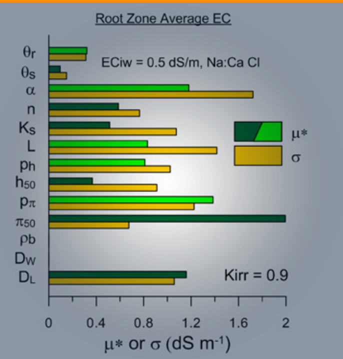
Published June 13, 2014

Original Research



Global sensitivity analyses of UNSATCHEM seasonal simulations of forage corn production identify the most important model parameters for designing and managing systems using degraded irrigation waters.

Global Sensitivity Analysis for UNSATCHEM Simulations of Crop Production with Degraded Waters

T.H. Skaggs,* D.L. Suarez, and D.L. Corwin

One strategy for maintaining irrigated agricultural productivity in the face of diminishing resource availability is to make greater use of marginal quality waters and lands. A key to sustaining systems using degraded irrigation waters is salinity management. Advanced simulation models and decision support tools can aid in the design and management of water reuse systems, but at present model predictions and related management recommendations contain significant uncertainty. Sensitivity analyses can help characterize and reduce uncertainties by revealing which parameter variations or uncertainties have the greatest impact on model outputs. In this work, the elementary effects method was used to obtain global sensitivity analyses of UNSATCHEM seasonal simulations of forage corn (*Zea mays* L.) production with differing irrigation rates and water compositions. Sensitivities were determined with respect to four model outcomes: crop yield, average root zone salinity, water leaching fraction, and salt leaching fraction. For a multiple-season, quasi-steady scenario, the sensitivity analysis found that overall the most important model parameters were the plant salt tolerance parameters, followed by the solute dispersivity. For a single-season scenario with irrigation scheduling based on soil water deficit, soil hydraulic parameters were the most important; the computed salt leaching fraction was also strongly affected by the initial ionic composition of the exchange phase because of its impact on mineral precipitation. In general, parameter sensitivities depend of the specifics of a given modeling scenario, and procedures for routine use of models for site-specific degraded irrigation water management should include site-specific uncertainty and sensitivity analyses. The elementary effects method used in this work is a useful approach for obtaining parameter sensitivity information at relatively low computational cost.

Abbreviations: CEC, cation-exchange capacity; EC, electrical conductivity; EFAW, threshold of plant available water ending irrigation; FAW, fraction of plant available water; IFAW, threshold of plant available water initiating irrigation; LF, leaching fraction; LR, leaching requirement; RZEC, root zone electric conductivity; SLF, salt leaching fraction; WLF, water leaching fraction.

T.H. Skaggs,* D.L. Suarez, and D.L. Corwin, U.S. Salinity Laboratory, USDA-ARS, 450 W. Big Springs Rd., Riverside, CA, 92507. *Corresponding author (todd.skaggs@ars.usda.gov).

Vadose Zone J.
doi:10.2136/vzj2013.09.0171
Received 40 Sept. 2013.

Developing sustainable agricultural systems and meeting the growing food demands of the 21st century will require improved management of water and land resources (National Research Council, 2010; Foley et al., 2011; Jägerskog and Clausen, 2012). In the last century, growing food demand was satisfied through various technological innovations, including a widespread expansion of irrigation such that irrigated cropland now constitutes almost 20% of all cropland. In meeting the food challenges of the current century, continued expansion of irrigation is not feasible due to diminishing land and water availability (Falkenmark and Rockström, 2006; Rockström et al., 2009; Strzepek and Boehlert, 2010; Sposito, 2013). Still, irrigated agriculture produces nearly 40% of the global food harvest, and thus irrigated agriculture will remain crucial to meeting food demand. The challenge for irrigated agriculture going forward is to sustain productivity in the face of reduced resource availability and to do so in a way that minimizes negative environmental impacts (National Research Council, 2010; Foley et al., 2011; Jägerskog and Clausen, 2012).

One strategy for maintaining or increasing productivity is to make greater use of marginal quality lands and waters (Rhoades et al., 1992; Oster, 1994; Wichelns et al., 2007; Shahid et al., 2013). In implementing such a strategy, a key factor for sustainability is soil salinity. Irrigation waters, especially recycled or otherwise marginal quality waters, contain salts that can accumulate in soils with time and reduce yields. In arid and semiarid regions where rainfall is not sufficient to flush the salts from the root zone, it is necessary to apply excess irrigation water to leach the soil. To avoid wasting water and to lessen impacts on groundwater quality it is desirable that soil leaching be minimized to the extent possible (Rhoades and Suarez, 1977; Corwin et al., 2007; Letey et al., 2011).

Methods of varying complexity are available for calculating the effects of different irrigation regimes on salt leaching, soil salinity, and crop yields (Corwin et al., 2007; Suarez, 2012). Classical guidelines for evaluating and managing soil salinity are based on the leaching fraction (LF) and leaching requirement (LR) concepts, where LF is the fraction of irrigation water that percolates below the root zone during a growing season and LR is the minimum LF that is required to maintain the root zone salinity at a level that does not reduce yields below acceptable limits (U.S. Salinity Laboratory Staff, 1954; Ayers and Westcot, 1985). The classical approach is among the simplest, and it is intended to be general, providing a conservative estimate of the leaching requirement that is appropriate across a range of soils and waters. A consequence of this generality is that in some cases the guidelines recommend more leaching than is necessary and overstate the negative impacts of irrigating with saline waters.

Given the increasing constraints on resources, the significance of any inefficiency in water and salinity management is magnified, and thus there is considerable interest in developing site-specific tools that can improve on the general guidelines. One approach is to use computer models that simulate in detail water flow and salt transport processes in the root zone (Corwin et al., 2007; Letey and Feng, 2007; Ditthakit, 2011; Letey et al., 2011; Oster et al., 2012; Suarez, 2012). In these models, variably saturated water flow is typically simulated with the Richards equation, modified to account for root water uptake under conditions of salinity and water stresses. Models may include chemical speciation, precipitation, and sorption reactions, with salt transport governed by advection–dispersion equations. The simulation models allow for consideration of site-specific soil, water, and crop parameters and can account for time-varying field conditions and processes (in contrast with the steady-state analysis of the classical guidelines).

While a modeling approach offers potential advantages, the technique is complex, and difficulties exist with respect to developing procedures for routine use. The models have a large number of parameters, many of which are likely to be unknown or unknowable for a particular application. Parameterization uncertainty can arise due to a lack of site-specific data or measurements, as well as the disparity between the small (plot or column) scales of the modeled processes and the large (field) scales that are relevant to irrigation and salinity management (e.g., Beven and Germann, 2013). Hence, while current simulation models offer potential advantages, at present it is recognized that the accuracy of any particular simulation or management recommendation carries significant uncertainty (e.g., Skaggs et al., 2013).

Sensitivity analyses can help characterize and reduce uncertainties by revealing which parameter variations or uncertainties have the greatest impact on model outputs. Results of sensitivity analyses can also be useful for directing future research and data collection efforts. As detailed by Cacuci (2003) and Saltelli et al. (2008), among others, many approaches to sensitivity analysis exist. The most basic sensitivity measure is the local sensitivity coefficient, defined as the first derivative of a model output with respect to a model parameter or input. Many methods are available for computing local sensitivity coefficients efficiently, and the coefficients have a number of important uses in modeling applications (e.g., Skaggs and Barry, 1996, 1997). However, as a general measure of model behavior, the coefficients are limited in that they provide sensitivity information only at a single point in the parameter space. Global sensitivity methods (Saltelli et al., 2008), on the other hand, integrate in some fashion sensitivities over the whole parameter space. In a review, Mishra et al. (2009) found several examples of global sensitivity analysis in the groundwater literature but concluded that such analyses were not yet part of mainstream modeling practice. Applications to vadose zone and/or crop models are similarly not abundant, but some examples include: sensitivity analysis of simulated soil moisture using a one-dimensional Richards equation (Mertens et al., 2005), sensitivity analysis of mobile–immobile model calculations of pesticide fate in soils (Cheviron and Coquet, 2009), sensitivity analysis for parameter estimation in a dynamic crop model (Varella et al., 2010), and parameter sensitivity analysis for modeling tracer transport in clayey soils (Skaggs et al., 2013). Most relevant to the present work, Alzraiee and Garcia (2013) recently applied four global sensitivity methods to a soil hydrosalinity model and found that the elementary effects method, the Monte Carlo filtering method, and the variance decomposition method all generated consistent results.

An important consideration for sensitivity analysis is that with complex models and modeling applications, sensitivity results are generally specific to a particular modeling scenario. For example, in the current context, a multitude of possible scenarios exists for degraded irrigation water management, and each scenario can have different degrees and types of uncertainty. An analysis aimed at a specific field and irrigation water may have relatively low uncertainty regarding certain soil properties such as, for example, cation-exchange capacity (CEC), whereas a more general analysis may require consideration of a greater range of parameter uncertainty. Similarly, the type (or meaning) of uncertainty may vary from case to case. In some instances an assigned uncertainty might reflect the analyst's knowledge (or lack thereof) of some soil physical property or its variability, whereas in other applications, such as system design, it might be of interest to introduce uncertain design parameters to test the robustness of a proposed management strategy. Thus, it is generally recommended that rather than seeking universal sensitivity results, sensitivity analysis should be made a routine part of any modeling analysis.

One explanation for why global sensitivity analyses are not yet common in vadose zone modeling is that the methods can be difficult to implement. Variance-based methods are among the best known and most powerful global sensitivity techniques, but they can be complicated to use and computationally expensive, typically requiring many thousands of model evaluations (e.g., Saltelli et al., 2008). For models with long run times, the computational requirements can be prohibitive. In such cases, less computationally demanding approaches, such as the elementary effects method (Morris, 1991), are attractive, and although they lack some of the power of variance-based methods, they can nevertheless provide valuable sensitivity information.

Our objective with this work was to use the elementary effects method (Morris, 1991) to evaluate UNSATCHEM model parameter sensitivities when simulating seasonal irrigated cropping scenarios. The Morris (1991) method has relatively modest computational requirements and permits an evaluation of the relative importance of model inputs and parameters. Example calculations are presented considering irrigation waters of differing quality and chemical composition. Parameter sensitivities are determined with respect to four model outputs or performance measures: relative crop yield, average root zone salinity, water leaching fraction, and salt leaching fraction. This work is intended to aid and encourage future research and development of probabilistic modeling tools and practices for the design and management of irrigation systems using marginal quality lands and waters.

Methods

UNSATCHEM

Simulations of irrigated crop production were performed using UNSATCHEM (Suarez and Šimůnek, 1997). A detailed description of the full UNSATCHEM model is available elsewhere (Suarez and Šimůnek, 1997; Šimůnek et al., 2013). We present here a brief summary the model system as implemented in our simulations.

One-dimensional variably saturated water flow is simulated with the Richards equation,

$$\frac{\partial\theta}{\partial t}=\frac{\partial}{\partial z}\left[K(h)\frac{\partial h}{\partial z}+K(h)\right]-S \qquad [1]$$

where θ (cm^3 cm^{-3}) is the volumetric water content, h (cm) is the pressure head, K (cm d^{-1}) is the hydraulic conductivity, t (d) is time, z (cm) is the vertical space coordinate, and S (d^{-1}) is a sink term accounting for root water uptake. The soil hydraulic properties are given by (van Genuchten, 1980),

$$S_e(h)=\frac{\theta(h)-\theta_r}{\theta_s-\theta_r}=\begin{cases}\left(1+|\alpha h|^n\right)^{-m} & h<0\\ 1 & h\geq 0\end{cases} \qquad [2]$$

$$K(h)=K_s S_e^L\left[1-\left(1-S_e^{1/m}\right)^m\right]^2 \qquad [3]$$

where S_e is the effective saturation; θ_s (cm^3 cm^{-3}) is the saturated water content; θ_r (cm^3 cm^{-3}) is the residual water content; K_s (cm d^{-1}) is the saturated hydraulic conductivity; n, α (cm^{-1}), and L are adjustable parameters; and $m = 1 - 1/n$. The sink term is formulated in terms of a maximum or potential transpiration rate and multiplicative water and salinity stress terms (Skaggs et al., 2006c):

$$S(z)=\beta(z)\alpha_h(h)\alpha_\pi(\pi)T_p \qquad [4]$$

where β (cm^{-1}) is the normalized root density distribution, T_p (cm^3 cm^{-2} d^{-1}) is the potential transpiration rate, and α_h and α_π are dimensionless stress response functions that specify reductions in uptake as a function of the soil matric, h (cm), and osmotic, π (cm) pressure heads, respectively. The stress response functions are (Skaggs et al., 2006c):

$$\alpha_h(h)=\frac{1}{1+(h/h_{50})^{p_h}} \qquad [5]$$

$$\alpha_\pi(\pi)=\frac{1}{1+(\pi/\pi_{50})^{p_\pi}} \qquad [6]$$

where the parameters h_{50} (cm) and π_{50} (cm) specify, respectively, the matric and osmotic heads at which uptake is halved, and p_h and p_π are exponents determining the "steepness" of the transition from full to reduced uptake. The actual transpiration rate, T_a (cm^3 cm^{-2} d^{-1}), is calculated as

$$T_a=T_p\int_{L_R}\beta(z)\alpha_h(h)\alpha_\pi(\pi)\mathrm{d}z \qquad [7]$$

where the integral is over the depth of the root zone, L_R.

Major components of the UNSATCHEM chemical system are Ca, Mg, Na, K, SO_4, Cl, alkalinity, and CO_2. The model accounts for equilibrium complexation and precipitation–dissolution reactions between these constituents. Partitioning between the adsorbed and liquid phases is based on the Gapon equation. Multicomponent solute transport is modeled with the advection–dispersion equation:

$$\frac{\partial\theta C_k}{\partial t}+\rho_b\frac{\partial\hat{C}_k}{\partial t}+\rho_b\frac{\partial\bar{C}_k}{\partial t}=\frac{\partial}{\partial z}\left(\theta D\frac{\partial C_k}{\partial z}\right)-\frac{\partial qC_k}{\partial z} \qquad [8]$$

where C_k ($\text{mmol}_c\ \text{cm}^{-3}$), $\hat{C}_k$ ($\text{mmol}_c\ \text{g}^{-1}$), and $\overline{C}_k$ ($\text{mmol}_c\ \text{g}^{-1}$) are, respectively, the liquid, solid, and adsorbed concentrations of the kth component; q ($\text{cm}^3\ \text{cm}^{-2}\ \text{d}^{-1}$) is the volumetric water flux density; ρ_b (g cm^{-3}) is the soil bulk density, and D ($\text{cm}^2\ \text{d}^{-1}$) is the dispersion coefficient. The dispersion coefficient is specified as $\theta D = D_L q + \theta D_W \tau$, where D_L (cm) is the longitudinal dispersivity, D_W ($\text{cm}^2\ \text{d}^{-1}$) is the molecular diffusion coefficient, and $\tau = \theta^{7/3}/\theta_s^{\,2}$ is the tortuosity factor.

Modeling Scenarios

Scenario I: Multiple Consecutive Growing Seasons

Oster et al. (2012) recently presented irrigation and cropping scenarios that were used to compare several transient-state model assessments of crop yield for different irrigation waters and irrigation regimes. We adopted the same scenarios for the present sensitivity analysis. Pertinent features of the Oster et al. (2012) modeling scenarios are as follows:

- Simulations were for the production of forage corn using soil and weather variables representative of conditions in San Joaquin Valley, CA.
- The simulated growing season was 20 wk. The potential transpiration rate, $T_p(t)$, was specified based on historical reference evapotranspiration, $ET_0(t)$, and a time-varying crop coefficient, $K_c(t)$, appropriate for corn production. The ET_0 data were obtained from CIMIS (http://www.cimis.water.ca.gov, accessed 9 Apr. 2014), and the crop coefficient data are given in Table 2 of Oster et al. (2012). Evaporation was assumed negligible, so potential transpiration was $T_p(t) = K_c(t)ET_0(t)$.
- The irrigation rate, $I(t)$, for a given simulation was specified as a fraction, K_{irr}, of the potential transpiration rate,

  $$I(t) = K_{irr} T_p(t) \qquad [9]$$

  Scenarios where the applied water was greater than ($K_{irr} > 1$) or less than ($K_{irr} < 1$) the potential transpiration rate were evaluated.
- Each simulation was run for multiple (10 or more) consecutive cropping seasons without any simulated fallow periods in between. Solute adsorption was not considered. Results were reported for the final season, when the system had achieved a quasi-steady state and any effects of initial conditions were eliminated.
- The irrigation water composition did not vary during a simulation. Different waters were considered for different simulations. The first three waters listed in Table 1 have chemical compositions similar to those used by Oster et al. (2012). The three waters listed have electrical conductivities (EC_{iw}) of 0.5, 3, and 6 dS m^{-1}. In the high and the low EC waters, the Na/Ca ratio is 1:1 and Cl is the dominant anion. The third water has a composition similar to that of the Pecos River in New Mexico.
- The simulated profile was 2 m deep, and the maximum rooting depth was 1 m.

Our UNSATCHEM simulations differed from those reported by Oster et al. (2012) in the following minor respects: (i) we used a finer uniform spatial discretization (1 vs. 2 cm); (ii) our growing season was longer by 4 d (140 vs. 136 d); (iii) the composition of the Pecos irrigation water in Table 1 is from Rhoades et al. (1973) and differs from that used by Oster et al. (2012); (iv) reference evapotranspiration was specified using daily historical values rather than weekly totals; and (v) we considered only two irrigation rates, $K_{irr} = 0.9$ and $K_{irr} = 1.1$. Also, Oster et al. (2012) observed that root growth and root distributions used in the model simulations had little effect on the model outcomes. Details are given by Oster et al. (2012) for the root distributions used with most of the tested models, but the UNSATCHEM details were omitted. For our simulations, we used a fixed root density distribution comparable to that described by Oster et al. (2012) for the other models: the normalized root density increased linearly from a value of zero at the soil surface to its maximum value at $z = -10$ cm, was maximal between $z = -10$ and -50 cm, and then decreased linearly to a value of zero at $z = -100$ cm.

Scenario II: Single Growing Season

For the second scenario, we considered a single season of crop production using agricultural drainage water for irrigation. The field was assumed to be initially nonsaline and nonsodic. The drainage water composition is given in Table 1 and was measured by Corwin et al. (2008) in a tile-drained field on the west side of San Joaquin Valley. The 20-wk growing season from Scenario I was used again with the same daily variation of potential transpiration. A different irrigation boundary condition was implemented. Rather than irrigate based on a predetermined fraction of potential transpiration, we supposed that daily observations of soil water content at the 25-cm soil depth were available for monitoring soil moisture. When the water content dropped below a specified threshold, daily irrigation was initiated at a fixed rate of 4 cm d^{-1}. Irrigation continued until the daily water content observation showed that the water content had increased above a second predetermined threshold. The two threshold values were defined in terms of the remaining fraction of plant available water (FAW),

$$\text{FAW} = \frac{\theta - \theta_{15,000}}{\theta_{333} - \theta_{15,000}} \qquad [10]$$

where $\theta_{15,000}$ and θ_{333} are the water content at $-15,000$ and -333 cm pressure head, respectively. Specific values for the FAW thresholds which initiated (IFAW) and ended (EFAW) irrigation are discussed below in the "Parameter Ranges" section. UNSATCHEM was modified to implement this custom irrigation boundary condition.

The simulations were initiated with a relatively dry soil profile having a uniform pressure head of $h = -5000$ cm. The initial chemical composition of the soil solution was specified to be the low EC water from Scenario I, with the understanding that at the first time step the model would bring the solution and exchange

Table 1. Irrigation water compositions.

Water type	EC†	TDS†	Ca	Mg	Na	K	HCO_3	SO_4	Cl
	dS m^{-1}	mg L^{-1}	————————————————			mmol$_c$ L^{-1}	————————————————		
Na/Ca Cl‡	0.5	234	1.9	0.1	1.9	0.1	0.2	0	3.8
Na/Ca Cl‡	6	3139	27.4	0.1	27.4	0.1	0.2	0	54.8
Pecos‡§	3	2417	17.0	9.1	11.4	0.08	3.1	22.4	12.1
Drainage¶	4.3	4158	25.3	13.5	23.7	0.5	1.2	54.6	6.4

† EC, electrical conductivity; TDS, total dissolved solids.
‡ Oster et al. (2012).
§ Rhoades et al. (1973).
¶ Corwin et al. (2008).

phases into equilibrium. The initial exchangeable Na and K percentages were fixed at 4 and 1%, respectively. As discussed below, the initial exchangeable Ca and Mg varied, as did the CEC.

Sensitivity Analysis

The elementary effects method (Morris, 1991) seeks to identify model parameters or inputs having the greatest impact on model outputs. The method is considered a screening approach because the emphasis is on categorizing the relative importance of model parameters rather than developing quantitative sensitivity measures. The technique is particularly useful for analyzing complex computer models having long run times because it requires relatively few model evaluations and does not assume or require any particular model structure (e.g., linearity). The method is global in the sense that model sensitivities over the whole parameter space are incorporated into the analysis.

Consider a model with output y and inputs (or parameters) $\mathbf{x} = [x_1, x_2, ..., x_k]$. Assume all inputs have been scaled or transformed so that they take on values uniformly in the interval [0, 1]. The model parameter space is therefore the k-dimensional unit cube. The most common form of the elementary effects method is based on a p-level discretization of the unit parameter space having a uniform spacing of $1/(p-1)$. Each x_i can thus take on values from $\{0, 1/(p-1), 2/(p-1), ..., 1\}$. The discretized space is termed Ω. Model evaluations are considered only at the grid points.

The elementary effect of the ith input is defined (Morris, 1991):

$$\mathrm{EE}_i = \frac{y(x_1, x_2, \ldots, x_{i-1}, x_i + \Delta, x_{i+1}, \ldots, x_k) - y(x_1, x_2, \ldots, x_k)}{\Delta} \qquad [11]$$

where Δ is a predetermined multiple of the grid spacing. Usually p is taken to be even and $\Delta \equiv (p/2)/(p-1)$. Evaluating Eq. [11] for various $\mathbf{x}$ drawn randomly from Ω produces a random sampling of EE_i. An assessment of model sensitivity to the ith parameter is given by the mean (μ_i) and standard deviation (σ_i) of the sampled EE_i values. A large mean value indicates that x_i is important to the computed model output y, whereas a large standard deviation indicates that the importance of x_i is dependent on interactions with other parameters or other nonlinearities. A potential drawback of using μ_i to gauge parameter importance is that in some cases negative and positive values of EE_i can essentially cancel each other out when calculating the mean, and the resulting diminished μ_i value could lead to an undervaluation of the parameter's significance. For this reason, Campolongo et al. (2007) recommended also calculating μ_i^*, which is defined as the mean of the absolute value of EE_i. Note that while Eq. [11] has the same general form as a standard local sensitivity coefficient, the perturbation Δ is much larger than would be used to approximate a derivative.

Morris (1991) devised an efficient method for generating r samples of EE_i for each model parameter. For a model with k inputs or parameters, the Morris (1991) method requires r sequences of $k + 1$ model runs, for a total of $r(k + 1)$ runs. The elementary effects μ_i and σ_i for each parameter are determined from the generated r samples of EE_i. Morris (1991) and Saltelli et al. (2008) give full algorithmic details for implementing the procedure efficiently. The outcome of the sensitivity analysis can depend on the choice of the parameters r and $\Delta = (p/2)/(p-1)$. The results presented below are for $r = 30$, $\Delta = 2/3$, and $p = 4$. We discuss these parameter choices in greater detail in the Discussion section.

Performance Measures

We evaluate parameter sensitivities with respect to four model outcomes: (i) crop yield, (ii) average root zone salinity, (iii) water leaching fraction, and (iv) salt leaching fraction. The first performance measure is a primary consideration from an agricultural production standpoint, while the second is an indication of the effects of an irrigation regime on soil quality. The final two measures are important for judging impacts on groundwater quality and salt balances, increasingly a focus of regulation. The performance measures are interrelated, all being determined or affected by the salt and water balances in the root zone. In Scenario I, performance measures were evaluated for the final simulated growing season in which the system had achieved a quasi-steady state.

Relative crop yield was calculated as (De Wit, 1958),

$$Y = \hat{T}_\mathrm{a} / \hat{T}_\mathrm{p} \qquad [12]$$

where $\hat{T}_a$ and $\hat{T}_p$ are the seasonal cumulative totals for actual and potential transpiration, respectively. Root zone electric conductivity (RZEC) was taken to be the depth average of the soil water electrical conductivity (EC_{sw}) profile at the end of the growing season,

$$\mathrm{RZEC} = \frac{1}{L_R}\int_{L_R} \mathrm{EC}_{sw}\, dz \qquad [13]$$

Note that RZEC can be determined from model outputs but that the model itself does not use this quantity. The water and salt leaching fractions were defined, respectively, as

$$\mathrm{WLF} = J_{L_R} / J_0 \qquad [14]$$

$$\mathrm{SLF} = Q_{L_R} / Q_0 \qquad [15]$$

where J_{L_R} and J_0 are the seasonal cumulative water fluxes at the bottom of the root zone and the soil surface, respectively, and Q_{L_R} and Q_0 are the corresponding salt mass fluxes. The salt flux at the base of the root zone was not calculated directly by the model but was determined from model outputs as

$$Q_{L_R} = [M_{rz}(t_2) - M_{rz}(t_1)] + Q_0 \qquad [16]$$

where $M_{rz}(t_1)$ and $M_{rz}(t_2)$ are the salt mass contained in the root zone at the beginning and end of the season, respectively, and, following UNSATCHEM conventions, downward fluxes are negative values.

Parameter Ranges

Table 2 lists model parameters considered in the sensitivity analyses and the parameter ranges (or uncertainties) assigned to them. As noted previously, parameter uncertainty depends on the particular modeling application. The parameter ranges considered here are fairly broad. It is likely that for specific field applications many of the parameter ranges could be narrowed given some limited amount of soils characterization data. The ranges given in Table 2 for the soil hydraulic parameters (θ_r, θ_s, α, n, K_s, L) correspond approximately to the range of textural-class-average parameter values reported by Schaap et al. (2001), excluding the two coarsest textures (sand and loamy sand). The plant parameter (h_{50}, p_h, π_{50}, p_π) values used by Oster et al. (2012) for forage corn are approximately at the center of the ranges given in Table 2. Osmotic uptake reduction parameters (π_{50}, p_π) are usually specified based on an assumed correspondence with plant salt tolerance parameters. The range given in Table 2 for p_π is the range observed for the corresponding salt tolerance exponent for forage corn (van Genuchten and Gupta, 1993). The range for π_{50} is approximately ±1000 cm about the value used by Oster et al. (2012); this assumed range will be further discussed in the Results section. The range given for h_{50} is from Cardon and Letey (1992) and is the range expected for corn based on the experimental work of Ehler (1983). Relatively little is known about the parameter p_h. Typically the value $p_h \approx 3$ is used based on an assumed correspondence with the salt tolerance exponent (Skaggs et al., 2006c). The range given in Table 2 is centered around $p_h = 3$ and is comparable in size to that prescribed for p_π. Oster et al. (2012) used a dispersivity value of $D_L = 8.6$ cm. Our specified $D_L \in [5\text{ cm}, 15\text{ cm}]$ is based on experience and a rule-of-thumb that says the dispersivity is approximately equal to one-tenth of the transport distance (e.g., Skaggs and Leij, 2002). The parameter ranges given for molecular diffusion and soil bulk density encompass commonly encountered values; experience suggests these parameters are not likely to be among the most important input factors.

For Scenario II, additional uncertain parameters are the irrigation threshold parameters IFAW and EFAW, the CEC, the initial ratio of exchangeable calcium to magnesium (ECa/EMg), and the Gapon selectivity coefficients ($K_{Mg\text{-}Ca}$, $K_{Ca\text{-}Na}$, and $K_{Ca\text{-}K}$). Irrigation scheduling guidelines based on moisture depletion typically advise irrigating when plant available water is about 40 to 60%. The ranges

Table 2. Input parameter ranges.

Parameter†	Units	Range Min.	Range Max.
Soil hydraulic parameters			
θ_r	$cm^3\ cm^{-3}$	0.04	0.12
θ_s	$cm^3\ cm^{-3}$	0.35	0.5
a	cm^{-1}	0.005	0.03
n		1.2	2
K_s	$cm\ d^{-1}$	8	50
L		−1.5	0.5
Plant parameters			
p_h		2	4
h_{50}	cm	−6500	−2500
p_π		1.6	4
π_{50}	cm	−7500	−5500
Transport parameters			
ρ_b	$g\ cm^{-3}$	1.2	1.8
D_W	$cm^2\ d^{-1}$	0.0001	0.001
D_L	cm	5	15
Soil chemical parameters (Scenario II only)			
CEC	$mmol_c\ kg^{-1}$	100	200
$K_{Mg:Ca}$		0.65	0.95
$K_{Ca:Na}$	$(mmol_c\ L^{-1})^{1/2}$	1.95	2.25
$K_{Ca:K}$	$(mmol_c\ L^{-1})^{1/2}$	0.2	0.5
ECa/EMg		0.5	7
Irrigation parameters (Scenario II only)			
IFAW		0.3	0.6
EFAW		0.7	1.0

† See “Methods” section for definitions of the parameters.

specified for the soil chemical parameters are broad and appropriate for a general analysis such as the current work; analyses for specific fields would permit lower parameter uncertainties.

Results and Discussion

Scenario I

We first consider the variation in model outputs generated by varying the parameters over the ranges indicated in Table 2. Table 3 gives the water and salt applications for the six modeled scenarios (three water compositions × two application rates), and Table 4 presents the corresponding minimum, maximum, and mean values of the four model outputs. The Table 4 results are based on $r(k + 1) = 30 \times (13 + 1) = 420$ realizations for each of the six scenarios.

As shown in Table 4, the low EC water (0.5 dS m^{-1}) scenarios generated some variation in crop yield, although as can be seen by the closeness of the mean to the maximum value, the yield distribution was highly skewed, with nearly all of the realizations resulting in yields of 97 to 100% for $K_{irr} = 1.1$ and 87 to 89% for $K_{irr} = 0.9$. A 90% crop yield would be the maximum possible for $K_{irr} = 0.9$ scenarios, where the depth of applied water was equal to 90% of the total potential transpiration. The small number of realizations that had lower yields occurred when n and K_s where both on the high end of the ranges in Table 2 and h_{50} and p_{50} were on the low end. Larger n and K_s values in Eq. [2] and [3] lead to more rapid soil drainage and lower water contents, while smaller h_{50} and p_{50} values correspond to lower water stress tolerance. In these few simulations, the combination of lower soil water contents, increased drainage, and low water stress tolerance resulted in lower water uptake and yields.

The highest EC water (6 dS m^{-1}) produced substantially lower yields, with mean values of 66 and 73% for the low and high irrigation rates, respectively. The yields varied considerably, ranging from 60 to 71% with $K_{irr} = 0.9$ and 64 to 82% with $K_{irr} = 1.1$. Results for the middle EC irrigation water (3 dS m^{-1}) were intermediate of the other two cases with respect to both the mean yield and the range of variation (Table 4).

Yield, root zone EC, and the water leaching fraction have direct, general relationships: increases in RZEC correspond to decreases in yield, while decreases in WLF correspond to increases in RZEC.

Table 3. Water and salt applications for simulated growing seasons, Scenario I.

		Applied salt		
Irrigation rate, K_{irr}	Applied water	Na/Ca Cl, EC = 3	Na/Ca Cl, EC = 6	Pecos, EC = 3
	cm	mg cm^{-2}		
0.9	65.3	15.3	205	158
1.1	79.8	18.7	250	193

Given those relationships, the means and ranges for RZEC and WLF in Table 4 are consistent with those discussed for yield. The salt leaching fraction is more complicated due to precipitation–dissolution reactions. The considered irrigation waters (Table 1) represent different extremes with respect to the potential for salt precipitation. The Pecos water contains appreciable HCO_3 and SO_4, and, when concentrated through the action of root water uptake, provides chemical conditions favorable for the precipitation of gypsum ($CaSO_4{\cdot}H_2O$) and calcite ($CaCO_3$). The two Na/Ca Cl waters, on the other hand, do not have any sulfate and have atypically low alkalinity values that limit calcite formation. In the simulations, both the high and low EC waters with Na/Ca Cl composition generated a small amount of calcite in the root zone. The high EC water in Table 1 has a very large Ca to alkalinity ratio, and the alkalinity in that case was a limiting factor for calcite formation. The total amount of precipitation with the high EC water was minor relative to the amount of salt added at the surface (Table 3), so the fraction of applied salt leaving the root zone approached 100% in all realizations (Table 4). With the low EC water, the generated calcite mass was comparable to that produced with the high EC water, but on a percentage basis, that mass was more consequential, especially in the $K_{irr} = 0.9$ simulations, where salt removal by precipitation reduced SLF to 90% on average (Table 4). With the Pecos water, both calcite and gypsum were precipitated in significant quantities, and the salt removal reduced SLF on average to 66% for $K_{irr} = 0.9$ and 71% for $K_{irr} = 1.1$ (Table 4).

Figure 1 shows elementary effects μ_i^* and σ_i computed for crop yield. The bars for μ_i^* are colored light green if μ_i was positive and dark green if μ_i was negative. Evaluating elementary effects and determining the relative importance of model parameters and their interactions typically requires some subjective judgment and interpretation (Morris, 1991), but the basic idea is to identify parameters or groups of parameters having effects that

Table 4. Summary of model outputs for Scenario I.†

	Irrigation water								
	Na/Ca Cl, EC = 0.5			Na/Ca Cl, EC = 6			Pecos, EC = 3		
K_{irr}	Min.	Max.	Mean	Min.	Max.	Mean	Min.	Max.	Mean
Relative yield, Y (%)									
0.9	77	89	89	60	71	66	76	84	81
1.1	87	100	99	64	82	73	81	97	91
Depth-averaged root zone electrical conductivity, RZEC (dS m^{-1})									
0.9	2	11	8	12	17	14	7	13	10
1.1	1	2	2	10	14	12	6	9	7
Water leaching fraction, WLF (%)									
0.9	0.04	14	1	21	33	27	6	16	10
1.1	9	21	10	26	42	33	12	26	17
Salt leaching fraction, SLF (%)									
0.9	73	96	90	99	100	100	62	71	66
1.1	93	100	96	99	100	100	68	77	71

† Based on 420 realizations for each of the six K_{irr}–water pairs.

are substantially different. Small differences are generally not considered important.

Starting with the highest EC irrigation water (6 dS m^{-1}) and lowest irrigation rate (K_{irr} = 0.9), we can distinguish three groups of parameters (Fig. 1c). The mean effect μ_i^* for the plant salt tolerance parameter π_{50} is considerably larger than that for any other parameter, indicating π_{50} was the most important or influential parameter with respect to predicting crop yield for that water and irrigation regime. Further, the modest size of σ_i (relative to μ_i^*) for π_{50} indicates that the significance of π_{50} was not strongly dependent on the values of other parameters. An intermediate level of significance is assigned to the salt tolerance exponent p_π and the solute dispersivity D_L. The remaining parameters are of comparatively minor significance, with ρ_b and D_W having essentially no effect at all. Among the parameters with lower mean effects, we note that the soil hydraulic parameters α and K_s and the water stress parameters h_{50} have $\sigma_i > \mu_i^*$, indicating that in this scenario the influence of these parameters varied considerably depending on the values of other parameters.

The elementary effects computed for the same water at the higher irrigation rate (K_{irr} = 1.1) were similar except that in this case p_π had a larger mean effect that was on par with the mean effect obtained for π_{50} (Fig. 1d). With the Pecos irrigation water (3 dS m^{-1}), p_π, π_{50}, and D_L were again of high or intermediate importance (Fig. 1e,f), as was the hydraulic parameter α, particularly in the case of K_{irr} = 0.9 (Fig. 1e). Parameter α again had $\sigma_i > \mu_i^*$, indicating a high level of interaction with other parameters.

In Fig. 1c–1f, the elementary effects EE_i computed for π_{50} were all negative, so $\mu_i = \mu_i^*$. The elementary effects method is mainly concerned with qualitative groupings of parameters, but a quantitative interpretation of μ_i in this cases is as follows: given all model parameters within the ranges prescribed by Table 2, decreasing π_{50} by Δ = 2/3 of the parameter's specified range produced, on average, an increase in yield of 2/3 ($-\mu_i$). For example, the value $\mu_i^* \approx -\mu_i$ = 0.07 for parameter π_{50} in Fig. 1c indicates that decreasing π_{50} by 1337 cm produced an average increase in yield of (2/3)0.07 = 0.05. The corresponding average yield increases associated with similarly increasing p_π or decreasing D_L were both 0.02 (Fig. 1c). Similar

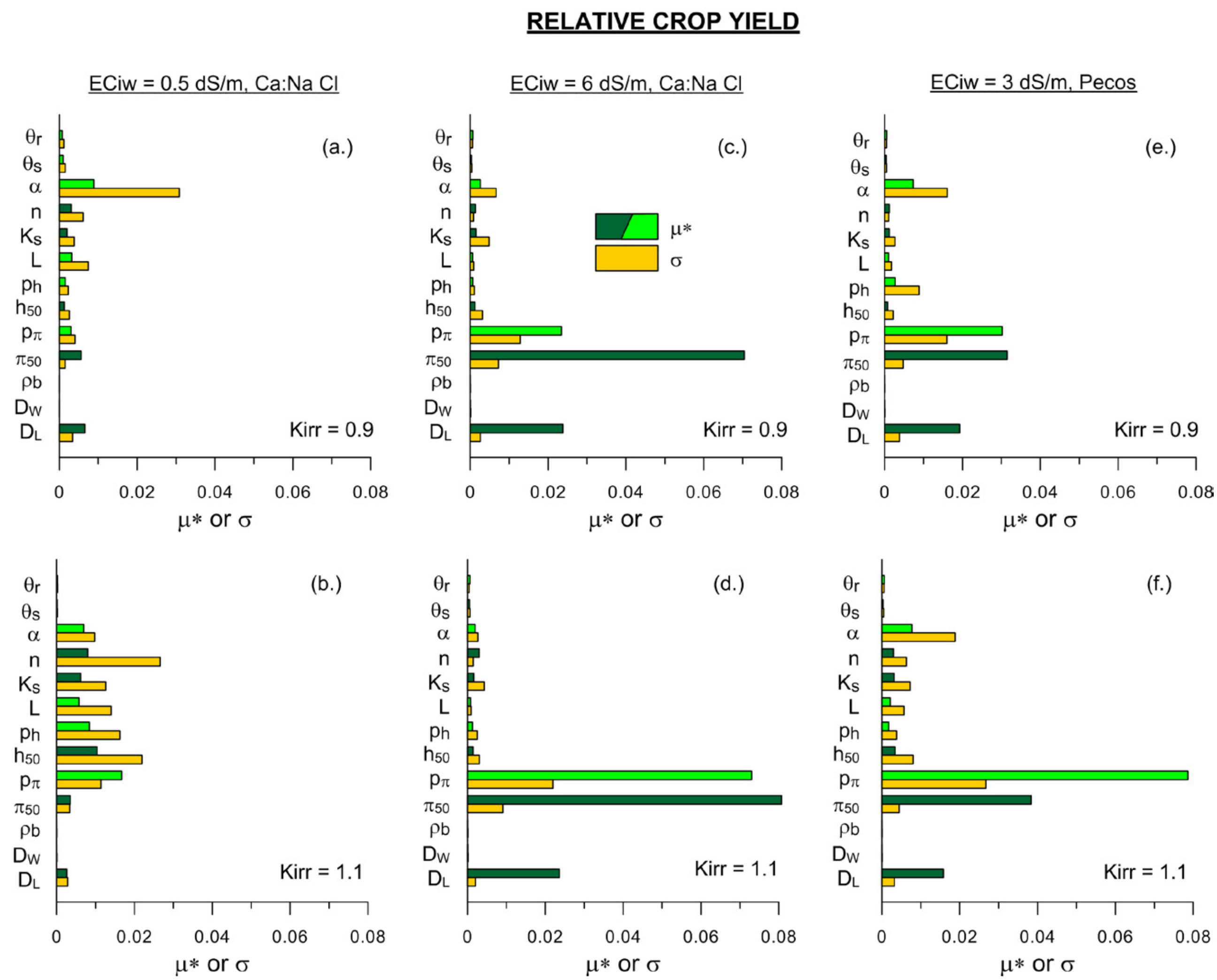


Fig. 1. Scenario I elementary effects computed with respect to crop yield (Y) for different irrigation water compositions and irrigation rate constants (K_{irr}). Bars for μ_i^* are light green if μ_i was positive and dark green if μ_i was negative.

increases may be inferred from Fig. 1d–1f. The sign of μ_i for D_L might seem counterintuitive in that decreasing dispersion would be expected to correspond to higher solute concentrations and thus *decreases* in yield. However, in this case lower dispersion also led to increased solid formation, which reduced solution concentrations.

The same reasoning regarding μ_i^* when applied to the other model parameters in Fig. 1c–1f (with some nuance allowing for cases with significant numbers of both negative and positive EE_i) leads to the conclusion that similarly perturbing any of the parameters identified above as belonging to the least significant groups led, on average, to changes in yield that were usually much less than 0.01. Hence, the importance of that parameter group was not just low relative to that of the others, it was low in the absolute sense of not having a practically significant effect on calculated yield.

Figures 1a and 1b show the elementary effects computed for yield using the good quality (low EC) irrigation water. For the lower irrigation rate (Fig. 1a), the most important parameter was α, and its influence was again strongly affected by the values of other parameters. With the higher irrigation rate, several of the hydraulic and plant parameters have comparable mean effects, and many show strong dependencies on the values of other parameters (Fig. 1b). However, consideration of the magnitude of the elementary effects, as well as the narrow range of yields computed with EC_{iw} = 0.5 dS m^{-1} (Table 4, as discussed above), leads to the conclusion that variations in model parameters were not greatly affecting the computed yield, which was always close to the maximum possible for a given irrigation rate (K_{irr}).

As noted, yield, RZEC, and WLF have direct relationships, so it is not unexpected that the computed elementary effects for the three performance measures would be similar. For the 3 and 6 dS m^{-1} irrigation waters, plots of elementary effects for RZEC and WLF were very similar to those presented for yield in Fig. 1, with π_{50}, p_π, and D_L standing out as the most important parameters (not shown). One minor difference was that with the Pecos water and K_{irr} = 0.9, α was relatively less important for RZEC than for yield (Fig. 1e). For the 0.5 dS m^{-1} water, the simulated WLF was nearly the same in all realizations (note the skewed distribution in Table 4), so the parameters had a minor effect on the outcome for both K_{irr} = 0.9 and K_{irr} = 1.1 (not shown). RZEC similarly did not vary with K_{irr} = 1.1, but some variation occurred with K_{irr} = 0.9. Figure 2 shows the elementary effects for the latter case. In this scenario involving deficit irrigation with high quality water, the parameters π_{50}, p_π, D_L, and α are again important, plus the water stress exponent p_h is relatively more important than in other cases, with significant dependence on other parameters indicated (Fig. 2). Mirroring the analysis presented above, we observe that a 1333-cm perturbation in π_{50} led on average to an absolute change in RZEC of 1.3 dS m^{-1}.

Figure 3 presents elementary effects for the salt leaching fraction. With the 6 dS m^{-1} irrigation water (Fig. 3c,d), SLF was near 100% for all realizations (Table 4), so essentially no sensitivity to parameter variations existed. With EC_{iw} = 0.5 dS m^{-1} and K_{irr} = 1.1, there was again relatively low variation in the calculated salt leaching fractions, so the magnitudes of the elementary effects were correspondingly small (Fig. 3b). Greater variation in SLF occurred in the remaining three scenarios. With EC_{iw} = 0.5 dS m^{-1} and K_{irr} = 0.9, the most important parameter was the soil hydraulic parameter *n*, which had both a large mean effect and standard deviation (Fig. 3a). A perturbation of 0.6 in *n* resulted on average in an absolute change in SLF of 0.05. With the Pecos water and K_{irr} = 0.9 (Fig. 3e), the hydraulic parameters, the plant salt tolerance parameters, and solute dispersivity all had comparable mean effects and large standard deviations, indicating significant parameter interactions. At the higher irrigation rate, p_π was the most important parameter, followed by π_{50} (Fig. 3f). A perturbation of 1.33 in p_π caused on average an absolute change in SLF of about 0.03.

Overall, for the considered irrigation waters and regimes, the most important parameters affecting the seasonal simulations presented for Scenario I were the plant salt tolerance parameters π_{50} and p_π. Across all scenarios and performance measurers where the output had substantial variability, the mean elementary effects for the salt tolerance parameters were either larger than those for the other parameters, or were on par with those from the group of parameters found to have a large or intermediate influence. Further, σ_i for π_{50} and p_π was usually relatively small, indicating that the parameters' strong influence on model output was mostly independent of the other parameters. The influences of the soil hydraulic parameters (particularly α and *n*) were relatively larger in the deficit irrigation scenarios and tended to be strongly affected by

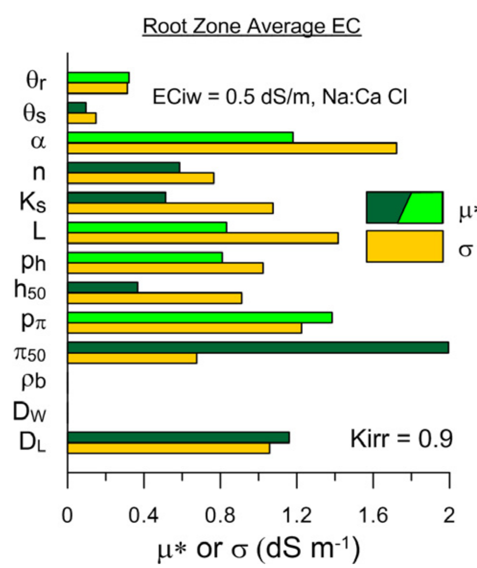


Fig. 2. Scenario I elementary effects computed with respect to root zone salinity (RZEC) using the low EC (0.5 dS m^{-1}) irrigation water and irrigation rate constant of K_{irr} = 0.9. Bars for μ_i^* are light green if μ_i was positive and dark green if μ_i was negative.

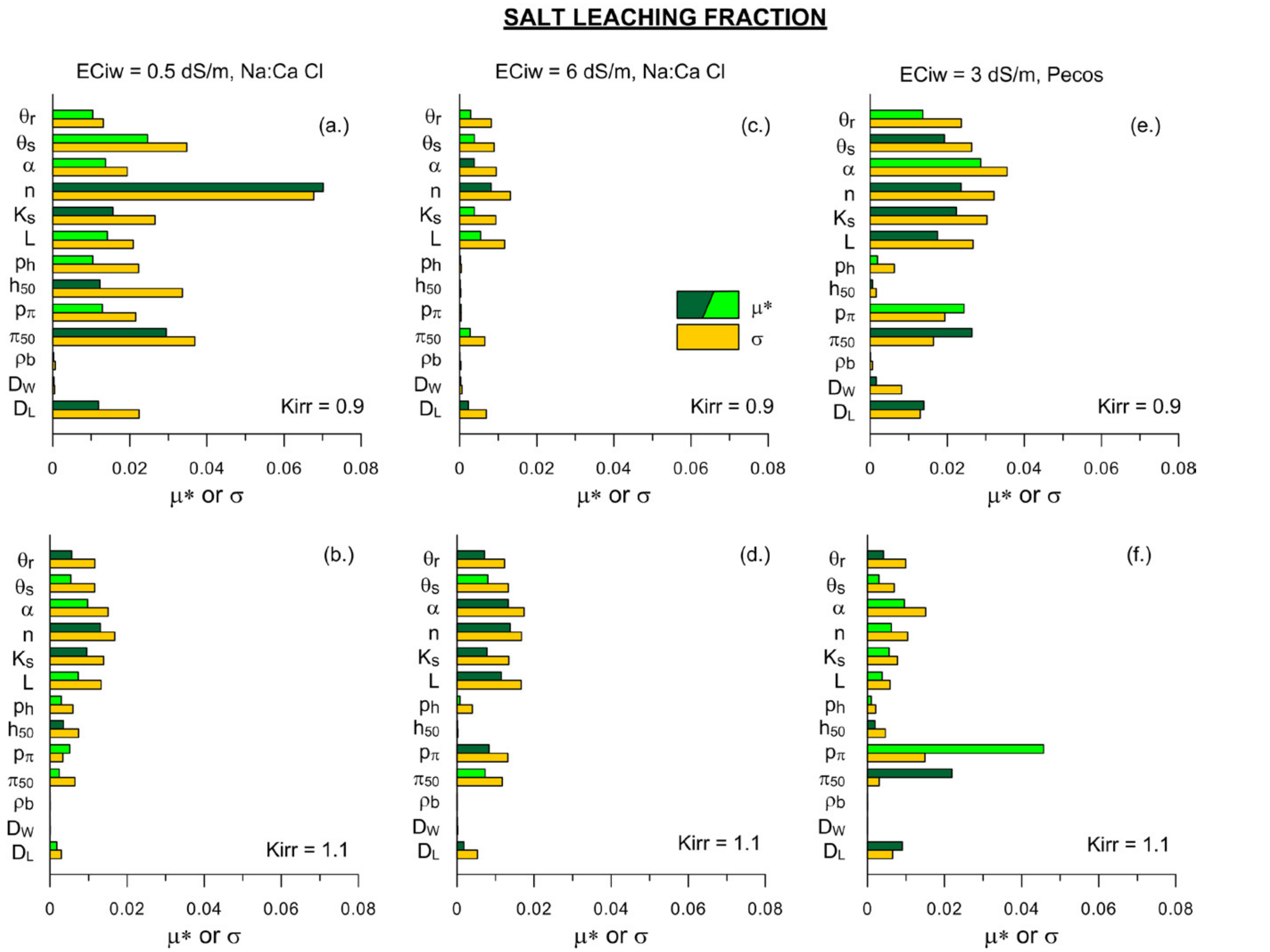


Fig. 3. Scenario I elementary effects computed with respect to the salt leaching fraction (SLF) for different irrigation water compositions and irrigation rate constants (K_{irr}). Bars for μ_i^* are light green if μ_i was positive and dark green if μ_i was negative.

the values of the other model parameters. The hydraulic parameters were also relatively more important to the salt leaching fraction than to the other considered model outcomes. The water stress parameters were generally of minor importance except in the scenarios with high quality irrigation water. The transport parameters ρ_b and D_W generally had negligible impacts on the model outputs. The solute dispersivity D_L was more significant, with the computed mean effects typically placing it among the group of parameters having an intermediate influence.

Scenario II

To simplify the parameterization slightly for Scenario II, we elected to follow the common practice of fixing the stress exponents at $p_h = p_\pi = 3$ and the conductivity exponent at $L = 0.5$ (van Genuchten and Gupta, 1993; Šimůnek et al., 2013). With this parameterization, all variability in plant water and salinity stress is specified by h_{50} and π_{50}, respectively, and one less parameter is needed to specify the hydraulic properties.

The irrigation scheme used in Scenario II resulted in a wide range of water applications relative to the potential transpiration rate. The ratio of (seasonal total) applied water to potential transpiration ranged from 0.45 to 1.7, with a mean value of 0.79 and a median value of 0.77. Deficit irrigation (ratio < 1) occurred in 83% of the cases. Compared with Scenario I (where the ratio was always 0.9 or 1.1), the realizations in Scenario II presented greater extremes of deficit or excess water applications.

Table 5 summarizes the model outputs generated for Scenario II. A broad distribution of values for all four performance measures was obtained. Yield ranged from 45 to 99%, while the average root zone EC ranged from 3 to 12%. The distributions for salt and water leaching fractions were similarly wide (WLF between 0 and 35%, SLF between 3 and 61%), although the distribution for WLF was skewed, with most realizations falling on the low end of the distribution.

The salt leaching fractions obtained in the (mostly) deficit irrigated, single season simulations of Scenario II was smaller than those obtained in the quasi-steady, multiple season simulations of Scenario I. As was the case with the Pecos water in Scenario I, the drainage water used for irrigation in Scenario II had a chemical composition that was conducive to gypsum and calcite formation. In all realizations, significant amounts of precipitated solids were formed. The possibility of high levels of salt precipitation in the root zone when initially applying low quality irrigation waters is well established (e.g., Jury et al., 1978). Drainage water composition in the San Joaquin Valley (and elsewhere) varies greatly depending on location, so the water used in the current study should not be viewed as representative of drainage waters in the larger region. Again, specific sites generally require specific analyses.

Figure 4 shows the elementary effects for all four performance measures. Compared with Scenario I, the soil hydraulic properties as a group show elevated relative importance with respect to all four measures. Perturbing α by 0.017 cm^{-1}, for example, produced on average an absolute change in computed relative yield of 0.21, a very big average effect. Although some of the increased parameter importance can be attributed to the generally drier soil conditions, mostly it is due to the moisture deficit-based irrigation scheme in which the hydraulic properties directly affected the timing and amount of irrigation. The relatively large σ_i for the hydraulic parameters (Fig. 4) is partly due to interactions among themselves in determining FAW and partly due to interactions with the irrigation threshold parameters IFAW and EFAW. The parameters IFAW and EFAW also had large σ_i and generally manifested an intermediate level of importance across all four performance measures.

The significance of the plant stress parameters and the solute dispersivity is relatively lower in this scenario, although the absolute magnitude of the elementary effects for those parameters is not greatly smaller than in the cases from the previous scenario when low quality irrigation water was used. Rather, it is the increase in size of other elementary effects that has led to a diminished relative importance.

The soil chemistry parameters were relatively unimportant with respect to computing yield and WLF for this single, initial season of irrigating with degraded water (Fig. 4). However, with respect to RZEC and SLF, the initial ratio of exchangeable Ca and Mg had the largest elementary effect μ_i^* of all parameters. This was partly due to the expansive range considered for ECa/EMg (Table 2), and partly due to the importance of the exchange phase as a source of Ca for calcite and gypsum formation. Cation exchange capacity and the Mg-Ca selectivity coefficient ($K_{\text{Mg-Ca}}$) had intermediate importance, also due to their effect on available Ca. Because initial exchangeable Na and K were fixed at relatively low values, $K_{\text{Ca-Na}}$ and $K_{\text{Ca-K}}$ were only of minor importance.

Table 5. Summary of model outputs for Scenario II.†

Performance measure‡	Min.	Max.	Mean
Relative yield (%)	45	99	69
RZEC (dS m^{-1})	2.9	12	5.8
WLF (%)	0	35	2.1
SLF (%)	2.6	61	17

† Based on 540 realizations.
‡ RZEC, average root zone salinity; WLF, water leaching fraction; SLF, salt leaching fraction.

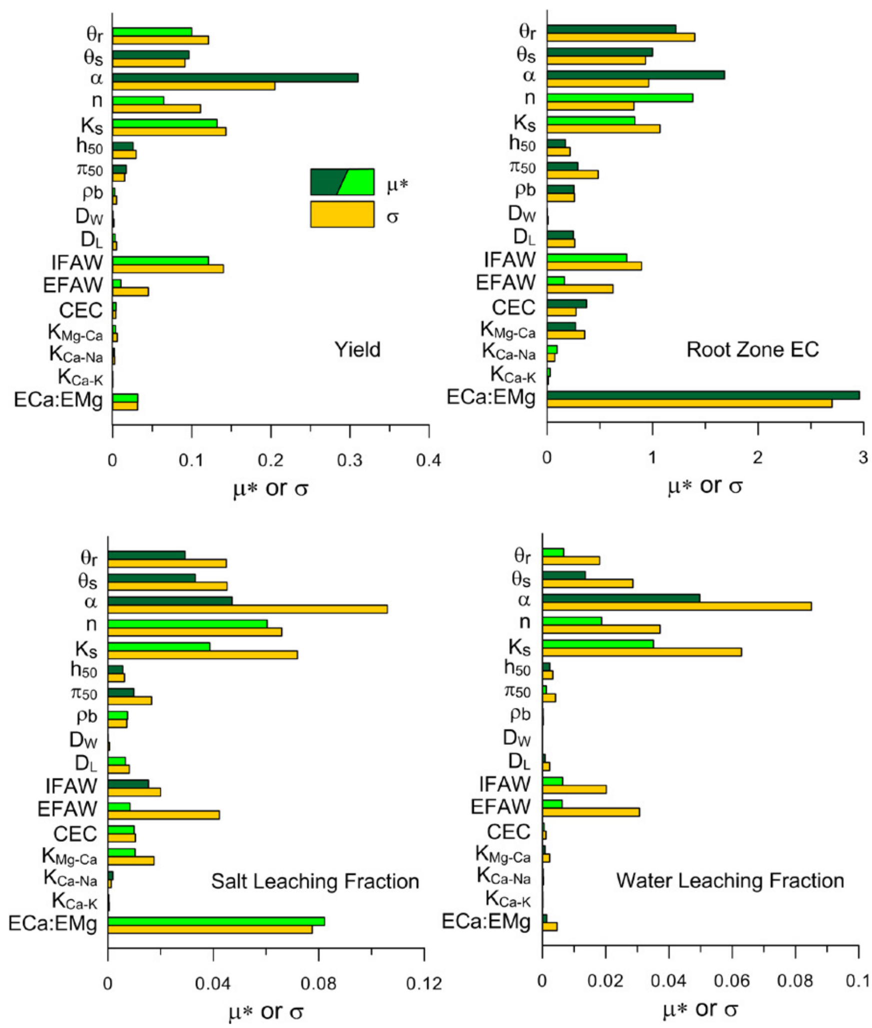


Fig. 4. Scenario II elementary effects computed with respect to four model outputs. Bars for μ_i^* are light green if μ_i was positive and dark green if μ_i was negative.

Discussion

As noted above, the obtained sensitivity results are dependent on the specifics of the considered scenarios. Although Scenario I used multiple growing seasons as a setup for the final calculation, both scenarios considered in the current work evaluated parameter sensitivities with respect to model simulations made for a single, full growing season; other timeframes may also be of interest.

The results also depend on the parameter ranges specified in Table 2. The "correct" level of uncertainty or variability to assign to a parameter will vary depending on circumstances. For soil hydraulic parameters, one might determine a range or distribution based on measurements made across a field, from soil survey data, or from estimates provided by pedotransfer functions such as described by Schaap et al. (2001). For other parameters, relatively less guidance may be available. As noted, salinity uptake reduction parameters are usually specified based on a presumed correspondence with whole-plant salt tolerance parameters such as those discussed by van Genuchten and Gupta (1993). However, relatively few data are available for field testing parameters obtained this way. Skaggs et al. (2006a,b,c) reported mixed results in attempting to derive model parameter values and bounds from literature studies of the salt tolerance of alfalfa (*Medicago sativa* L.) and tall wheatgrass [*Thinopyrum elongatum* (Host) D.R. Dewey]. In Table 2, the 2000-cm range ascribed to π_{50} for forage corn is considerably smaller than would be inferred for alfalfa or tall wheatgrass based on the results of Skaggs et al. (2006a,b,c). Rerunning our Scenario I calculations using a 4000-cm range for π_{50} leads to mean elementary effects for π_{50} that are much larger than those of any other parameter, leading to the conclusion that π_{50} is by far the most important model parameter. Future research aimed at determining appropriate field values for π_{50} would be of great benefit toward reducing uncertainty in model simulations of degraded water use.

Lastly, the outcome of the Morris (1991) sensitivity analysis can depend on the choice of the algorithmic parameters r (the number of random parameter trajectories), p (the level of discretization), and $\Delta = (p/2)/(p - 1)$ (the size of the parameter perturbation). Various authors have reported good results using the relatively small values $p = 4$ ($\Delta = 2/3$) and $r = 10$ (Saltelli et al. (2008), and references given therein on p. 119). Others have found it advantageous to use significantly larger values, such as $p = 40$ and $r = 100$ (Yang, 2011). For our computations, we experimented with different values and found that conclusions regarding the importance of model parameters obtained for $p = 4$ and $r = 10$ were unchanged when larger values were used, although some minor fluctuations in the computed elementary effects were seen at $r = 10$ realizations. We opted to report results for $r = 30$, where the fluctuations where largely removed. Using values larger than $p = 4$ (i.e., smaller than $\Delta = 2/3$) had a negligible effect. If a performance measure were a linear function of a model parameter, then the computed elementary effect would not be affected by the choice of Δ. Similarly, if a model response to a parameter perturbation is monotonic and not excessively nonlinear, then the choice of Δ will have only a limited effect. That was the case in our computations, at least with respect to the model parameters having the largest impact on model output (plant salinity stress parameters).

Summary and Conclusions

Global sensitivity analyses were performed for UNSATCHEM seasonal simulations of forage corn production with differing irrigation rates and water compositions. Two scenarios were evaluated. The first considered a single season of crop production after many irrigation cycles had brought the system to a quasi-steady state. The analysis found that overall the most important model parameters were the plant salt tolerance parameters π_{50} and p_{π}, followed by the solute dispersivity D_L. The relative importance of soil hydraulic parameters, particularly α and n, increased in scenarios involving lower irrigation rates (drier soils) and better quality (low EC) irrigation water. In several scenarios considered, model outputs varied only slightly in response to variations in all parameters. General trends included the following: (i) decreasing irrigation water quality increased the relative importance of plant salinity stress parameters, and (ii) the importance of hydraulic parameters is relatively higher when irrigation rates are low (drier soil conditions).

The second scenario considered a single season of degraded water irrigation on a cropped field that was initially nonsaline and nonsodic. Irrigation scheduling was based on soil water deficit as determined by daily "observations" of soil moisture. Sensitivity analyses for this scenario found that soil hydraulic parameters had overall high importance due to both the relatively dry soil conditions and the direct impact of hydraulic properties on irrigation scheduling. With respect to salt leaching, the most important model parameter was the ratio of exchangeable Ca to Mg in the initial soil. The initial exchange phase is a source of Ca and affects the amount of gypsum and calcite that formed in the root zone during the growing season.

With respect to further developing modeling techniques for degraded irrigation water and salinity management, the results of this study indicate that future work aimed at determining appropriate field parameter values and bounds for different crops and conditions would improve model predictions and reduce uncertainty. Procedures for routine use of models for site-specific management should include uncertainty and sensitivity analyses. The elementary effects method used in this work is a useful approach for obtaining parameter sensitivity information at relatively low computational cost.

References

Alzraiee, A.H., and L.A. Garcia. 2013. Global sensitivity analysis of variably saturated flow and transport parameters and its implication for crop yield and root zone hydrosalinity. J. Irrig. Drain. Eng. (in press) doi:10.1061/(ASCE)IR.1943-4774.0000638.

Ayers, R.S., and D.W. Westcot. 1985. Water quality for agriculture. Food and Agriculture Organization of the United Nations, Rome.

Beven, K., and P. Germann. 2013. Macropores and water flow in soils revisited. Water Resour. Res. 49(6):3071–3092. doi:10.1002/wrcr.20156

Cacuci, D.G. 2003. Sensitivity & uncertainty analysis. Vol. 1. Theory. CRC Press, New York.

Campolongo, F., J. Cariboni, and A. Saltelli. 2007. An effective screening design for sensitivity analysis of large models. Environ. Model. Softw. 22(10):1509–1518. doi:10.1016/j.envsoft.2006.10.004

Cardon, G.E., and J. Letey. 1992. Plant water uptake terms evaluated for soil water and solute movement models. Soil Sci. Soc. Am. J. 56(6):1876–1880. doi:10.2136/sssaj1992.03615995005600060038x

Cheviron, B., and Y. Coquet. 2009. Sensitivity analysis of transient-MIM HYDRUS-1D: Case study related to pesticide fate in soils. Vadose Zone J. 8(4):1064–1079. doi:10.2136/vzj2009.0023

Corwin, D.L., S.M. Lesch, J.D. Oster, and S.R. Kaffka. 2008. Short-term sustainability of drainage water reuse: Spatio-temporal impacts on soil chemical properties. J. Environ. Qual. 37:S-8–S-24. doi:10.2134/jeq2007.0140

Corwin, D.L., J.D. Rhoades, and J. Simunek. 2007. Leaching requirement for soil salinity control: Steady-state versus transient models. Agric. Water Manage. 90(3):165–180. doi:10.1016/j.agwat.2007.02.007

De Wit, C.T. 1958. Transpiration and crop yields. Versl. Landbouwk. Onderz. Vol. 64. Wageningen Univ., the Netherlands. p. 59–84.

Ditthakit, P. 2011. Computer software applications for salinity management: A review. Aust. J. Basic Appl. Sci. 5(7):1050–1059.

Ehler, W.L. 1983. The transpiration ratios of *Agave americana* L. and *Zea mays* L. as affected by soil water potential. J. Arid Environ. 6:107–113.

Falkenmark, M., and J. Rockström. 2006. The new blue and green water paradigm: Breaking new ground for water resources planning and management. J. Water Resour. Plan. Manage. 132(3):129–132. doi:10.1061/(ASCE)0733-9496(2006)132:3(129)

Foley, J.A., N. Ramankutty, K.A. Brauman, E.S. Cassidy, J.S. Gerber, M. Johnston, N.D. Mueller, C. O'Connell, D.K. Ray, P.C. West, C. Balzer, E.M. Bennett, S.R. Carpenter, J. Hill, C. Monfreda, S. Polasky, J. Rockström, J. Sheehan, S. Siebert, D. Tilman, and D.P.M. Zaks. 2011. Solutions for a cultivated planet. Nature 478(7369):337–342. doi:10.1038/nature10452

Jägerskog, A., and T.J. Clausen. 2012. Feeding a thirsty world— Challenges and opportunities for a water and food secure future. Stockholm International Water Inst., SIWI, Stockholm.

Jury, W.A., H. Frenkel, and L.H. Stolzy. 1978. Transient changes in the soil-water system from irrigation with saline water: I. Theory. Soil Sci. Soc. Am. J. 42(4):579–585. doi:10.2136/sssaj1978.03615995004200040009x

Letey, J., and G.L. Feng. 2007. Dynamic versus steady-state approaches to evaluate irrigation management of saline waters. Agric. Water Manage. 91(1–3):1–10. doi:10.1016/j.agwat.2007.02.014

Letey, J., G.J. Hoffman, J.W. Hopmans, S.R. Grattan, D. Suarez, D.L. Corwin, J.D. Oster, L. Wu, and C. Amrhein. 2011. Evaluation of soil salinity leaching requirement guidelines. Agric. Water Manage. 98(4):502–506. doi:10.1016/j.agwat.2010.08.009

Mertens, J., H. Madsen, M. Kristensen, D. Jacques, and J. Feyen. 2005. Sensitivity of soil parameters in unsaturated zone modelling and the relation between effective, laboratory and in situ estimates. Hydrol. Processes 19(8):1611–1633. doi:10.1002/hyp.5591

Mishra, S., N. Deeds, and G. Ruskauff. 2009. Global sensitivity analysis techniques for probabilistic ground water modeling. Ground Water 47(5):727–744. doi:10.1111/j.1745-6584.2009.00604.x

Morris, M.D. 1991. Factorial sampling plans for preliminary computational experiments. Technometrics 33(2):161–174. doi:10.1080/00401706.1991.10484804

National Research Council. 2010. Toward sustainable agricultural systems in the 21st century. The National Academies Press, Washington, DC.

Oster, J.D. 1994. Irrigation with poor quality water. Agric. Water Manage. 25(3):271–297. doi:10.1016/0378-3774(94)90064-7

Oster, J.D., J. Letey, P. Vaughan, L. Wu, and M. Qadir. 2012. Comparison of transient state models that include salinity and matric stress effects on plant yield. Agric. Water Manage. 103:167–175. doi:10.1016/j.agwat.2011.11.011

Rhoades, J.D., R.D. Ingvalson, J.M. Tucker, and M. Clark. 1973. Salts in irrigation drainage waters: I. Effects of irrigation water composition, leaching fraction, and time of year on the salt compositions of irrigation drainage waters. Soil Sci. Soc. Am. J. 37(5):770–774. doi:10.2136/sssaj1973.03615995003700050038x

Rhoades, J.D., A. Kandiah, and A.M. Mashali. 1992. The use of saline waters for crop production. Food and Agriculture Organization of the United Nations, Rome.

Rhoades, J.D., and D.L. Suarez. 1977. Reducing water quality degradation through minimized leaching management. Agric. Water Manage. 1(2):127–142. doi:10.1016/0378-3774(77)90036-1

Rockström, J., M. Falkenmark, L. Karlberg, H. Hoff, S. Rost, and D. Gerten. 2009. Future water availability for global food production: The potential of green water for increasing resilience to global change. Water Resour. Res. 45. doi:10.1029/2007WR006767.

Saltelli, A., M. Ratto, T. Andres, F. Campolongo, J. Cariboni, D. Gatelli, M. Saisana, and S. Tarantola. 2008. Global sensitivity analysis: The primer. John Wiley & Sons, Hoboken, NJ.

Schaap, M.G., F.J. Leij, and M.Th. van Genuchten. 2001. Rosetta: A computer program for estimating soil hydraulic parameters with hierarchical pedotransfer functions. J. Hydrol. 251(3–4):163–176. doi:10.1016/S0022-1694(01)00466-8

Shahid, S.A., M.A. Abdelfattah, and F.K. Taha, editors. 2013. Developments in soil salinity assessment and reclamation: Innovative thinking and use of marginal soil and water resources in irrigated agriculture. Springer, Dordrecht, New York.

Šimůnek, J., M. Šejna, H. Saito, M. Sakai, and M.Th. van Genuchten. 2013. The HYDRUS-1D software package for simulating the movement of water, heat, and multiple solutes in variably saturated media, Version 4.17. HYDRUS Software Series 3. Dep. of Environmental Sciences, Univ. of California, Riverside.

Skaggs, T.H., and D.A. Barry. 1996. Sensitivity methods for time-continuous, spatially discrete groundwater contaminant transport models. Water Resour. Res. 32:2409–2420. doi:10.1029/96WR01138

Skaggs, T.H., and D.A. Barry. 1997. The first-order reliability method of predicting cumulative mass flux in heterogeneous porous formations. Water Resour. Res. 33:1485–1494. doi:10.1029/97WR00660

Skaggs, T.H., and F.J. Leij. 2002. Solute transport: Theoretical background. In: J.H. Dane and G.C. Topp, editors, Methods of soil analysis. Part 4. SSSA Book Ser. 5. SSSA, Madison, WI. p. 1353–1380. doi:10.2136/sssabookser5.4.c56

Skaggs, T.H., J.A. Poss, P.J. Shouse, and C.M. Grieve. 2006a. Irrigating forage crops with saline waters. 1. Volumetric lysimeter studies. Vadose Zone J. 5:815–823. doi:10.2136/vzj2005.0119

Skaggs, T.H., P.J. Shouse, and J.A. Poss. 2006b. Irrigating forage crops with saline waters. 2. Modeling root uptake and drainage. Vadose Zone J. 5:824–837. doi:10.2136/vzj2005.0120

Skaggs, T.H., D.L. Suarez, and S. Goldberg. 2013. Effects of soil hydraulic and transport parameter uncertainty on predictions of solute transport in large lysimeters. Vadose Zone J. 12. doi:10.2136/vzj2012.0143

Skaggs, T.H., M.Th. van Genuchten, P.J. Shouse, and J.A. Poss. 2006c. Macroscopic approaches to root water uptake as a function of water and salinity stress. Agric. Water Manage. 86:140–149. doi:10.1016/j.agwat.2006.06.005

Sposito, G. 2013. Green water and global food security. Vadose Zone J. 12. doi:10.2136/vzj2013.02.0041

Strzepek, K., and B. Boehlert. 2010. Competition for water for the food system. Phil. Trans. R. Soc. B 365(1554):2927–2940. doi:10.1098/rstb.2010.0152

Suarez, D.L. 2012. Modeling transient root zone salinity (SWS model). In: W.W. Wallender and K.K. Tanji, editors, Agricultural salinity assessment and management, 2nd ed. ASCE Manual and Reports on Engineering Practice, no. 71. ASCE, Reston, VA. p. 855–897.

Suarez, D., and J. Šimůnek. 1997. UNSATCHEM: Unsaturated water and solute transport model with equilibrium and kinetic chemistry. Soil Sci. Soc. Am. J. 61(6):1633–1646. doi:10.2136/sssaj1997.03615995006100060014x

U.S. Salinity Laboratory Staff. 1954. Diagnosis and improvement of saline and alkali soils. USDA Handb. 60. U.S. Gov. Print. Office, Washington, DC.

van Genuchten, M.Th. 1980. A closed-form equation for predicting the hydraulic conductivity of unsaturated soils. Soil Sci. Soc. Am. J. 44:892–898. doi:10.2136/sssaj1980.03615995004400050002x

van Genuchten, M.Th., and S.K. Gupta. 1993. A reassessment of the crop tolerance response function. J. Indian Soc. Soil Sci. 41:730.

Varella, H., M. Guérif, and S. Buis. 2010. Global sensitivity analysis measures the quality of parameter estimation: The case of soil parameters and a crop model. Environ. Model. Softw. 25(3):310–319. doi:10.1016/j.envsoft.2009.09.012

Wichelns, D., L. Raschid-Sally, P.S. Minha, P. Drechsel, A. Bahr, and P. McCornick. 2007. Agricultural use of marginal-quality water—Opportunities and challenges. In: D. Molden, editor, Water for food, water for life: Comprehensive assessment of water management in agriculture. Earthscan, London and International Water Management Institute, Colombo.

Yang, J. 2011. Convergence and uncertainty analyses in Monte-Carlo based sensitivity analysis. Environ. Model. Software 26(4):444–457.