop parameters. This review demonstrated that 1) Advanced inverse modeling techniques provide a powerful alternative to direct measurements by using optimization algorithms to estimate critical parameters from field data. 2) Sensitivity analysis (both local and global) is indispensable for evaluating model robustness, identifying influential parameters, and mitigating calibration issues like equifinality. 3) Well-calibrated, integrated models enable a robust, physically sound framework for generating site-specific irrigation schedules, moving beyond traditional homogeneous management. We also identify key challenges, including data scarcity and computational demands. To address these, we advocate for the future development of quasi-3D hybrid modeling platforms that leverage high-resolution data from easily available resources, laboratories, remote sensing, and IoT networks. This integrative approach holds significant promise for advancing next-generation precision irrigation, enhancing water use efficiency, and strengthening global agricultural resilience.

Keywords: Precision irrigation, Inverse modeling, Sensitivity Analysis, Soil hydraulic properties, Vadose Zone.

1. Introduction

The fast growing global population coupled with the escalating impacts of climate change and increasing freshwater scarcity, has intensified the demand for sustainable and efficient agricultural water management (FAO, 2023). Precision irrigation has therefore emerged as a critical strategy to optimize water use efficiency, enhance crop productivity, and minimize the environmental impacts (Lakhiar et al., 2024). Achieving effective precision irrigation requires a comprehensive understanding of the complex interactions within the soil–plant–atmosphere continuum (SPAC) framework, as well as to consider about the spatial and temporal variability in soil moisture, crop water demand, and environmental conditions. The vadose zone, which extends from the soil surface to the groundwater table, is the critical interface where these interactions occur. Its dynamics are governed by complex, nonlinear physical processes, primarily described by Richards' equation for variably saturated water flow and the convection-dispersion equation for solute transport. Accurately simulating these processes is fundamental to predicting crop water requirements.

The application of process-based models often faces a significant challenge like the accurate determination of key soil hydraulic properties (e.g., saturated hydraulic conductivity, van Genuchten parameters) and crop-related properties (e.g., root growth, crop coefficients). These parameters are often highly variable in space and time and are difficult to measure directly at relevant scales. These difficulties lead to the adopt the inverse modeling techniques, where model parameters are estimated by minimizing the discrepancy between simulated outputs and observed field data (e.g., soil moisture time series and yield) using optimization algorithms. Successing of this calibration process is typically evaluated by statistical metrics like the Root Mean Square Error (RMSE) or the Nash-Sutcliffe efficiency coefficient.

Furthermore, the robustness of these models must be evaluated under uncertainty. Sensitivity Analysis (SA) serves this purpose by quantifying how uncertainty in the model inputs (parameters, initial conditions) contributes to uncertainty in model outputs. SA methods range from local approaches, evaluating perturbations around a nominal parameter set, to global methods, which explore the entire parameter space. This process is indispensable for identifying the most influential parameters, guiding data collection efforts, and diagnosing model structure.

Traditional irrigation scheduling methods, which often rely on empirical guidelines or fixed calendars, are limited in their capacity to address the heterogeneity inherent in agricultural fields (Ahmed et al., 2023). These conventional approaches may lead to either under- or over-irrigation, resulting in yield loss or excessive water consumption (Umutoni and Samadi, 2024). In contrast, physically based and process-oriented models offer robust frameworks to simulate dynamic soil water movement, crop growth, and evapotranspiration processes (Rezaei, 2016). Crop growth models such as WOFOST (WOrld FOod STudies), CERES (Crop Environment Resource Synthesis), and AquaCrop (Crop-Water Productivity Model of FAO) have been extensively utilized to assess crop responses to variable irrigation regimes and climate variability (Moroozeh et al., 2023; Rezaei, 2016). Simultaneously, hydrological models including HYDRUS (Windows application for simulating water, heat, and solute movement), SWAP (Soil Water Atmosphere Plant), and SWAT (Soil & Water Assessment Tool) provide detailed insights into soil water and solute transport mechanisms within the vadose zone, enabling better prediction of water availability for plants (Rezaei, 2016; Rezaei et al., 2021; Šimůnek et al., 2024b). Furthermore, the escalating impacts of climate change introduce additional variability and uncertainty, necessitating robust modeling frameworks that can adapt to changing conditions.

A pivotal aspect of the successful application of these models lies in the accurate determination of soil hydraulic and crop-related parameters (Rezaei et al., 2016a; Šimůnek et al., 2024b). Inverse modeling techniques have gained prominence as powerful tools for parameter estimation, enhancing model calibration by reconciling observed field data with simulated outputs (Rossi et al., 2015; Wöhling et al., 2009; Zhang et al., 2018). Furthermore, sensitivity analysis methods contribute to identifying key parameters influencing model predictions and to evaluating model robustness under uncertainties (Rezaei et al., 2016a).

Despite significant progress, challenges remain in scaling these models from plot to regional levels, incorporating high-resolution spatial variability, and dealing with data limitations. Addressing these challenges necessitates the development of integrated modeling platforms that couple crop growth and soil hydrology models with advanced data assimilation techniques and remote sensing inputs. This review aims to synthesize current advances in crop growth and hydrological modeling as applied to precision irrigation. It highlights the principles, applications, and limitations of key modeling frameworks, including inverse modeling and sensitivity analysis, and discusses their role in improving irrigation management decisions. By bridging modeling techniques with emerging technologies, this study contributes to the foundation for developing next-generation decision support systems that promote sustainable water use and enhance crop productivity under changing environmental conditions. This review also acknowledges the research limitations inherent in these integrated approaches, particularly concerning data scarcity, scaling challenges, and computational demands, and discusses pathways to overcome them.

2. Modeling Approach

Achieving an optimal balance between water supply and crop water demand is a central challenge in sustainable agricultural water resource management. The vadose zone, encompassing both the soil matrix and root zone, represents a complex environment governed by highly nonlinear and dynamic interactions (Šimůnek et al., 2024a). Traditional irrigation scheduling methods often fall short due to limitations such as the high cost of sensor deployment, difficulty in acquiring accurate in situ or laboratory measurements, and limited adaptability to variable field conditions (Rezaei et al., 2021). As a result, modeling approaches have gained traction as effective alternatives for simulating irrigation timing and quantities.

In recent decades, there has been a marked transition from allocation-based methods to data-driven and quantitative irrigation management strategies (Elmaloglou and Malamos, 2003; Jenkins and Block, 2024; Li et al., 2012; Paudyal and Dasgupta, 1990; Raman et al., 1992; Sanaee-Jahromi et al., 2001; Violino et al., 2023). At the core of this evolution lies the development and application of mathematical, numerical, conceptual, and physically-based models. These models can function independently or be integrated with crop growth and hydrological models to facilitate more precise and responsive irrigation planning (Rezaei, 2016). Their widespread adoption in irrigation system design and management underscores their practical values.

Modeling approaches offer several advantages. They provide a systematic and replicable framework for quantifying complex processes within the vadose zone, including soil moisture dynamics, evapotranspiration, solute transport, and plant-water interactions (Jones et al., 2017). Furthermore, these models can be calibrated to estimate crop water requirements under varying climatic conditions, soil properties, salinity and sodicity levels, and crop types (Rezaei et al., 2016a; Rezaei et al., 2021; Šimůnek et al., 2024a). Such integrative modeling frameworks support the implementation of precision irrigation and contribute to optimizing water use efficiency in agriculture as illustrated in the conceptual framework in Figure 1.

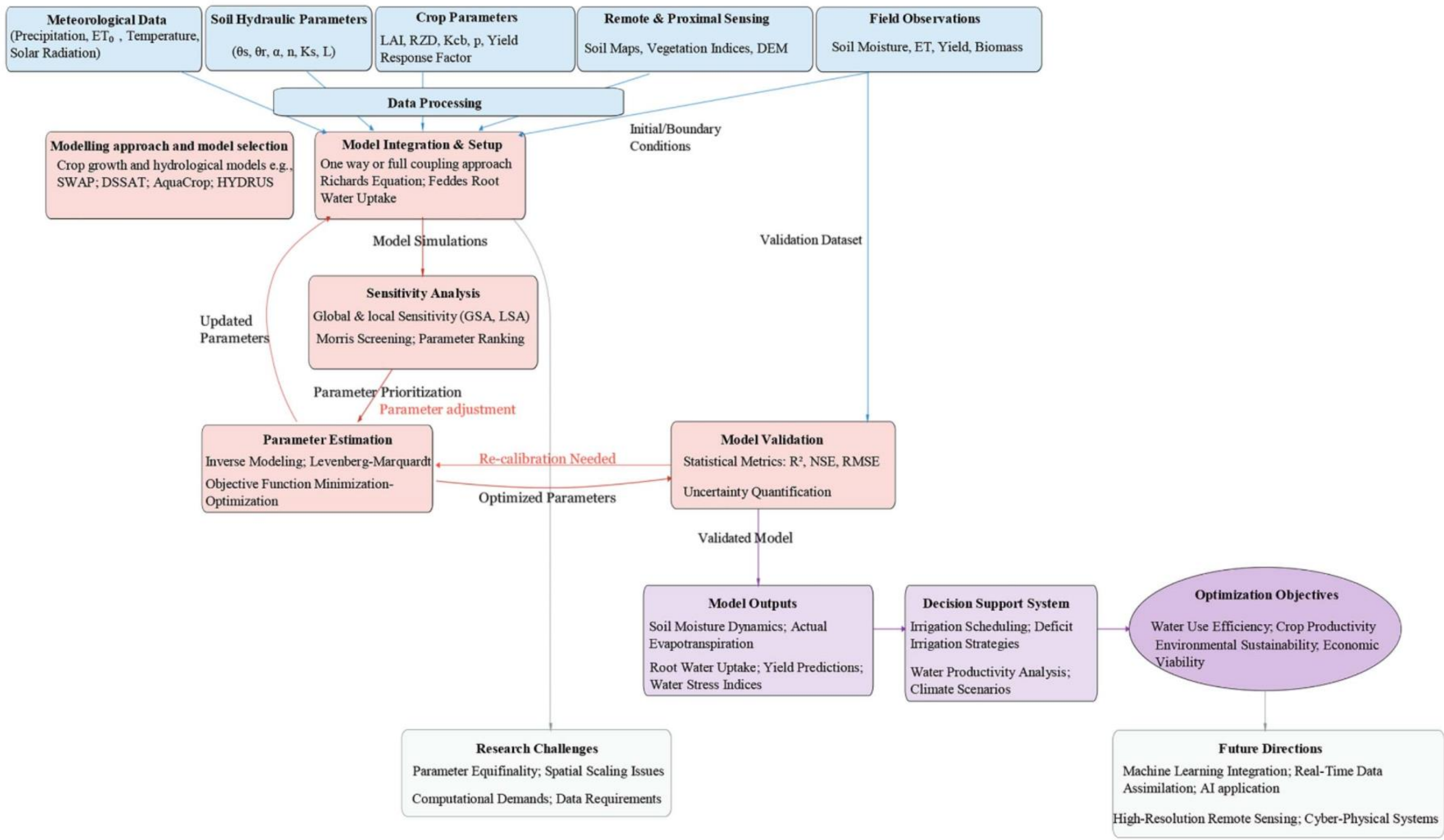

Fig 1. A conceptual flowchart illustrating the integrative modeling approach for precision irrigation, highlighting the coupling of crop and hydrological models, the central role of parameter estimation and sensitivity analysis, and the feedback loop with field data and management decisions.

2.1. Crop growth modeling

Crop growth models are essential tools for understanding plant development and evaluating the effects of water and nutrient management on crop performance (Kundathil et al., 2023). Over the past three decades, numerousm models have been developed to simulate crop growth and soil–water interactions with varying degrees of complexity, including statistical, mechanistic, deterministic, stochastic, static, dynamic, descriptive, and explanatory frameworks (Rauff and Bello, 2015; Sargun and Mohan, 2020; Vazifedoust et al., 2008) These models form the basis of decision support systems for irrigation and fertilization scheduling, climate impact assessments, and sustainable agricultural planning.

Typically grounded in soil water balance principles and yield–water relationships, crop models are employed to simulate plant responses to varying environmental and management conditions. Applications include assessing irrigation strategies (Darouich et al., 2014), evaluating climate change scenarios (Gobin, 2010; Semenov, 2009), designing and managing irrigation systems (Darouich et al., 2014; Li et al., 2011; Shang and Mao, 2006), investigating water-saving practices (Fang et al., 2010; Gongalves et al., 2007), and testing the feasibility of deficit irrigation (Geerts et al., 2010; Salemi et al., 2011). These models consider key variables such as weather patterns, soil characteristics, crop traits, and management practices to simulate plant growth dynamics across time. By enabling scenario analysis, crop models provide valuable insights for optimizing water and nutrient use, improving crop yield, and supporting resilient farming systems.

Despite their benefits, crop models are subject to limitations. These models are typically grounded in key assumptions such as homogeneity within field units, simplified representations of root architecture and water uptake, and often neglect complex interactions with pests, diseases, and micronutrient limitations. Their accuracy depends heavily on reliable input data (e.g., weather, soil, and crop parameters), proper calibration and validation, and, in some cases, advanced computational resources and modeling expertise (see Table 1 references). Table 1 summarizes several widely used crop growth models and their respective applications.

2.2. Hydrological modeling

Despite the significant contributions of crop growth models to agricultural productivity assessment, their hydrological components often rely on oversimplified assumptions such as fixed rooting depths and static field capacity concepts. These limitations underscore the need for dedicated hydrological modeling approaches capable of accurately simulating water dynamics and solute transport within the vadose zone—a region characterized by highly nonlinear, heterogeneous, and dynamic processes. Since the early 1970s, soil–water modeling has evolved from empirical approximations to sophisticated, physically-based formulations that enable the exploration of interactions within the soil–plant–atmosphere continuum(Bultot and Dupriez, 1976; Neuman et al., 1974; Toksoz and Kirkham, 1971; Zaradny and Feddes, 1979). Early models such as the Stanford Watershed Model (Crawford and Burges, 1966). laid the conceptual foundation for simulating watershed hydrology and remain historically significant in shaping the trajectory of modern modeling frameworks.

Hydrological models are often classified according to their underlying assumptions, complexity, spatial and temporal resolution, and computational methodologies. First, based on mathematical structure, models are divided into deterministic and stochastic classes (Ghonchepour et al., 2021). Deterministic models yield a unique solution for a given set of inputs, suitable for mechanistic analyses with well-defined boundary conditions. Stochastic models incorporate random variables or probabilistic parameters to account for natural variability and data uncertainty, making them more adaptable to real-world complexities (Jajarmizadeh et al., 2012). Second, temporally, models can be static, providing steady-state approximations without considering temporal evolution, or dynamic, which simulate time-dependent processes. Dynamic models are further differentiated as event-based—suited for simulating storm events or irrigation cycles—and continuous, which represent long-term processes like seasonal recharge and evapotranspiration.

Third, according to their physical basis, models are categorized as empirical, conceptual, or physically-based. Empirical (or data-driven) models rely solely on statistical correlations derived from historical input–output datasets and are useful where physical insight is limited (Hu et al., 2021). Conceptual models introduce simplified process representations, often through interconnected reservoirs simulating rainfall infiltration, percolation, surface runoff, and drainage. These models strike a balance between realism and manageability but demand rigorous calibration. Physically-based models, also referred to as mechanistic models, employ first-principle equations such as Richards' equation for water flow and Fickian-based formulations for solute transport (Feng et al., 2025). These models simulate the spatial and temporal evolution of state variables—such as water content, matric potential, and solute concentration—using partial differential equations that require discretization and numerical solution. Their strength lies in their predictive capacity and process fidelity, though they necessitate substantial data input, including soil hydraulic properties, boundary fluxes, and meteorological forcing (Feng et al., 2025).

Fourth, with regard to spatial representation, hydrological models are typically lumped or distributed. Lumped models simplify spatial variability by

Table 1. Commonly used soil-crop growth models, and their application domains.

Model	Full name	Application/ Description	Reference
WOFOST	WOrld FOod STudies	A mechanistic-simulation model for the quantitative analysis of water use, the growth and production of annual field crops.	(Van Keulen and Wolf, 1986)
CGMS	Crop Growth Monitoring System	A combination of GIS and WOFOST model for spatial yield prediction.	(Hooijer and van der Wal, 1994)
SUCROS	Simple and Universal Crop Simulator	Simulates potential growth of a crop under supplied water and nutrients and prevailing weather condition.	(Spitters et al., 1989)
SIMCOY	SIMulation of COrnYileld	Simulate yields under different management options.	(Brown and 1969; Place and Brown, 1987)
CERES	Crop Environment REsource Synthesis	A dynamic crop model simulating phenological development, biomass formation, soil water content, and nitrogen balance for cereals (barley, maize, sorghum, millet, rice and wheat).	(Jones and Kiniry, 1986)
APSIM	Agricultural Production System sIMulator	Simulates crop and pasture production, soil water and nutrient dynamics, and erosion under varying production systems.	(McCown et al., 1996)
Beta model	Beta model	Uses multiplicative functions to describe temperature and photoperiod interactions under management scenarios.	(Gao et al., 1992)
SWACROP	Soil WAter Content and Crop	(Huygen, 1992)	(Huygen, 1992)
MACROS	Modules of an Annual CROp Simulator	Simulates crop growth and water movement for various crops and weather; estimates water balance for different soils.	(Penning de Vries et al., 1989)
CROPWAT	CROP WATer	A decision-support tool to calculate crop and irrigation water requirements based on soil, climate, and crop data.	(Smith, 1991)
ISAREG	Irrigation Scheduling REGen	Performs the water balance for a multilayered soil profile; simulates irrigation scheduling and assesses the impacts of water stress and salinity on crop yield. Irrigation planning and water stress impact analysis under varying soil and salinity conditions.	(Teixeira and Pereira, 1992)
BUDGET (Raes, 2002)	a soil water and salt balance model	A set of validated subroutines describing the various processes involved in water extraction by plant roots and water movement in the soil profile. Calculates the water storage and salt content in a cropped soil profile as affected by input and withdrawal of water	(Raes, 2002)
OSIRI	Outil Simplifié pour une Irrigation Raisonnée et Individualisée (i.e. simple decision-making tool for sustainable individual monitoring of irrigation)	A simple tool aimed at optimizing irrigation water and rainfall use, taking into account heterogeneities of the irrigation parameters and of the environmental factors	(Chopart et al., 2007)
ISM	Irrigation Scheduling Model	Irrigation scheduling model under various management options for both single and multiple fields	(George et al., 2000)
PILOTE		An operative water balance model which predicts actual evapotranspiration and yield of crops; Determines the water stress index	(Mailhol et al., 1996)

Table 1. (Continued).

Model	Full name	Application/ Description	Reference
SIMDualKc	Simulation (soil water balance) Dual crop coefficient (Kc)	Simplifying implementation of the computation of the crop coefficient and crop evapotranspiration using the dual crop coefficient approach over a range of cultural practices and to provide ET information for use in irrigation scheduling and hydrologic water balances	(Rosa et al., 2012)
AquaCrop	Modeling crop yield response to water	The FAO crop-model to simulate yield response to water of several herbaceous crops; Estimation of crop productivity in relation to water supply and agronomic management in a framework based on current plant physiological and soil water budgeting concepts	(Raes et al., 2009)
DAISY	An open soil-crop-atmosphere system model	A mechanistic-dynamic model for simulation of water and nitrogen dynamics and crop growth in agro-ecosystems. The model aims at simulating water balance, nitrogen balance and losses, development in soil organic matter and crop growth and production in crop rotations under alternate management strategies	(Abrahamsen and Hansen, 2000)
AFRC-Wheat	Wheat phenology model	A mechanistic model that incorporates crop response to water and nitrogen constraints. Model processes include phenological development, partitioning of photosynthesis, growth of leaf and stems, senescence, biomass accumulation, and root system dynamics.	(Weir et al., 1984)
APSIM	Agricultural Production Systems Simulator	A farming systems model that consists of several modules integrated to perform farming systems simulation including water balance, N and P transformations, soil pH, erosion and a full range of management controls	(Araya et al., 2015; Brown et al., 2011; Keating et al., 2003; Kloss et al., 2012)
CROPGRO	CROP GROwth	A generic, physiological, process-oriented legume crop growth model	(Hoogenboom et al., 1992)
CropSyst	Crop System	A multi-year, multi-crop, daily time step cropping systems simulation model developed to serve as an analytical tool to study the effect of climate, soils, and management on cropping systems productivity and the environment	(Stockle et al., 1994)
LINTUL	Light INTerception and UtiLization simulator	A generic and simple crop growth model that can simulate crop growth under both potential, water limited and nitrogen limited conditions and under climatic change; The main simulated processes are: photosynthesis, phenological development, assimilate distribution to crop organs, water uptake, nitrogen uptake, evapotranspiration, soil water balance, and nitrogen balance	(van Oijen, 1992)
SIRIUS	A mechanistic model of wheat response to environmental variation	Responses to environmental variations, and in practice by farmers to optimize water and nitrogen applications	(Brooking et al., 1995)
CoupModel	Coupled heat and mass transfer model for soil-plant-atmosphere system	A process-oriented, dynamic model which describes water-heat-carbon and nitrogen flows in the soil-plant-atmosphere system as a function of climate at various time and spatial scales	(Jansson and Karlberg, 2001)
CENTURY		A general model of plant-soil nutrient cycling which is being used to simulate carbon and nutrient dynamics for different types of ecosystems including grasslands, agricultural lands, forests and savannas	(Parton et al., 1992)

Table 1. (Continued).

Model	Full name	Application/ Description	Reference
EPIC	Erosion-Productivity Impact Calculator	A cropping systems model that was developed to estimate soil productivity as affected by erosion	(Williams et al., 1983)
DSSAT	Decision Support System for Agrotechnology Transfer	Soil water balance and crop management; Includes the CERES models for cereals and the CROPGRO models for legumes (dry bean, soybean, peanut and chickpea); and models for root crops (cassava, potato) and other crops (sugarcane, tomato, sunflower and pasture)	(Tsuji et al., 1994)
InfoCrop	A dynamic simulation model for the assessment of crop yields	A generic crop model designed to simulate the effects of weather, soils, agronomic management (including planting, nitrogen, residues and irrigation)	(Aggarwal et al., 2006)
Expert-N	The nitrogen balance modeling tool for agricultural and forest ecosystems	A development system with the aim to improve the process understanding of the turnover and transport of matter and the energy fluxes in the soil-plant-atmosphere system; The focus are the simulations of matter cycling in forest, grassland, and crop ecosystems from the field to the regional scale	(Baldioli et al., 1994)
HERMES		A model to describe plant growth and water and nitrogen dynamics in the soil-plant system.	(PC-Agrar., 1994)
LPJmL	Lund-Potsdam-Jena managed Land	Simulates the global terrestrial carbon cycle and the response of carbon and vegetation patterns under climate change	(Sitch et al., 2003)
MONICA		A dynamic, process-based simulation model which describes the transport and bio-chemical turn-over of carbon, nitrogen and water in agro-ecosystems	(Nendel et al., 2011)
SALUS	System Approach to Land Use Sustainability	Designed to model continuous crop, soil, water and nutrient conditions under different management strategies for multiple years	(Hoffmann et al., 1993)
LINGRA-N	LINtul-GRAssland-Nitrogen	A simple generic grass growth model which can calculate grass growth and yields under potential (i.e. optimal), water limited (i.e. rain fed) and nitrogen limited growing conditions	(Wolf, 2012)
SIMPLACE	Scientific Impact assessment and Modeling PLatform for Advanced Crop and Ecosystem management	A modular modeling framework to support decisions for the management of a wide range of crops and ecosystems under changing resource availability and climate conditions; The framework is developed with standard technologies, which reduce the effort in model development and customization	(Gaiser et al., 2013)

aggregating inputs and outputs over entire fields or catchments, facilitating rapid analysis with minimal data requirements but assiuming hetrogenity (Hu et al., 2021). In contrast, distributed models incorporate spatial heterogeneity in land use, topography, soil types, and hydraulic properties, enabling fine-scale resolution of spatial patterns in water and solute fluxes (Fenicia et al., 2016). While computationally demanding, distributed models are indispensable for site-specific irrigation management and landscape-scale hydrological assessments.

Fifth, based on computational procedures, models are either analytical or numerical. Analytical models offer closed-form solutions to governing equations and are valued for their elegance and mathematical clarity, though their applicability is restricted to idealized conditions with uniform properties and simple boundaries. Numerical models—utilizing finite difference, finite element, or finite volume methods—are capable of solving complex systems with nonlinearities, variable boundary conditions, and multi-domain coupling (Fenicia et al., 2016). These models generate outputs in the form of spatial-temporal distributions of state variables, which can be visualized and interpreted to inform irrigation planning, salinity management, or drainage system design (Rezaei, 2016).

Ultimately, the selection of a hydrological model must be guided by the specific objectives of the study, the scale of application, available data, and computational resources. Physically-based numerical models, although data- and resource-intensive, provide the highest level of process representation and are increasingly being integrated with crop models to improve the sustainability and precision of agricultural water management. Table 2 presents an overview of widely adopted hydrological models and their key characteristics.

3. Soil Hydrological Model

Over recent decades, substantial progress has been made in conceptualizing and mathematically modeling water flow and solute transport in the vadose zone. Numerous analytical and numerical models have emerged to simulate water and solute movement across soil profiles—from the surface to the groundwater table. Among them, the Richards equation (Richards, 1931) for variably saturated flow and the convection–dispersion equation for solute transport based on Fick's law remain fundamental tools in vadose zone hydrology.

Deterministic solutions of these equations are widely applied to predict water and solute behavior under various environmental conditions and to interpret laboratory and field experiments (Šimůnek et al., 2024a). These models serve as powerful tools for extrapolating findings across diverse soil types, cropping systems, climatic conditions, and management practices (Šimůnek et al., 2013). Modeling approaches range from analytical solutions for idealized systems to fully coupled numerical schemes that incorporate complex nonlinear and transient processes, such as non-equilibrium flow or reactive solute transport (van Genuchten et al., 2014).

Despite the availability of advanced numerical models, their practical implementation often requires extensive effort in data preparation, mesh design, and output visualization. To overcome these limitations and promote broader use, Šimůnek et al. (2006b) developed HYDRUS-1D, a user-friendly, Windows-based interface for simulating variably saturated water flow and heat/solute transport. This platform solves the Richards equation and the advection–dispersion equations using Galerkin-type finite element methods (Celia and Binning, 1992), while also incorporating root water uptake, dual-porosity, and dual-permeability flow domains. It supports vertical, horizontal, and inclined flow orientations, and can handle a wide range of boundary conditions, including atmospheric, prescribed head or flux, free drainage, and constant head conditions.

HYDRUS-1D also includes an inverse modeling module based on the Levenberg–Marquardt optimization algorithm (Levenberg, 1944; Marquardt, 1963) for estimating soil hydraulic and solute transport parameters using transient or steady-state observations (Šimůnek et al., 2013). The HYDRUS family has since expanded to include HYDRUS-2D/3D (Šimůnek et al., 2006a; Šimůnek et al., 2006b), capable of simulating water, heat, and solute transport in two- and three-dimensional variably saturated media. The latest release, HYDRUS 2024, offers enhanced functionality for simulating complex soil–plant–atmosphere interactions (Šimůnek et al., 2024a). Collectively, these models constitute a robust, flexible platform for investigating the dynamics of water and solutes in heterogeneous, structured, and reactive soils under diverse environmental and agronomic scenarios.

4. Inverse Modeling and Parameter Estimation

Accurate estimation of soil hydraulic properties is essential for enhancing water use efficiency in hydrological modeling (Rezaei et al., 2016a; Šimůnek and Hopmans, 2002). However, direct measurement of these parameters in the laboratory or field is often labor-intensive, costly, or insufficiently accurate—particularly when scaling up to field applications (Verbist et al., 2012; Wöhling et al., 2008). Therefore, model calibration becomes a critical step, involving the adjustment of model inputs—such as hydraulic parameters, initial states, and boundary conditions—to minimize discrepancies between simulated and observed soil moisture dynamics (Šimůnek et al., 2012). Figure 2 represents a schematic of inverse modeling and parameter estimations.

Table 2. Overview of Widely Used Hydrological Models and Their Core Applications.

Model	Full name / Description	Application	Refrence
SWAP	Soil-Water-Atmosphere-Plant for simulating water, solute, and heat transport in the vadose zone.	Simulation of unsaturated/saturated soil processes at field scale during crop seasons and over long-term periods.	(van Dam et al., 1997)
SWAT	Soil And Water Assessment Tool for large-scale watershed modeling.	Assessment of land management impacts on water, sediment, nutrients, and pesticides in ungauged or gauged basins.	(Arnold et al., 1993)
VIC (Liang et al., 1994)	Variable Infiltration Capacity model with water and energy balance components.	Simulation of hydrological fluxes (infiltration, runoff, baseflow) using semi-distributed grid-based structure.	(Liang et al., 1994
HydroGeoSphere	3D integrated surface–subsurface flow model.	Simulation of rainfall–runoff processes, soil moisture redistribution, and runoff harvesting techniques.	(Therrien et al., 2009)
MACRO	Dual-porosity model for water and solute transport in macroporous soils.	Simulation of preferential flow and solute leaching in layered soils under non-steady-state conditions.	(Jarvis and Larsson, 1998)
HYSWASOR	Hysteretic Soil Water and Solute Transport model in the root zone.	Simulates root water uptake under non-uniform osmotic/pressure heads with hysteresis.	(Dirksen et al., 1993)
DHSVM	Distributed Hydrology Soil Vegetation Model.	Quantifies the effects of topography and vegetation on spatial hydrological processes such as interception, transpiration, and runoff.	(Wigmosta et al., 1994)
CREST	Coupled Routing and Excess Storage model.	Cell-to-cell simulation of atmospheric, surface, and subsurface water fluxes and storages in distributed systems.	(Wang et al., 2011)
SWMS-2D	Two-dimensional model for water and solute transport in variably saturated soils.	Solves Richards' and convection-dispersion equations in 2D to simulate water and solute flow in soil.	(Šimůnek et al., 1994)
GSFLOW	Ground-water and Surface-water FLOW model	Simulates coupled surface/groundwater systems in complex watersheds including lakes, rivers, and vadose zones.	(Markstrom et al., 2008)
VS2DI	Variably Saturated 2D/3D Transport Model.	Simulates water, heat, and solute movement in porous media under variably saturated conditions.	(Healy and Essaid, 2012)
MODFLOW	Modular 3D finite-difference groundwater model.	Widely used to simulate groundwater flow in confined/unconfined aquifers, and complex hydrogeological systems.	(McDonald and Harbaugh, 1983)
WBM / WTM	Water Balance/Transport Model	simulates runoff, groundwater recharge, and surface/subsurface transport at grid scale based on climatic forcing.	(Fekete et al., 1999)
FEFLOW	Finite Element groundwater flow and transport simulator.	Simulates saturated/unsaturated groundwater flow, contaminant transport, and thermal exchange in porous and fractured media.	(Diersch and Kolditz, 1998)
MIKE SHE	Integrated hydrological modeling system (physically based and spatially distributed).	Comprehensive simulation of surface water, groundwater, channel flow, and unsaturated flow in catchment-scale studies.	(Kourgialas and Karatzas (2015); Mertens et al. (2005))
IWFM	Integrated Water Flow Model	Resource planning model that simulates stream–aquifer interactions, surface water, and agricultural demands.	(Dogrul, 2007)
SPAW	Soil-Plant-Air-Water model	Simulates daily water budgets in agricultural fields including wetlands and reservoirs under variable field conditions.	(Saxton et al., 1974)
SVAT	Soil Vegetation Atmosphere Transfer model	Investigates heat and water fluxes in river basins and large-scale hydrological modeling.	(Noilhan and Planton, 1989)
HYDRUS (1D/2D/3D)	Finite-element models for water, heat, and solute transport in variably saturated media.	Widely used in soil–plant–atmosphere systems to model water and solute movement, irrigation optimization, and salinity dynamics.	(Šimůnek et al., 2006b)

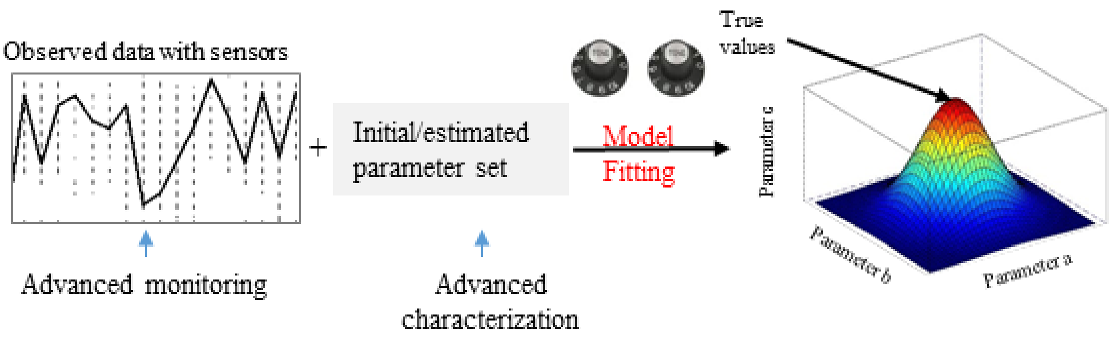

Fig 2. A schematic of inverse modeling and parameter estimations, illustrating observed data can be used for sensitive model parameter estimations.

Traditionally, calibration has been conducted through manual trial-and-error methods. While conceptually straightforward, this approach becomes cumbersome, subjective, and inefficient when dealing with complex systems and a high number of interacting parameters. To address these limitations, researchers have developed automated calibration techniques, particularly inverse modeling, which offers an objective and systematic alternative (Mertens et al., 2005). One widely used optimization algorithm in inverse modeling is the Levenberg–Marquardt method, which facilitates single-objective parameter estimation by iteratively minimizing the difference between observed and simulated data (Abbasi et al., 2004; Abbasi et al., 2003; Jacques et al., 2012; Liu et al., 2023; Šimůnek et al., 2013).

Inverse modeling has proven especially valuable for estimating unsaturated soil hydraulic parameters from transient data sets in both laboratory and field conditions. As defined by Hopmans et al. (2002), it is a process that infers unknown causes (i.e., hydraulic parameters) from observed effects (e.g., water content or pressure head), in contrast to direct modeling. This methodology typically relies on solving the Richards equation, enabling the simultaneous estimation of the soil water retention curve and the unsaturated hydraulic conductivity function. The key advantages of inverse modeling include: i) Greater flexibility in defining boundary conditions for transient experiments; ii) Simultaneous determination of multiple hydraulic functions; iii) Enhanced accuracy and speed of parameter optimization; and iv) Applicability in field settings under variable and non-ideal boundary conditions (Šimůnek et al. (2024a); Hopmans et al., 2002; Vrugt et al., 2008; Wöhling and Vrugt, 2011).

The inverse modeling approach is based on minimizing the objective function which expresses the discrepancies between the simulated and observed values. Despite these advantages, inverse modeling is not without challenges. In the optimization process, an objective function is measuring an agreement between measured and simulated data by statistic criteria such as the root-mean-square errors (RMSE), the coefficient of determination (r^2), and the Nash–Sutcliffe coefficient of model efficiency (C_e). It is directly or indirectly related to the adjustable parameters to be fitted. Minimizing the objective function generates the best-fit parameters. Maximum probability density function (pdf) and a minimum least-squares criterion should be achieved (Šimůnek and Hopmans, 2002). The objective functions can be around any observed variable which is used as inverse input data such as soil water content, infiltration and water retention data for all soil layers with unit or different weighting. When multiple local minima or a global minimum occur in a range of parameter values on the basis of the convexity of the objective function (which can be increased by inclusion of prior information (initial input values of parameters)), the model solution is called non-unique. Non-uniqueness, non-identifiability, and instability often compromise parameter estimation. Non-uniqueness arises when multiple parameter sets yield similar model outputs, often due to flat or convex objective function surfaces. Providing prior information, such as plausible parameter bounds, can help mitigate this issue. Non-identifiability occurs when distinct parameter combinations produce indistinguishable system responses, complicating the derivation of a unique solution. Instability, on the other hand, reflects sensitivity to small errors in input data or model structure, leading to disproportionately large variations in estimated parameters. Together, these issues contribute to the ill-posedness of inverse problems (Chou and Voit, 2009; Rezaei et al., 2016a).

To address these challenges, sensitivity analysis is commonly employed (Chou and Voit, 2009; Rezaei, 2016; Rezaei et al., 2016a). This involves systematically evaluating how model outputs respond to changes in individual parameters, thereby identifying the most influential ones. By focusing on a reduced set of sensitive parameters, the risk of over-parameterization and

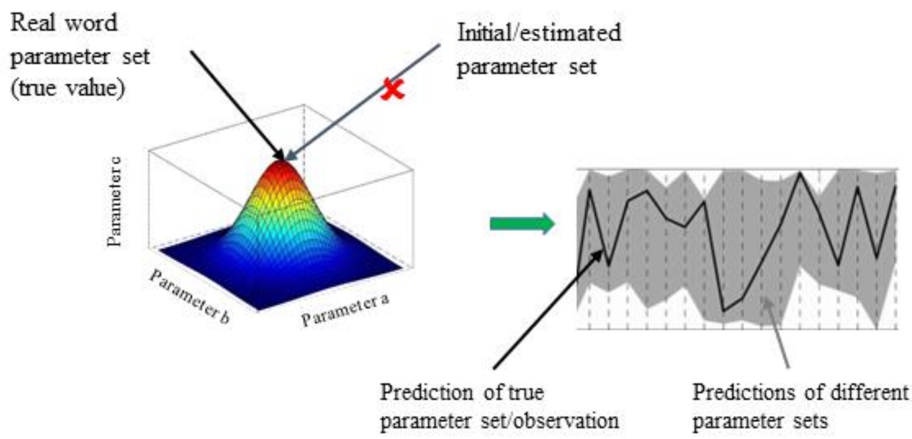

Fig 3. A schematic of different set of initial values e.g., hydraulic properties on model predictions, illustrating sensitivity analysis.

identifiability issues can be reduced (Hopmans et al., 2002). The effectiveness of sensitivity analysis is influenced by several factors, including the number and type of parameters being optimized, the quality of observational data, and the structure of the model. Rocha et al. (2006) and van Genuchten et al. (2012) highlight the use of one-at-a-time sensitivity approaches for refining inverse modeling procedures and reducing uncertainty in simulations.

In sum, inverse modeling represents a robust, data-driven approach for parameter estimation in vadose zone hydrology, especially when paired with optimization and sensitivity analysis techniques. Its integration into hydrological modeling frameworks significantly enhances model reliability and predictive capacity under field conditions.

4.1. Initial values of soil hydraulic parameters

Accurate simulation of soil water dynamics and solute transport requires a thorough understanding of the interactions among soil, water, atmosphere, and plant systems. Within this context, reliable initial estimates of soil hydraulic parameters, particularly soil water content, are critical. The accuracy of the inverse modeling process strongly depends on these initial values, as they influence the convergence, stability, and reliability of the optimized parameters (Figures 2 and 3). Therefore, providing well-constrained and physically meaningful initial estimates is essential for both forward and inverse modeling of water, solute, and energy fluxes in the vadose zone (Rezaei et al., 2016b).

Soil heterogeneity is a fundamental characteristic of natural systems, governed by factors such as macropore structure, aggregation, texture, and soil layering. These physical heterogeneities introduce spatial variability in water retention and hydraulic conductivity, which directly impact the soil's ability to store and transmit water at the field scale (Teixeira et al., 2014). Quantifying this variability remains a key research challenge, as accurate representation of spatial patterns is necessary to improve predictive performance of hydrological models.

Numerous techniques for characterizing soil hydraulic properties have been developed and refined over the past decades. Classical methods, such as those compiled by Klute (1986) and Dane and Topp (2002), involve direct laboratory or field measurements. These approaches, while accurate, are often expensive, time-consuming, and labor-intensive. More recently, state-of-the-art reviews such as Minasny et al. (2013) have introduced novel techniques and highlighted the importance of balancing accuracy with practical feasibility. An overview of these methods is presented in Tables 3 and 4.

Given the limitations of direct measurement, indirect estimation methods have gained prominence. In numerical modeling, soil water retention characteristics are typically described using closed-form analytical expressions, such as those by van Genuchten or Brooks-Corey, which require shape parameters as input. These parameters are either measured experimentally or inferred through fitting procedures using soil water retention curve (SWRC) data. To improve efficiency, pedotransfer functions (PTFs) are often employed to estimate hydraulic parameters based on more readily available soil properties (Cornelis et al., 2005). While PTFs offer a practical alternative, their accuracy depends on the quality and representativeness of the training dataset.

Several studies have systematically compared different analytical models for representing the SWRC, including unimodal and bimodal formulations, and evaluated their performance in diverse soil types and conditions (Cornelis et al., 2005; Khlosi et al., 2008). These approaches contribute to a growing toolbox of methodologies aimed at capturing the physical behavior of soil water movement, while minimizing the reliance on extensive laboratory measurements.

Table 3. Overview of soil hydraulic parameters determination techniques for saturated hydraulic conductivity (K) and soil water retention curve (SWRC).

Method Type	Measurement Domain	Application to K	References	Application to SWRC	References
Direct	Laboratory	Constant Head Soil Core Method, Falling Head Method, Steady Flow Soil Column, Long Column, Steady-State Centrifuge, Wind and Hot-Air Methods, Suction Crust Infiltrometer, Bypass Flow, Tension Disc Infiltrometer, Evaporation Method	Fodor et al. (2011); Jačka et al. (2014); Kelishadi et al. (2014); Schindler et al. (2010));–(Rezaei et al. (2023); Rezaei et al. (2016b)	Hanging Water Column (*Haines Apparatus*), Pressure Cell, Pressure Plate Extractor, Long Column, Suction Table, Sand Box, Controlled Liquid Volume, Freezing Method, Steady-State Centrifuge, Wind and Hot-Air Methods, Suction Crust Infiltrometer, Bypass Flow, Tension Disc Infiltrometer	Schindler et al. (2010); Schwen et al. (2014); Šimůnek et al. (1999 ; Rezaei et al. (2023); Rezaei et al. (2016b)
	Field	Single-/Double-/Concentric-Ring Infiltrometers, Pressure Infiltrometer, Constant Head Well Permeameter, Rainfall Simulator, Inverse/Auger-hole Method, Piezometer Method, Mini Disc Infiltrometer, Instantaneous Profile, Plane of Zero Flux, Constant Flux Vertical TDR, Guelph Permeameter, Tension Disc Infiltrometer	Rezaei et al. (2021); Rezaei et al. (2023); Rezaei et al. (2016b)	Instantaneous Profile, Plane of Zero Flux, Constant Flux Vertical TDR, Tension Disc Infiltrometer	Rezaei et al. (2021); Rezaei et al. (2023); Rezaei et al. (2016b)
Indirect	Inverse Modeling	Multistep Outflow Method, Evaporation Method, Tension Disc Infiltrometer, Field Drainage	Schindler et al. (2010); Schwartz and Evett (2003); Šimůnek and van Genuchten (1996, 1997)	Multistep Outflow Method, Evaporation Method, Tension Disc Infiltrometer, Field Drainage	Latorre et al. (2015); Rashid et al. (2015); Rucker et al. (2005); Schindler et al. (2010); Šimůnek and van Genuchten (1996, 1997); Verbist et al. (2009)

Table 4. Overview of soil hydraulic parameter estimation techniques.

Technique	Description	References
Geostatistics	Spatial interpolation methods to estimate hydraulic properties and provide their tempo-spatial maps	Bardossy and Li (2008); Gumiere et al. (2014); Horta et al. (2014); Miháliková et al. (2015)
Proximal soil sensing and Remote sensing	Finding a correspondence between soil hydraulic properties, and an easily measurable parameters e.g., ECa, using sensors such as EMI, GPR and models like DEM to predict high resolution spatial and temporal soil properties	Brosten et al. (2011); Chaplot et al. (2011); Cosentini et al. (2012); Dafflon et al. (2009); Doolittle and Brevik (2014); Farzamian et al. (2015); Gooley et al. (2014); Jonard et al. (2015); Lesmes and Friedman (2005); Mawer et al. (2015); Mohanty (2013); Niu et al. (2015); Schmugge (2013); Sudduth et al. (2013)
Pedotransfer functions and soil inference systems	Prediction hydraulic parameters from more easily measurable and more readily available soil properties like particle size distribution, organic matter content, dry bulk density, etc., using simple to such sophisticated models in aim of e.g., Neural network analysis	Botula et al. (2014); Gwenzi et al. (2011); Moreno et al. (2014); Nguyen et al. (2015); Ostovari et al. (2015); Vereecken et al. (2010)
Digital soil mapping and assessments	Describe approaches that seek to map soil properties with aid of digital techniques (data processing, GIS)	Chaplot et al. (2010); Finke (2012); Gooley et al. (2014); Shin et al. (2013)
Markov Chain Monte Carlo simulation	Sampling method for sets of hydraulic parameters feeding into the model	Coppola et al. (2009); Shin et al. (2013); Verbist et al. (2012); Wöhling and Vrugt (2008)
Pedogenetic modeling	Regional to Global modeling of soil change; it helps making spatial prediction of soil properties, quantifying the uncertainty of prediction and delineating area of risks	Finke and Hutson (2008); Mirus et al. (2009); Nimmo et al. (2009)
Inverse modeling	Indirect modeling to approximate hydraulic properties in combination with another methods such as PTF or monte carlo simulation	Mirus et al. (2009); Shin et al. (2013); Verbist et al. (2012); Vrugt et al. (2004); Wöhling and Vrugt (2008)

5. Sensitivity Analysis

Sensitivity analysis (SA) is a fundamental step in model evaluation, aiming to quantify how variations in input parameters or initial conditions influence model outputs (Fig. 3). This is particularly critical when input parameters are uncertain, poorly defined, or difficult to measure directly. By identifying the most influential variables, SA improves confidence in model predictions and assists in prioritizing data collection and experimental design. It is also closely linked to uncertainty analysis, which quantifies the total uncertainty in model responses arising from uncertain inputs (Rocha et al., 2006). Early studies, such as that of Dane and Hruska (1983), highlighted challenges in the uniqueness of inverse modeling solutions, showing that parameter sensitivity is strongly influenced by boundary conditions. Hopmans et al. (2002) further emphasized that higher parameter sensitivity enhances the convergence rate in inverse modeling procedures. However, the degree of sensitivity is not constant; it depends on multiple factors, including the nature and number of optimized parameters, the model structure, the numerical scheme, and the quality of the input data (Russo et al., 1991).

From a methodological perspective, sensitivity analysis can be viewed as a form of feature importance evaluation and parameter selection within the model calibration workflow. In this context, model parameters are analogous to "features" in machine learning, and SA provides a robust framework for ranking them by their influence on predictive outcomes. By identifying and retaining only the most sensitive parameters for calibration, SA effectively performs dimensionality reduction, mitigating the curse of dimensionality, reducing the risk of over-parameterization, and enhancing the stability and efficiency of the inverse modeling process. This function is directly comparable to the objectives of feature selection algorithms in statistics and machine learning (e.g., regularization techniques like LASSO), albeit applied here to process-based physical models.

To mitigate the issue of non-uniqueness and to stabilize the inverse modeling process, it is recommended to minimize the number of parameters subject to optimization and to constrain insensitive parameters to their observed or measured values (Schwartz and Evett, 2003). This strategy enhances the identifiability of critical parameters and reduces computational complexity. Time-dependent or dynamic sensitivity analysis is particularly valuable in hydrological modeling under changing environmental conditions, such as during periods of irrigation or drought. It allows for identifying the most relevant parameters across specific time windows, which can significantly enhance model efficiency and accuracy. Several studies have introduced summary sensitivity indices to condense temporal sensitivity information into interpretable metrics (Rezaei et al., 2016a; Abbasi et al., 2003a; Li et al., 2012; Mertens et al., 2005; Rocha et al., 2006; Šimůnek and van Genuchten, 1996; Verbist et al., 2012; Zhou et al., 2012).

Broadly, sensitivity analysis methods can be classified into two main categories (Rezaei et al., 2016a): i) Local Sensitivity Analysis (LSA) which evaluates the effect of small perturbations in input parameters around a nominal value, typically using derivative-based approaches. It is computationally efficient but may not capture nonlinear or interaction effects in complex systems. ii) Global Sensitivity Analysis (GSA) which examines the full parameter space by varying inputs across their entire distribution, often using Monte Carlo or variance-based methods. GSA provides a more comprehensive picture of parameter influence, though it is more computationally intensive.

Overall, sensitivity analysis serves as a diagnostic and optimization tool that enhances model transparency, improves parameter selection strategies, and ultimately strengthens the model's predictive capability. Its integration into modeling workflows is essential for ensuring robust, reliable simulations in soil-water-plant-atmosphere systems. While this review focuses on SA as the primary method for feature (parameter) selection in process-based models, it is acknowledged that other statistical and machine-learning-driven feature selection approaches exist and could be integrated in future hybrid modeling frameworks.

5.1. Global sensitivity analysis

Global sensitivity analysis is a robust and widely adopted framework that quantifies the contribution of input parameter uncertainty to the variance observed in model outputs. Unlike local methods that assess perturbations near a fixed point, GSA considers the entire range of parameter values by incorporating probability distributions, thus offering a more comprehensive understanding of model behavior (Saltelli et al., 2008). Several techniques have been developed for GSA, including sampling-based approaches such as Monte Carlo simulations (Spear and Hornberger, 1980), screening methods like the Morris one-at-a-time (OAT) procedure (Morris, 1991), and variance decomposition methods such as the Sobol indices (Sobol, 1993).

Additionally, response surface methodologies allow for the replacement of complex process-based models with computationally efficient meta-models (Kleijnen et al., 1992), while regression-based approaches have been employed as simplified alternatives in high-dimensional systems (Iman and Helton, 1988). These techniques enable the identification of both individual parameter effects and their interactions, thereby facilitating model simplification and prioritization of calibration efforts. Overall, GSA enhances model interpretability and predictive reliability by elucidating which parameters most significantly influence the system response. For a comprehensive overview of GSA methods and their applications in environmental modeling, readers are referred to Loosvelt (2013). Each mentioned methods has its specific formula to be calculated therefore they are not represented here.

5.2. Local sensitivity

Local sensitivity analysis is a simpler yet foundational approach in the modeling workflow, aiming to evaluate the sensitivity of model outputs to small perturbations in input parameters near a nominal value. Typically, it involves partial derivatives or finite differences computed using one-at-a-time (OAT) perturbations. This method provides detailed information on how specific inputs influence outputs at a particular point in the parameter space (Rezaei et al., 2016a). Techniques such as the finite difference method, direct differential method, Green's function, and complex-step derivative approximation have been developed to perform LSA with high precision (De Pauw, 2005). Furthermore, an OAT approach (local or global) does not provide direct information about higher- and total-order parameter interaction as is provided by variance-based SA (Saltelli et al., 2008). However, by evaluating the parameter sensitivities in time, insight is given about potential interaction when similar individual effects are observed. The latter can be quantified by a collinearity analysis (Brun et al., 2001), but will be done graphically in this contribution. A dynamic sensitivity function can be written as follows:

$$SF(t) = \frac{\partial y(t)}{\partial x} \qquad [1]$$

where *SF(t)*, *y(t)*, and *x* denote the sensitivity function, output variable and parameter respectively. If an output variable *(y)* significantly changes (evaluated by calculating the variance or coefficient of determination or by visualizing in a scatter plot) due to small changes of the parameter of interest *x*, it is called a sensitive parameter.

This partial derivative can be calculated analytically or numerically with a finite difference approach by a local linearity assumption of the model on the parameters. Local sensitivity functions evaluate the partial derivative around the nominal parameter values. The central differences of the sensitivity function are used to rank the parameter sensitivities and can be expressed as follows:

$$\Delta x_j = p_f . x_j \qquad [2]$$

$$CAS = \frac{\partial y(t)}{\partial x} = \lim_{\Delta x_j \to 0} \frac{\Delta(t, x_j + \Delta x_j) - y(t, x_j - \Delta x_j)}{2\Delta x_j} \qquad [3]$$

$$CTRS = \frac{\partial y(t)}{\partial x} . \frac{x_j}{y}, \quad CPRS = \frac{\partial y(t)}{\partial x} . x_j \qquad [4]$$

where p_f is the perturbation factor, x_j is the parameter value and Δx_j is the perturbation, CAS is the Central Absolute Sensitivity, CTRS is the Central Total Relative Sensitivity analysis, and CPRS is a Central Parameter Relative Sensitivity. Since the parameters and variables have different orders of magnitude for which the sensitivity is calculated, direct comparison of the sensitivity indices with CAS is not possible. Hence, recalculation towards relative and comparable values is needed. In order to compare the sensitivity of the different parameters towards the different variables, CTRS is preferred. CPRS is sufficient when the sensitivity of different parameters is compared for a single variable, i.e., soil-water content.

Time-variant LSA is particularly useful in hydrological modeling, as it reveals which parameters are influential during specific simulation periods, such as during irrigation or drought phases. This temporal sensitivity insight allows modelers to prioritize key variables, minimize the number of parameters to be calibrated, and fix insensitive ones to their measured values, improving computational efficiency and reducing equifinality. While LSA is limited in its ability to capture interactions between parameters or global effects, it remains an essential step for initial model assessment and parameter screening (Rezaei, 2016).

5.3. Classical sensitivity analysis

In addition to global and local methods, classical sensitivity analysis—often referred to as manual sensitivity analysis—provides a pragmatic approach to evaluating model responsiveness. This technique primarily involves systematic alterations to key model settings, such as boundary conditions, root distribution profiles, and spatial discretization schemes, to observe the resulting variations in output (Rezaei et al., 2016). Unlike global or local methods, classical sensitivity analysis does not rely on statistical or numerical algorithms. Instead, it offers a practical route for modelers to investigate how adjustments in conceptual and structural components influence simulation outcomes, often using expert knowledge or field experience to guide the variations.

This approach typically includes modifying boundary condition scenarios (e.g., switching between free drainage, fixed pressure heads, or deep drainage), testing various root distribution depths and densities, or adjusting root water uptake functions (Hupet et al., 2002; Wollschlager et al., 2009). Other influential factors may include changes in the leaf area index (LAI), the extinction coefficient of radiation, or the resolution and configuration of spatial discretization grids (Carrera-Hernández et al., 2012). The overarching aim is to minimize the mismatch between observed and simulated data through iterative trial-and-error adjustments. Although classical sensitivity analysis lacks the quantitative robustness of global or local methods, it remains a valuable diagnostic tool, particularly in complex models where boundary and structural assumptions strongly influence simulation accuracy.

6. Field-Scale Heterogeneity through Quasi-3D Modeling

Field-scale soil water dynamics are intrinsically governed by spatial heterogeneities in soil hydraulic properties, which control the storage and conduction of water (Rezaei et al., 2017). Furthermore, spatial variations in bottom boundary conditions, particularly groundwater level (GWL) fluctuations, and topography are first-order controls on soil water content variability, water flow paths, and root water uptake. Despite their importance, efficient techniques for characterizing this physical variability at relevant scales remain a primary objective of hydrological research (Teixeira et al., 2014).

Consequently, developing irrigation management strategies that respond to heterogeneous field conditions—optimizing soil water status across large fields with variable soil, groundwater, and topography—is essential for sustainable agriculture. While modern technologies like automated sensor networks can quantify soil-water status and flow processes, their deployment is often limited to discrete points due to cost and labor constraints (Bastiaanssen et al., 2004). As a powerful alternative, advanced numerical modeling of vadose zone processes provides a framework to simulate the critical interactions between soil, vegetation, atmosphere, and groundwater, thereby enabling improved control of soil water status for precision irrigation (Zhu et al., 2012).

Due to the complexity of these hydrological systems, models often employ conceptual simplifications (Rezaei et al., 2017). A common simplification is the assumption of one-dimensional (1D) vertical flow, which implies; i. Lateral flow and transport are negligible (Sherlock et al., 2002; Tian et al., 2012), an assumption that fails when the capillary fringe is involved (Abit et al., 2008). ii. The bottom boundary is represented simplistically (e.g., constant head or unit-gradient drainage) rather than a dynamically simulated water table (Carrera-Hernández et al., 2012). iii. Soils are treated as effectively homogeneous within layers, with isotropic hydraulic properties (Niswonger and Prudic, 2009). iv. The porous matrix is rigid, and fluid density is independent of solutes or temperature (Kuznetsov et al., 2012).

These simplifications, while computationally efficient, introduce significant structural uncertainty. Consequently, key challenges include evaluating model uncertainty and sensitivity across scales, managing computational cost, and ultimately leveraging models for irrigation optimization (Wöhling et al., 2009; Wöhling et al., 2008). Model outputs are sensitive to uncertainties in structure, input parameters, the geometry of soil layers, and boundary conditions (Vrugt et al., 2008). While methods like Bayesian inference, Monte Carlo simulation, and data assimilation (e.g., Ensemble Kalman Filter) have been employed to quantify these uncertainties, they are primarily applied at the plot scale (Carrera-Hernández et al., 2012; Li et al., 2015; Verbist et al., 2012; Verma et al., 2009; Vrugt et al., 2008; Wöhling and Vrugt, 2008). A significant gap therefore persists between field-scale modeling capabilities and practical irrigation management.

The central challenge for regional water management is to accurately simulate integrated water flow—from the soil surface through the vadose zone to the groundwater—within a spatially variable context. Generalizing management from a single 1D model plot to an entire field is fraught with uncertainty. In response, two numerical approaches have emerged; A) Fully 3D models that solve the Richards equation in three dimensions (Šimůnek et al., 2024a). These models are often computationally prohibitive for large-scale agricultural applications unless high-performance computing is used (Kuznetsov et al., 2012). B) Quasi-3D integrated models, which offer a pragmatic and computationally efficient alternative. This approach tightly couples an array of 1D vadose zone models (simulating vertical processes) with a 2D groundwater model (simulating lateral saturated flow and water table dynamics) (Arnold et al., 1993; Saxton et al., 1974; Šimůnek et al., 2006b; Therrien et al., 2009; van Dam et al., 1997). In such modelling setup, the field is represented by a collection of parallel non-interacting vertical columns representing different field conditions in terms of soil saturated hydraulic conductivity (K_s) groundwater level (GWL) and root zone-first layer depth (FLD), etc. which can be obtained from different methodologies (Tables 3 and 4). This architecture explicitly captures the critical interaction between the unsaturated zone and spatial variations of model parameters and of boundary conditions (e.g., dynamic groundwater table) other variables (e.g., soil hydraulic properties) across the field, the key drivers of field-scale soil moisture patterns (Rezaei et al., 2017). In such case, the uncertainty in model output (quasi 3D modeling approach) can be reduced when using the high-resolution information while a fast performance can be achieved. Ultimately, these approaches aim to optimize variable irrigation requirement within the field using a 2D modeling technique (quasi 3D).

Despite their advantages, the application of these integrated models for operational irrigation is complicated by parameterization challenges and computational demands, limiting their feasibility for end-users like farmers. Future research must focus on simplifying the parameterization of quasi-3D frameworks by integrating remote and proximal sensing data to make them a practical tool for field-scale precision water management.

7. Future Perspectives

Advancements in precision irrigation modeling hinge upon integrating continuous long-term field data with cutting-edge technologies such as Internet of Things (IoT) sensors and artificial intelligence (AI) for real-time monitoring and adaptive management. Future research should emphasize the development of hybrid modeling frameworks that couple crop growth dynamics with soil hydrology, remote sensing inputs, and machine learning algorithms to enhance prediction accuracy under variable climatic and edaphic conditions.

Future advancements in precision irrigation modeling will be increasingly driven by AI and Machine Learning (ML). ML algorithms can serve as powerful surrogates (meta-models) for computationally expensive process-based models, enabling rapid scenario analysis and optimization. Furthermore, ML techniques are adept at extracting patterns from large, heterogeneous datasets generated by IoT sensors, proximal sensing, and remote sensing platforms. Their integration into hybrid modeling frameworks can enhance parameter estimation, facilitate data assimilation for real-time model updating, and improve the prediction of crop water needs under complex, non-linear conditions that are challenging for traditional models.

A persistent hurdle remains the scaling of models from the plot to the landscape and regional level. This transition is hampered by inherent spatial heterogeneity of soil and crop properties, data scarcity for regional parameterization, and significant computational demands. Addressing these challenges requires a multi-faceted approach: (1) improved spatially explicit parameterization through advanced geostatistics and the integration of remote sensing data; (2) the development of probabilistic frameworks and ensemble modeling techniques (e.g., Bayesian averaging) to quantify and propagate uncertainty across scales; and (3) the creation of multi-scale modeling architectures that balance computational efficiency with physical realism.

Scaling these models from plot to landscape and regional levels remains a formidable challenge due to inherent soil and crop heterogeneity, data scarcity, and computational constraints. Addressing these issues requires improved spatially explicit parameterization, probabilistic approaches for uncertainty quantification, and enhanced user-friendly platforms that facilitate stakeholder engagement and decision support.

Finally, for these technological advances to realize their full impact, they must be translated into practical, accessible, and economically viable tools for end-users. Future research must therefore focus not only on algorithmic innovation but also on developing user-friendly platforms that provide clear decision support to farmers and water managers. Embedding these tools within supportive policy frameworks and addressing key adoption barriers—such as initial investment costs, technical expertise requirements, and perceived risks—is crucial for bridging the gap between research and widespread practical implementation. Moreover, embedding these technological advances within sustainable management frameworks and agricultural policies is crucial to ensure practical adoption and maximize environmental and economic benefits. Interdisciplinary collaborations among agronomists, hydrologists, data scientists, and policymakers will be pivotal to drive innovations that foster resilient and resource-efficient irrigation systems. Ultimately, these efforts will contribute to climate-smart agriculture by enabling adaptive irrigation strategies tailored to site-specific conditions, thereby enhancing food security and conserving water resources globally.

8. Conclusion

Precision irrigation is essential for improving water use efficiency and ensuring sustainable agriculture amid climate variability and resource constraints. This review highlights the critical role of integrated modeling approaches—combining crop growth models, soil hydrological simulations, and inverse parameter estimation—in enabling data-driven, site-specific irrigation management, promoting resilient and resource-efficient agriculture under changing climatic conditions. These models simulate the complex soil–plant–atmosphere interactions, optimizing irrigation timing and amounts to reduce water loss and enhance crop yield. While models such as WOFOST, CERES, AquaCrop, HYDRUS, SWAP, and SWAT have advanced our understanding of crop and soil water dynamics, challenges remain in scaling up, incorporating spatial variability, and addressing data scarcity. Ultimately, integrating advanced modeling with real-time monitoring and decision-support systems will be pivotal in transforming irrigation practices. However, for this transformation to be successful, these systems must be designed to be not only scientifically robust but also user-friendly, cost-effective, and accessible to farmers. Interdisciplinary collaborations that include agronomists, hydrologists, data scientists, economists, and policymakers are essential to develop economically and environmentally sustainable variable rate irrigation strategies that are adopted on the ground, thereby promoting resilient and resource-efficient agriculture under changing climatic conditions.

Conflicts of Interests

All authors declare that they have no conflicts of interest in the publication of this paper.

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