Parameterization Guidelines and Considerations for Hydrologic Models

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Abstract. *Imparting knowledge of the physical processes of a system to a model and determining a set of parameter values for a hydrologic or water quality model application (i.e., parameterization) are important and difficult tasks. An exponential increase in the literature has been devoted to the use and development of these models over the years. Few articles, however, have been devoted to developing general parameterization guidelines to assist in hydrologic model application, which is the main objective of this article along with discussing a few important parameters and extracting several case studies from the literature. The following guidelines were extracted from reviewing a special collection of 22 articles along with other relevant literature: (1) use site-specific measured or estimated parameter values where possible, (2) focus on the most uncertain and sensitive parameters, (3) minimize the number of optimized parameters, (4) constrain parameter values to within justified ranges, (5) use multiple criteria to help optimize parameter values, (6) use "soft" data to optimize parameters, and (7) use a warm-up period to reduce model dependence on initial condition state variables. A few soil and hydrology related parameters common to many models are briefly described along with a discussion of measurement and estimation methods and parameter sensitivity (curve number, Manning's "n", soil bulk density and porosity, soil hydraulic conductivity, soil field capacity and wilting point, and leaf area index). Weather and management inputs are also discussed, as they are critical hydrologic system information that must be imparted to the model. Several case studies from previously reported research illustrate implementation of the parameterization guidelines. This research will help improve model parameterization, resulting in more consistency, better representation of the field or watershed, and a reduced range of parameter value sets resulting in acceptable model simulations.*

Keywords. *Hydrologic processes, Model calibration, Multiple criteria, Optimization, Parameters, Validation.*

Model input includes variables and parameters, but the distinction between them is not always clear and can depend on the context (Bard, 1974). A parameter can be defined as "a distinguishing or defining characteristic or feature, especially one that may be measured or quantified" or "a constant element or aspect, especially serving as a limit or boundary" (Barber, 2005). Parameters are typically integral coefficients built into the structure of models to "define the characteristics of the catchment area or flow domain" (Beven, 2001). James (2005) describes parameters as model inputs that "generally remain invariable through all or part of the simulation run" and as constants that "control independent component processes." Model input can also be in the form of time-series variables such as precipitation, radiation, wind speed, and temperature. Model users are responsible for assembling the necessary time-series data and for assigning values to parameters. While model user manuals often provide value ranges for many parameters, this guidance is often inadequate to assign values for many specific applications.

Arnold et al. (2012) referred to parameterization as "parameter assignment" and "imparting the analyst's knowledge of the physical processes of the watershed to the model." Zeckoski et al. (2015) defined model parameterization as the process of determining a set of parameter values deemed suitable for model use in a specific study area. The hydrologic and other processes modeled by the 25 hydrologic and water quality models in the ASABE special collection (Moriasi et al., 2012) include rainfall interception and evapotranspiration, unsaturated zone flow, overland

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flow, saturated zone flow, erosion and sediment transport, channel flow, carbon/nitrogen (C/N) cycling, plant growth, and soil and water quality (e.g., pesticides and phosphorus). Each of these processes has many associated parameters. In fact, referring to the model MIKE SHE, Jaber and Shukla (2012) stated that "using all of its components, the number of parameters to adjust and input can be staggering." This is especially true when modeling a large area where measured or estimated parameter values can change significantly within small spatial scales vertically and horizontally. A further complication is that many of the measured or estimated parameter values for a given field condition can include considerable uncertainty (e.g., Baroni et al., 2010). Therefore, determining a suitable set of parameter values (i.e., parameterization) for hydrologic and water quality models is both a difficult and important task.

From the beginning of hydrologic modeling in the 1960s, parameterization has been problematic. For example, Huggins and Monke (1968) reported that parameter optimization for watershed models was not desirable, partly because the vast number of adjustable parameters results in a parameter set that lack "uniqueness." More recently, Park et al. (2014) reported that although using a single watershed model output variable, such as streamflow, is a common target for optimizing parameters, this approach has problems in generating consistent (or unique) parameter sets. Developing general parameterization guidelines for hydrologic models could help in this regard.

Highly detailed mathematical modeling of hydrologic processes began to be published in the 1960s due to the rapid development of the computer (e.g., Crawford and Linsley, 1962; Huggins and Monke, 1968). After the 1960s, the continued growth in scientific publishing over the 20th century (e.g., Larsen and von Ins, 2010) contributed to an exponential increase in published journal articles across the agricultural and hydrological sciences. Between 1960 and 1969, only three journal articles can be found with Web of Science using the terms [(hydrolo* or agricul*) and (simulat* or computer*) and model*]. Figure 1 shows an exponential increase in published research on the subject over the years, based on conducting the same search for each decade between 1970 and 2009. The number of citations for the year following the respective decade for these articles increased in a similar pattern (fig. 1). For example, between 2000 and 2009, more than 8700 articles were published on the subject, with more than 25,000 citations of these articles in 2010.

Despite the vast quantity of published research over the last few decades and the long history of parameterization issues, such as lack of parameter set uniqueness, relatively little has been published that focuses specifically on developing general guidelines for parameterization practice using hydrologic and agricultural models. The summary chapter of a recent book focusing on parameterization and calibration of selected models concluded that standard protocols for parameterizing agricultural system models should be developed (Ahuja and Ma, 2011).

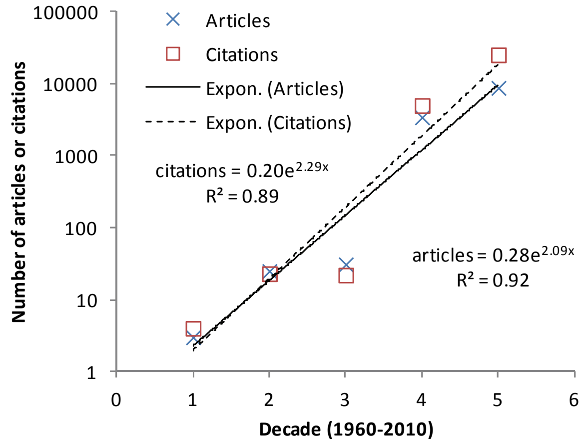

Figure 1. Research articles, reviews, and citations on agricultural or hydrologic modeling after 1960. Decade 1 is 1960-1969, and decade 5 is 2000-2009. Articles are totals per decade. Citations are number of citations at the end of each decade (e.g., the number of citations for modeling in the 1990s is reported as citations in 2000).

Our main objective is to develop general guidelines for hydrologic model parameterization. Thus, the model parameterization discussions from the 22 articles in the special collection on calibration and validation (Moriasi et al., 2012) were reviewed along with other selected articles on the subject. A few of the most common or important soil and hydrology related parameters for the models contained in the special collection (Moriasi et al., 2012) are discussed. Additionally, weather and management input are discussed because they are critical for accurate model simulations, representation of the system, and parameterization. Finally, several case studies from the literature are included to illustrate specific parameterization guidelines.

To limit the scope and more strongly focus this article on developing parameterization guidelines, we do not discuss in detail important subjects associated with parameterization, such as model performance measures and criteria, scale, uncertainty, and sensitivity. These are covered in the current special collection, respectively, by Moriasi et al. (2007), Baffaut et al. (2015), Moriasi et al. (2015), Guzman et al. (2015), and Yuan et al. (2015). In this current special collection on model calibration and validation, each article addresses in detail a different aspect of calibration and validation, such as strategies, processes, and parameterization.

Parameterization Guidelines

In general, model applications often use a combination of measured, estimated, and optimized parameter values. Refsgaard and Storm (1996) recommended that parameter values should be determined from available field data to the highest possible degree, that optimized parameter values should be assessed relative to physically acceptable ranges, and that the number of real optimized parameters should be kept low. Engel et al. (2007) presented a procedure for standard application of hydrologic and water quality models and repeated the parameterization recommendations of Refsgaard and Storm (1996). Engel et al. (2007) also reported that the most sensitive parameters and those with the greatest uncertainty are the ones typically optimized.

Even detailed field-measured parameter values are sometimes only the starting point, and parameters may need to be optimized, as reported for WEPP and DAISY (Flanagan et al., 2012; Hansen et al., 2012). Fields are often heterogeneous even at small scales (e.g., meter), and effective parameters may need to be used (Hansen et al., 2012). Models discussed in the special collection (Moriasi et al., 2012) other than DAISY and WEPP also use the concept of effective parameters (e.g., DRAINMOD; Skaggs et al., 2012). Interpreting the field as a single unit with effective parameters is a common approach to simplify heterogeneity (Djurhuus et al., 1999).

Madsen (2003) stated that physically based catchment-scale models need to be optimized because determination of parameter values for each grid point is not possible due to experimental constraints and scaling problems, such as differences between the measurement scale and model grid scale. In addition, model parameters are often a conceptual representation of abstract watershed characteristics and must be determined through trial and error (Gupta et al., 1998). Furthermore, existing methods to estimate parameters *a priori* for hydrologic models without optimization are problematic and need improvement because of estimated parameter uncertainty (Duan et al., 2006). For example, soil parameters such as saturated hydraulic conductivity may need to be optimized even though they can be estimated from existing databases if soil texture is known. Duan et al. (2006) had eight participating modelers run eight models on 12 basins using *a priori* parameters and then perform a second set of model runs after parameter optimization for selected calibration periods. The results showed that parameter optimization improved the simulations. Qi et al. (2013) reported that use of water retention parameters estimated from soil texture (Rawls et al., 1982) for RZWQM input and simulation resulted in overestimated soil water content for a field near Sidney, Montana. Other than inherent errors in parameter estimation techniques, parameters need adjustment from initial values (default, measurement, estimate, literature, etc.) because of several factors, including cost and time constraints to obtain accurate *a priori* estimates, uncertainty due to spatial and temporal variability, microclimate heterogeneity, and management effects (Ma et al., 2011).

The guidelines discussed in the following sections and listed in table 1 all contribute to good parameterization practice, where parameterization is defined as the process of imparting the analyst's knowledge of the physical processes of a system to a model and determining a set of suitable parameter values for use in the model (Arnold et al., 2012; Zeckoski et al., 2015). These guidelines were extracted from the previous special collection of 22 articles on calibration and validation of hydrologic and water quality models (Moriasi et al., 2012) and other relevant literature.

Measurement and Estimation (Guideline 1)

Parameter values should be measured when possible. Reasons include helping constrain parameter values by defining initial distributions (e.g., minimum and maximum values) and minimizing parameter and prediction uncertainty, as reported for MACRO (Jarvis and Larsbo, 2012). In the absence of direct measurements, initial estimates of parameters such as soil-water related parameters can be determined through literature and databases (e.g., estimated

Table 1. Parameterization guidelines and associated references.

Parameterization Guideline	Reference from Special Issue[a]	Other Relevant Literature	Case Study References
1. Use site-specific measurements where possible or estimate parameters based on knowledge of the site.	MACRO, WARMF, HYDRUS, SHAW, MIKE SHE, DRAINMOD	Refsgaard and Storm (1996), Engel et al. (2007)	Malone et al. (2004), Thorp et al. (2007), Abaci and Papanicolaou (2009), Meng et al. (2010)
2. Optimize and focus on uncertain or sensitive parameters.	MACRO, SWAT, SHAW, EPIC/APEX, ADAPT, RZWQM, MIKE SHE	Yan and Haan (1991), Engel et al. (2007), Wang and Chen (2012)	Santhi et al. (2001), Scorza et al. (2007)
3. Minimize the number of optimized parameters.	MIKE SHE	Yan and Haan (1991), Refsgaard (1997), Wallach et al. (2001)	Thompson et al. (2004)
4. Constrain optimized or estimated parameter values within accepted ranges and justify values, especially those that fall outside expected intervals.	ADAPT, SWAT, EPIC/APEX, COUPMODEL, BASINS/HSPF	Refsgaard and Storm (1996), Engel et al. (2007)	Santhi et al. (2001), Malone et al. (2004), Thompson et al. (2004), Thorp et al. (2007), Abaci and Papanicolaou (2009), Tian et al. (2012)
5. Use multiple criteria to optimize parameter values (more than one model output or target is compared with observed data).	MT3DMS, SHAW	Boyle et al. (2000), Doherty and Johnston (2003), Raat et al. (2004), Dai et al. (2010)	Santhi et al. (2001), Scorza et al. (2007), Thorp et al. (2007)
6. Use hard and soft data to optimize parameters (soft data are qualitative knowledge from experimentalists, such as estimated ET).	BASINS/HSPF	Seibert and McDonnell (2002)	Thorp et al. (2007)
7. Use warm-up period to reduce model dependence on estimates of initial condition state variables.	MIKE SHE, DAISY, ADAPT	Yang et al. (2012)	Meng et al. (2010)

[a] Listed by model name for clarity: ADAPT = Gowda et al. (2012), BASINS/HSPF = Duda et al. (2012), COUPMODEL = Jansson (2012), DAISY = Hansen et al. (2012), DRAINMOD = Skaggs et al. (2012), EPIC/APEX = Wang et al. (2012), HYDRUS = Simunek et al. (2012), MACRO = Jarvis and Larsbo et al. (2012), MIKE SHE = Jaber and Shukla (2012), MT3DMS = Zheng et al. (2012), RZWQM= Ma et al. (2012), SHAW = Flerchinger et al. (2012), SWAT = Arnold et al. (2012), and WARMF = Herr and Chen (2012).

values based on readily available soil survey data such as soil texture and bulk density; Jarvis and Larsbo, 2012). Many input parameter values that represent site-specific conditions in each of the 25 models can be determined through measurements or derived from GIS spatial data related to elevation, soils, and land use (e.g., WARMF, HYDRUS, SHAW, MIKE SHE, DRAINMOD). Methods to estimate important parameter values are discussed in the "Important Parameters" section. Effort devoted to determining and/or measuring parameter values should focus on parameters that display the highest sensitivities to the model output of interest, as reported for VS2DI (Healy and Essaid, 2012).

Optimizing the Most Sensitive and Uncertain Parameters and Minimizing the Number of Optimized Parameters (Guidelines 2 and 3)

Parameters selected for optimization are typically those that are most sensitive and/or uncertain, as reported for MACRO, SWAT, SHAW, EPIC/APEX, ADAPT, RZWQM, and MIKE SHE (Jarvis and Larsbo, 2012; Wang et al., 2012; Gowda et al., 2012; Ma et al., 2012; Jaber and Shukla, 2012). In addition to spatial variability and the measurement and estimation uncertainty associated with parameter values that was discussed in the preceding sections, uncertainty can result from parameters that are difficult to measure or define physically, as illustrated in the "Case Studies" section (e.g., kinematic exponent and runoff curve number; Santhi et al., 2001; Scorza et al., 2007).

In some cases, optimization should be performed with the fewest number of parameters possible, as reported for MIKE SHE (Jaber and Shukla, 2012). In one of the earlier and most cited articles focusing on hydrologic model parameterization, Refsgaard (1997) emphasized that good parameterization practice included optimizing as few parameters as possible and stressed the importance of maintaining a reasonably low ratio of the number of adjusted parameters to the amount of field data. In one of the case studies discussed in the "Case Studies" section, Thompson et al. (2004) specified that a goal of parameterization was to minimize the number of optimized parameters in conformance with the recommendation of Refsgaard and Storm (1996). Wallach et al. (2001) built on this concept and proposed a formal method to rank potential parameters to be adjusted during optimization according to model improvement and reduced the number of adjusted parameters to minimize the prediction error. Wang and Chen (2012) reviewed parameterization techniques for models of greenhouse gas emission from soils. Their recommendations included adjusting the most important or sensitive parameters. Yan and Haan (1991) also optimized only the four most sensitive parameters for the PRMS hydrologic model.

Model predictions for many processes are often very sensitive to soil and hydrology related parameters. This is partly because parameterization of some processes depends on other processes. For example, correct parameterization of sediment and crop growth processes depends on correct simulation of runoff and infiltration processes. Therefore, parameter optimization should often proceed in a sequential fashion, focusing initially on the most independent parameters or processes and then the more dependent ones. Soil-water or hydrology related parameters are typically optimized first, followed by sediment, and then nutrients, plant growth, and other constituents, as reported for RZWQM, SWAT, and BASINS/HSPF (Ma et al., 2012; Arnold et al., 2012; Duda et al., 2012). Several iterations of this sequence may be required to obtain an acceptable set of parameters for RZWQM (Ma et al., 2012).

Justifying Parameter Values (Guideline 4)

Except under extenuating circumstances that should be discussed and justified, optimized parameter values are typically constrained to within published or physically realistic ranges, as reported for ADAPT, SWAT, EPIC/APEX, COUPMODEL, and HSPF (Gowda et al., 2012; Arnold et al., 2012; Wang et al., 2012; Jansson, 2012). As illustrated in the "Case Studies" section, optimized parameter values can be justified by constraining the parameters close to literature values, previous research or measurements within the site, or the physical characteristics of the site (e.g., curve number, soil hydraulic parameters; Santhi et al., 2001; Malone et al., 2004; Thorp et al., 2007; Abaci and Papanicolaou, 2009; Tian et al., 2012). Where realistic parameter ranges are not available through literature or field measurements (e.g., denitrification rate coefficients), an alternative technique illustrated in the case studies is to compare the primary model process affected (e.g., denitrification) with literature values of the process under similar conditions (Thorp et al., 2007).

Multiple-Criteria Optimization (Guideline 5)

One issue with adjusting many parameters is the non-uniqueness of parameter sets. For MT3DMS, Zheng et al. (2012) reported that non-uniqueness issues can be reduced by keeping the number of adjusted parameters to a minimum and by including multiple and independent targets to constrain the model. Flerchinger et al. (2012) also reported that a multi-objective framework avoids subjectivity and information loss in model acceptability criteria by simultaneously minimizing observed and simulated differences of multiple functions for SHAW. Flerchinger et al. (2012) reported that the key characteristic of the multi-objective framework is that the optimization does not rely on a single criterion (e.g., average soil water content through the profile) but considers the performance of other criteria as well (soil water content at multiple depths).

The use of multiple-criteria optimization (i.e., using more than one aspect of the observed target data) is discussed considerably in the literature. In one of the earlier and most cited articles concerning this approach, Boyle et al. (2000) partitioned streamflow into rainfall-driven, quick non-driven, and slow non-driven components. The slow non-driven streamflow was considered baseflow, while the fast non-driven streamflow was dominated by interflow. Boyle et al. (2000) reported that adjusting parameters to optimize for a single criterion may bias the model toward high flow events while producing poor simulations for baseflow or hydrograph recession.

While modeling nitrogen fate using the catchment model INCA, Raat et al. (2004) found that using multiple criteria related stream NO_3 and NH_4 concentrations resulted in acceptable simulations. This method reduced the model uncertainty associated with parameter equifinality. Equifinality in hydrologic modeling suggests that an acceptable model prediction can be achieved with many different parameter sets (Beven, 1993). Using the distributed hydrologic model MIKE SHE, Dai et al. (2010) also reported that the multiple-criteria approach should be advantageous for constructing uncertainty bounds around model inputs. Doherty and Johnston (2003) suggested that using multiple criteria reduces the problems associated with calibrating to local objective function minima. Local objective function minima occur when small changes in selected individual parameters do not improve predictions while larger changes or interactions between parameters could significantly improve predictions. The "Case Studies" section illustrates the multiple-criteria approach (e.g., baseflow and total flow; nitrate concentration in drain flow, denitrification, and mineralization; soil moisture profiles, cumulative subsurface drain flow, soil bromide concentration profiles, and bromide concentrations in drain water; Santhi et al., 2001; Scorza et al., 2007; Thorp et al., 2007).

SOFT DATA (GUIDELINE 6)

Seibert and McDonnell (2002) introduced the concept of parameter optimization based on using soft data in addition to hard data, which is discussed in detail by Arnold et al. (2015). Hard data are field measurements, while soft data are qualitative knowledge from experimentalists (e.g., evapotranspiration may not be measured but will have estimated values under the conditions of the study). This approach may reduce the model fit somewhat for the observed data but model the behavior of the study catchment or field more realistically and more fully utilize available information. Although none of the 22 articles in the special collection explicitly discussed using soft data for parameter optimization, Duda et al. (2012) reported that annual water balances simulated by BASINS/HSPF should be consistent with expected values for the region, such as ET, even when observed values are not available. In the "Case Studies" section, use of soft data is illustrated through use of literature values for denitrification, net mineralization, and ET (Thorp et al., 2007).

WARM-UP PERIOD (GUIDELINE 7)

Parameterization often requires discretization schemes in time and space. When temporal input variables are involved, parameterization may require initial estimates of various state variables, such as initial soil water content, water table elevation, or soil carbon/nitrogen pools. While these inputs can be uncertain and depend on other parameters, such as soil hydraulic conductivity and bulk density, the influence of these initial conditions diminishes over time, as they are frequently updated during a model simulation. Consequently, parameterization may require simulation of an initialization period (or warm-up period) before the output is compared with observed data, as reported for MIKE SHE, DAISY, and ADAPT (Jaber and Shukla, 2012; Hansen et al., 2012; Gowda et al., 2012). When a single storm event (runoff or erosion) is simulated by a model such as WEPP, parameterization of the initial conditions is especially critical (Flanagan et al., 2012). Previously published applications of the models described in the special collection edited by Moriasi et al. (2012), such as SWAT, have included an initial warm-up period (e.g., Meng et al., 2010; see the "Case Studies" section). Using the distributed hydrologic model WetSpa, Yang et al. (2012) reported that a warm-up period for distributed hydrologic modeling is essential to reduce the sensitivity of model predictions to the initial state variables, such as initial soil water content and groundwater storage. In applying the WEPP model, Abaci and Papanicolaou (2009) reported that it is common to run model simulations for long periods to remove the effects of the initial conditions on the model predictions.

IMPORTANT PARAMETERS

Many of the 25 models in the special collection include hundreds of adjustable parameters, so even a brief discussion for the majority of these is not possible. We limit our discussion to a few of the most common and sensitive soil and hydrology related parameters because they affect other processes such as chemical and sediment transport and crop growth, and because several of the models recommend optimizing the parameters associated with the hydrology component first (e.g., Ma et al., 2012; Arnold et al., 2012; Duda et al., 2012).

The following parameters will be discussed: basic hydrology-related parameters (curve number and Manning's "n"), basic soil properties (porosity and dry bulk density), hydraulic conductivity and its interaction with soil water retention in unsaturated soils, field capacity and wilting point, and leaf area index. A brief description of each parameter along with examples of measurement and estimation methods is presented in table 2. The discussions associated with each important parameter include a brief description of the parameter, its sensitivity, and measurement and estimation methods.

NRCS CURVE NUMBER (CN)

For any given land use/cover and soil hydrologic conditions (hydrologic soil-cover complex; USDA-NRCS, 2004), the CN is an indicator of the potential for runoff generation. The key strength of this parameter lies in its simplicity, which accounts for its widespread use in hydrologic and water resources applications. In theory, the CN could range between 0 (no runoff) and 100 (all rainfall is runoff). However, values typically range between 30 and 98 (e.g., USDA-NRCS, 1986). For example, depending on the soil type and land use conditions, CN values for paved roads and parking lots usually range from 83 to 98, while those for forest lands range from 30 to 83, CN values for cropland usually range from 74 to 83 (Parajuli et al., 2009a, 2009b). For any land use, CN values are not static but vary based on a variety of antecedent factors including rainfall (amounts, intensity, duration), soil moisture conditions, cover, and temperature (USDA-NRCS, 2004; Kannan et al., 2007; D'Asaro and Grillone, 2012; Epps et al., 2013; Banasik et al., 2014).

Table 2. Parameter description with examples of measurement and estimation methods.

Parameter Name (symbol and units) and Description	Examples of Measurement and Estimation Methods
Curve number (CN, unitless): A non-dimensional indicator of runoff generation considering non-frozen soils.	Estimated based on land use and hydrologic soil group (e.g., USDA-NRCS, 1986; Hawkins, 1993; USDA-NRCS, 2004; Hawkins et al., 2009).
Manning's roughness coefficient ("n", s $m^{-1/3}$): A measure of surface roughness.	Originally based on field studies related to discharge, surface water profile, and hydraulic reach characteristics for channel coefficients (Chow, 1959) and surface runoff characteristics for overland flow coefficients (Woolhiser, 1975). Values are typically assessed based on channel and surface cover characteristics or through a visual comparison with reference sites (Barnes, 1967; Engman, 1986).
Porosity and bulk density (m^3 m^{-3} and g cm^{-3}): Soil void volume per total soil volume and mass of dry soil per volume of soil.	Measured by weighing a dried soil core of known volume (Jury et al., 1991). Estimated based on soil texture (Rawls et al., 1982) and based on soil type (e.g., USDA-NRCS, 2004, 1995).
Saturated hydraulic conductivity (K_s, m s^{-1}): The rate at which water moves through a porous medium when saturated under a unit hydraulic gradient.	Measured in the laboratory using constant head (for coarse soils) and falling head (for clayey soils) methods (Klute and Dirksen, 1986). Measured in the field using slug tests and pumping tests (Fetter, 2000). Estimated based on soil texture and other more easily determined soil properties (Rawls et al., 1982; Schaap et al., 2001) and based on soil type (e.g., USDA-NRCS, 1995, 2004).
Field capacity and wilting point (θ_{fc}, m^3 m^{-3}): Volumetric soil water content under a soil matric potential of -1/3 and -15 bar.	Measured by applying suction of -1/3 or -15 bar to a saturated soil sample (Klute and Dirksen, 1986). Estimated based on electrical conductivity (Jung et al., 2007; Jiang et al., 2007), based on soil texture and other more easily determined soil properties (Rawls et al., 1982; Schaap et al., 2001; Givi et al., 2004; Saxton and Rawls, 2006; Nemes et al., 2009; Srivastava et al., 2013), based on *k*-nearest neighbor technique (Nemes et al., 2006, 2008), and based on soil type (e.g., USDA-NRCS, 1995, 2004).
Leaf area index (LAI, m^3 m^{-3}): Area of one side of crop or vegetation leaves per unit soil surface area.	Measured using an LAI-2000 Plant Canopy Analyzer (Amatya et al., 1996; Breda, 2003; Haboudene et al., 2004; Jonkheere et al., 2004; Weiss et al., 2004; Behera et al., 2010; Irmak and Mutiibwa, 2010; Brauman et al., 2012; Domec et al., 2012). Estimated using NDVI index from remote sensing data (Breda, 2003; Haboudene et al., 2004; Weiss et al., 2004; Jonkheere et al., 2004; Behera et al., 2010; Panda et al., 2014).

The simulated water budget is particularly sensitive to the CN in hydrologic modeling applications, and thus CN is often a key calibration parameter (SWAT, SWIM, CREAMS/GLEAMS, AnnAGNPS, EPIC/APEX). Early in the development of the ADAPT model, CN was reported as the most sensitive parameter for simulated surface runoff (Chung et al., 1992). More recently, Bonuma et al. (2013) reported that CN was among the most sensitive parameters for SWAT-simulated watershed discharge in southern Brazil. In addition to the sensitivity of surface runoff to CN (e.g., Ponce and Hawkins, 1996), the parameter influences a number of other hydrology components, including total flow, groundwater flow, and soil water, among others (Gitau, 2003; White and Chaubey, 2005).

CN values for various land use types and hydrologic soil groups in average antecedent moisture conditions (often termed as CN-II, CN-AMC II, or CN2) are available (e.g., USDA-NRCS, 1986; Hawkins, 1993; USDA-NRCS, 2004; Hawkins et al., 2009).

Manning's Roughness Coefficient ("n")

Manning's "n" quantifies the resistance to flow (Arcement and Schneider, 1989; Shih and Rahi, 1982). It is a measure of surface roughness in units of s $m^{-1/3}$ that can be applied to overland flow, flow in hydraulic conduits such as culverts, simple open-channel flow, floodplains, and marshes. Manning's coefficient is typically used in the empirical Manning's equation to estimate average flow velocity in stream channels as a function of cross-sectional hydraulic radius, slope of the water surface, and surface roughness. The equation is often used to estimate average velocity of open channel and closed conduit flow where it is not practical to measure flow by other means. Manning's "n" values, often cited without units, can range from 0.016 to 0.150 for channel flow and from 0.008 to 0.500 for overland flow (Chow, 1959; Engman, 1986).

Manning's "n" influences the time of concentration, time to peak, baseflow, peak runoff, and the shape of runoff hydrographs. Because Manning's "n" is inversely related to sediment transport capacity, it is often used to calibrate both hydrologic and sediment components in models. Manning's "n" was considered to be a sensitive parameter for calibrating erosion in CREAMS/GLEAMS but was not explicitly listed as a sensitive parameter for calibrating hydrology (Knisel and Douglas-Mankin, 2012). Manning's "n" has been recommended as a useful parameter for calibrating peak flow timing in several models (SWAT, EPIC, KINEROS2/AGWA). Watershed-wide multipliers have been recommended for calibrating Manning's "n" in KINEROS2 (Renard et al., 1993; Goodrich et al., 2012). Both overland and channel Manning's "n" are listed as key parameters for calibrating the shape and timing of event hydrographs in WARMF (Herr and Chen, 2012). Manning's "n" is often used for calibrating erosion in the WEPP model (Flanagan et al., 2012). The MIKE SHE documentation mentions Manning's values as principle calibration parameters for both overland and channel flow but does not specify which hydrologic components are directly affected (Jaber and Shukla, 2012). Using the DRAINMOD-based watershed-scale model, Kim et al. (2012) found that Manning's roughness had less effect on simulating drainage flow in forested streams than other parameters related to depressional storage and ET.

Manning's "n" values were originally developed from field studies conducted in the late 1950s through the early 1980s (Chow, 1959; Woolhiser, 1975; Engman, 1986). Field studies (e.g., Barnes, 1967; Benson and Dalrymple, 1967; Schaffner et al., 2010) provide reference values of Manning's "n". Many models assign default values or present users with a menu of values from internal databases. As with the other parameters discussed here, this parameter is not static but exhibits seasonal variability (Shih and Rahi, 1982) and is affected by a variety of in-channel factors such as vegetation, geometric and surface irregularities, water depth, and the presence of obstructions (Shih and Rahi, 1982; Arcement and Schneider, 1989). Procedures have been used in some models to quantify Manning's "n" by incorporating spatial and/or temporal variations, including changes in stream levels; provisions for representing monthly values by land use or source in the HSPF model (Bicknell et al., 2005); spatially variable roughness coefficients based on regional regressions with drainage area, longitudinal bed slope, and mean annual flow (Mohamoud and Parner, 2006); and the XSECT program used to generate cross-sectional hydraulic tables in HSPF (Moyer and Bennett, 2007). MIKE SHE also requires Manning's "n" to be input as a spatial layer (Jaber and Shukla, 2012). This natural variability helps explain the wide range of observed values, for example, in the Piedmont floodplain, where values range from 0.033 to 0.243 (Moyer and Bennett, 2007). Thus, where possible, it is best to use field-based values that are computed from known channel conditions, including cross-sectional geometry, discharge, and bed and bank material (Arcement and Schneider, 1989). In addition, given the complex nature of channels, these values should be assessed for individual stream reaches (as in SWAT).

POROSITY AND BULK DENSITY

Porosity (ϕ) is an indicator of soil pore space (Hillel, 1998; Delleur, 2010; Yu et al., 1993), i.e., the maximum space available in the soil body that can be occupied by water and/or air. By definition, it is the ratio of pore volume in a soil sample to the total sample volume including both soil and pore spaces. Thus, it is measured in volume/volume ($m^3\ m^{-3}$) and is often presented as a percentage (Domenico and Schwartz, 1997) or as a decimal (Yu et al., 1993). Porosity also provides some indication of compaction. Porosity is related to bulk density (ρ_b), which is itself an indicator of soil compaction. Ideally, the volumetric water content at saturation (θ_s) is equivalent to the porosity. In field conditions, however, air is often trapped in soils such that the field-saturated water content is less than θ_s.

In general, porosity is determined indirectly based on the soil bulk density and soil particle density. Dry soil bulk density (ρ_b) is determined directly based on the mass of oven-dry soil obtained using an undisturbed soil sample mass (M_s) and the total volume of that sample (V_t) as follows: $\rho_b = M_s V_t^{-1}$. Porosity (ϕ) is related to V_t and the volume of oven-dry soil (V_s) from the same sample as follows: $\phi = 1 - (V_s V_t^{-1})$ or $1 - (\rho_b \rho_s^{-1})$, where ρ_s is the particle density. For most mineral soils, the value of ρ_s is typically assumed equal to the value for silica, 2.65 g cm^{-3}.

Porosity and bulk density can also be determined indirectly using non-destructive or non-invasive methods such as neutron scattering (Gardner et al., 2001), gamma ray attenuation (Hillel, 1998; Campbell and Henshall, 2001), and x-ray tomography (Corwin et al., 1997). These methods, however, are usually more costly and often less efficient.

Soil porosity typically ranges between 0.25 and 0.75 (Yu et al., 1993), with coarse-particle soils having a lower porosity than soils with finer particles (Yu et al., 1993; Hillel, 1998; Delleur, 2010). A number of references provide soil porosity values for a variety of soils types (e.g., Freeze and Cherry, 1979; Rawls et al., 1982; Domenico and Schwartz, 1997). Soil bulk density typically ranges between 1.1 and 1.6 g cm^{-3} for most soils (Yu et al., 1993). For some models, these (typical) parameter values are presented with the model documentation. Often, model applications use tabulated and/or literature values as a means of initially estimating parameter values and for obtaining ranges within which parameter adjustments can be made. Where available, site-specific values have been used (e.g., Gitau, 2003; Mutiti and Levy, 2010). In model applications, parameter values are obtained (e.g., Geza et al., 2009) and/or refined (e.g., Gowda and Mulla, 2005) through parameter optimization.

Soil physical properties such as bulk density, available water capacity (defined in the "Field Capacity and Wilting Point" section), and hydraulic conductivity were reported as the most sensitive parameters for SWAT-G for hydrology-related predictions (Lenhart et al., 2002). Another study showed that soil bulk density, curve number, and available soil water content were the most sensitive parameters for streamflow prediction using SWAT (Feyereisen et al., 2007). Soil porosity was found to be one of the most sensitive parameters governing water hydrology processes in GLEAMS (Cryer and Havens, 1999). For the water quality model RISK-N, nitrate flux and concentration were both influenced by soil porosity along with initial nitrate content and water input (Oyarzun et al., 2007).

The porosity can affect model-simulated subsurface flow and runoff. For example, WARMF (Geza et al., 2009) and KINEROS2 (Goodrich et al., 2012) simulate runoff when the topsoil layer is saturated; in this case, saturation is indicated when the simulated water content equals the porosity. Although the two properties are related, soil bulk density is often used when there is interest in simulating hydrologic processes within different soil layers (Chaudhari et al., 2013). Porosity and bulk density have an influence on the hydraulic conductivity (Rawls et al., 1998), which in turn affects subsurface flow (Rawls et al., 1998; Geza et al., 2009). However, factors affecting porosity and/or bulk density are not always accounted for within models. Porosity and bulk density are generally not constant (Yu et al., 1993; Corwin et al., 1997; Hillel, 1998) but are affected by factors such as compaction, tillage and reconsolidation (Green et al., 2003), organic matter content, cracking, and shrinking and swelling (Yu et al., 1993; Hillel, 1998). The ideal would be to use site-specific values, as these would capture the spatial variability within a simulated area. Unfortunately, such data are not always available, and thus tabular values and/or parameter optimization are needed (Hansen et al., 2012).

HYDRAULIC CONDUCTIVITY

We discuss hydraulic conductivity and its interaction with soil water retention because soils store and transmit water and associated chemicals at rates and amounts controlled by these parameters in constitutive relationships between state variables. In the models with more physically based unsaturated soil processes (e.g., RZWQM, HYDRUS), the primary state variables for soil water are the volumetric water content θ (m^3 m^{-3}) and matric potential ψ (m) or negative pressure head.

Hydraulic conductivity is the rate at which water moves through a porous medium under a unit hydraulic gradient (Dingman, 2002). The rate when pores are full of water is defined as saturated hydraulic conductivity (K_s). Although hydraulic conductivity varies with soil water content, K_s is usually incorporated in models as an input parameter because unsaturated hydraulic conductivity can be mathematically expressed as a function of saturated conductivity and additional parameters. Soil capillary forces work against gravity to retain water in the root zone and to moderate the rate of vertical drainage of water and leaching of associated chemicals. As soils drain, smaller pores hold the remaining water, which can reduce the unsaturated hydraulic conductivity (K) dramatically from its saturated value (K_s).

K_s may be measured in a laboratory using constant head (for coarse soils) and falling head (for clayey soils) methods (Klute and Dirksen, 1986). In these methods, undisturbed soil cores are extracted, usually using a 76.2 mm diameter × 76.2 mm length sampler. In saturated porous media, slug tests and pumping tests are widely accepted approaches for *in situ* estimation of K_s from pressure or water level measurements (Fetter, 2000). In unsaturated surface soils, an infiltrometer is used to measure *in situ* unsaturated or field-saturated K (Evett et al., 1999). Unsaturated K can also be determined through indirect methods such as soil electrical conductivity (Doussan and Ruy, 2009). K_s can be estimated using texture, bulk density, and organic matter information through pedotransfer functions (Nemes et al., 2005). An example of software that estimates K_s through easier-to-determine soil properties is Rosetta (Schaap et al., 2001). Rawls et al. (1982) listed typical saturated hydraulic conductivity values for different soil types. The K_s values can range from >50 cm h^{-1} for sand to <0.01 cm h^{-1} for clay (e.g., Clapp and Hornberger, 1978; Rawls et al., 1982).

Hydraulic conductivity is implemented differently in different models, which affects parameter sensitivity. For example, some models such as RZWQM simulate water infiltration into the soil matrix using the Green-Ampt equation where K_s is one of the variables (e.g., Malone et al., 2003). In other models such as SWAT, surface runoff is driven by the NRCS curve number (CN) method where K_s is not a variable. However, CN is adjusted based on the surface soil water content, and in SWAT K_s affects the time for soil water in excess of field capacity to drain from one layer to the next (Anand et al., 2007). The K_s influences other components in the hydrology budget in addition to runoff because it drives the rate of water movement through the soil profile. Several of the models include both vertical K_s and lateral K_s, which affect subsurface drainage (e.g., RZWQM and DRAINMOD).

Mapfumo et al. (2004) found that SWAT-simulated soil water content was less sensitive to K_s than available water capacity (defined below), bulk density, CN, and field capacity (defined below). Other research has found K_s to be one of the more sensitive parameters for SWAT-simulated water balance (e.g., Stratton et al., 2009). With a similar runoff routine as SWAT, APEX-simulated corn yield, streamflow, and herbicide loss were sensitive to K_s in an agricultural watershed in Missouri (Mudgal et al., 2012). For the WEPP model, effective K_s is one of the four typical parameters that were adjusted against measured data in model calibration (Flanagan et al., 2012). Sensitivity analysis showed that an increase of K_s by 100% can result in a 25% increase in WEPP-simulated runoff for claypan soils in Missouri (Blanco-Canqui et al., 2002). Model-simulated subsurface drainage has been reported to be sensitive to lateral K_s (e.g., Haan and Skaggs, 2003; Ma et al., 2007).

Haan and Skaggs (2003) found that K_s was one of the most sensitive parameters in simulating drainage flux, but estimates of K_s may be very uncertain and often biased. For example, Skaggs et al. (2006) found 20 to 30 times higher effective K_s for the top 90 cm of a fine sandy loam soil at a harvested forest site compared with the published NRCS Soil Survey data. The difference was primarily due to site preparation for regeneration of pine stands rather than due to the harvesting itself. Skaggs et al. (2011) reported two orders of magnitude higher effective K_s for the top 70 cm of forest soil layers compared with the corresponding agricultural site.

Relationships Between Soil Water Storage and Unsaturated Hydraulic Conductivity

Mualem (1976) developed a mathematical model for K, using the analogy of a bundle of capillary tubes, in which K was a function of effective saturation (S_e), and S_e was a function of matric potential (ψ). Mualem (1976) derived his relationship by assuming that an incremental change in soil water content is related to a pore-water distribution function in which ψ is inversely proportional to the pore radii. Mualem (1976) explored a dataset of 45 soils to estimate an optimal value of the saturation exponent of 0.5 in a general range of values (-1.0 to 2.5). However, subsequent studies recommended an optimal value of -1, and the range may be broader than Mualem (1976) indicated.

Subsequently, van Genuchten (1980) developed the commonly used S-shaped equation for soil water retention characteristics with empirically fitted parameters. He combined this water retention (storage) function with Mualem's model to predict unsaturated soil hydraulic conductivity relative to K_s. Many investigators have measured soil water retention data and fit their experimental data to closed-form functions, including those of van Genuchten (1980) and Brooks and Cory (1964). However, soil water flux data for estimating unsaturated hydraulic conductivity are rarely measured. Green (1994) gave an example using the van Genuchten (vG) equation, which fits the water retention data well. However, the combined Mualem-van Genuchten (MvG) equation with a saturation exponent of 0.5 overestimated measured values of K at high values of soil-water suction. The MvG equation fit K very well over six orders of magnitude, but only by using an exponent value of 4.7, which exceeds the upper value explored by Mualem (1976). A simpler exponential equation by Gardner (1958), $K(\psi) = e^{-\alpha\psi}$, did not fit those data well over the full range of K, and the fit could not be improved by further parameter adjustment. Gardner's equation is used in analytical equations (e.g., Green and Freyberg, 1995) for its log-linearity. Rucker et al. (2005) presented a method for improved parameter equivalence between the MvG and Gardner equations, given the utility of Gardner's exponential form.

Salas et al. (2014) used the same unsaturated soil K data (Green et al., 1964) to illustrate potential time scales associated with soil hydraulic properties at different saturations. Assuming gravity drainage (no capillary gradient), a range of six orders of magnitude in K from saturation to an expected wilting point (15 bar) indicates a potential range of temporal responses in soils. For example, one year is 31.5×10^6 s, so the same amount of water draining in about half a minute at saturation would take a full year at 15 bar, illustrating how capillarity holds water in soils against gravity. Another impressive contrast is the change in K going from saturation to 1 m of suction. In this example, very little water is drained (approx. 0.05 $m^3\ m^{-3}$), but K decreases by a factor of approximately 20. Thus, water is stored in the root zone for plant extraction at a maximum daily rate (e.g., potential evapotranspiration of 0.01 m d^{-1}), which is similar to drainage rates of wet soils.

Field Capacity and Wilting Point

The term "field capacity" is commonly used but often not well defined or even incorrectly defined as the water content below which there is no soil water drainage. Soils drain under gravitational force (no capillary gradient) throughout the range of possible soil water contents at rates determined by $K(\psi)$. However, drastically reduced rates of drainage allow soil water to be stored over a range of time scales (minutes to years). Even so, field capacity is often a key parameter in many of the 25 hydrologic models reported in the special collection edited by Moriasi et al. (2012).

Available water capacity is the soil water that is available to plants for growth. In many models (e.g., MACRO, MIKE SHE, SWAT, SWIM, WARMF, EPIC, APEX, CREAMS/GLEAMS, HSPF, KINEROS), it is defined by two points: the field capacity, which is the amount of water held in the root zone of the soil profile once gravity drainage has become negligible (Jury et al., 1991), and the permanent wilting point, which is defined as the root-zone water content at which the plant wilts and cannot recover (Hillel, 1998). The available water capacity is then the difference between these two points. However, these definitions are far from universal. First, in fine-textured soils, drainage progressively decreases with time after rainfall, and it is difficult to determine when drainage becomes negligible. Second, wilting depends on several factors, including the plant itself, soil wetness, and evaporative demand. As a result, more specific definitions have been used. The USDA-NRCS defines the two points as the amount of water held in the root zone as a function of pressure potential: -1/3 bar for field capacity and -15 bar for permanent wilting point. In other models (e.g., TOUGH, ADAPT, SHAW, COUPMODEL, RZWQM, HYDRUS, DRAINMOD, VS2DI), water held in the soil is characterized by the soil water retention curve and parameterized differently.

Soil water content and available water capacity are closely related through several hydrological processes. Soil water is a critical variable for many hydrologic and soil-plant-air exchange processes: evapotranspiration, plant growth, infiltration, and surface runoff, to name a few. Chopart and Vauclin (1990) emphasized the importance of correctly estimating soil water content among other needed components to achieve good predictions of actual evapotranspiration. In shrink-swell clays, Kazemi et al. (2008) showed that low soil water allowed deeper and faster transport of herbicides through cracks in the soil profile. Thus, correct estimation of soil water content in these soils is also critical for pollutant transport. Fiener et al. (2006) showed how low soil water content increases grass waterway effectiveness during heavy summer rainfall events.

Numerous sensitivity analyses of hydrologic models have verified that field capacity and wilting point, and the available water capacity, are very sensitive parameters affecting water balance and model performance (Murty et al., 2014); Jha, 2011; Faramarzi et al., 2010; Mapfumo et al., 2004) and crop yields (Faramarzi et al., 2010). Faramarzi et al. (2010) showed that available water capacity can be so sensitive that improving soil water capacity by appropriate soil management practices could be considered a way to address water scarcity. McGechan and Vinten (2004) found that *E. coli* losses estimated with MACRO were influenced primarily by soil water content at the time of grazing. As indicated by Shao et al. (2013), it is important that these parameters are kept within an acceptable range, given the soil texture and soil type. The sensitivity of the parameter makes it tempting to assign values outside this acceptable range, thus improving model performance for the wrong reasons.

Field capacity and wilting point can be determined experimentally in the laboratory by applying suctions of -1/3 and -15 bar, respectively, to a saturated soil sample (Klute and Dirksen, 1986). When water drainage has stopped, the remaining gravimetric moisture content of the soil sample is determined. Field capacity (not precisely at -1/3 bar) can also be measured in the field by saturating an area, covering the area with a tarp that prevents evaporation and protects the area from rain, and measuring soil moisture every day until there is very little change from one day to the next (Dane and Toppe, 2002). If soil moisture cannot be measured in the field (e.g., with a neutron probe), a typical number of days after a saturating rainfall can be used, after which a soil sample can be collected to measure gravimetric soil water content in the laboratory. The number of days depends on the soil texture; typically, drainage rates decrease dramatically after one day for sandy soils, after two days for silt loams, and after three days for silty clay loams. However, other factors also affect the number of days, such as type of clay, organic matter, soil structure, antecedent moisture, and impeding layers (Hillel, 1998), and should be considered when developing a sampling protocol.

Alternatively, indirect field methods of measuring available water capacity have been developed. For example, Jung et al. (2007) and Jiang et al. (2007) used apparent electrical conductivity to estimate this parameter in soils that have a restrictive layer of dense clays. This technique provides the ability to estimate soil water capacity in a field on a very dense grid, thus providing a sense of the range of values that exist within a field. For larger watersheds, modelers rely on soil surveys and soil maps, and the associated soil physical and hydraulic properties (e.g., the SSURGO map and associated database; USDA-NRCS, 1995). For each soil type, ranges of values can be found for field capacity and wilting point, or for available water capacity.

Relationships between field capacity, wilting point, and soil texture have been proposed based on texture, organic matter, and soil water content from thousands of soil samples. Rawls et al. (1982) provided pedotransfer functions and associated nomographs to estimate field capacity and wilting point as a function of soil texture and organic matter. These relationships were recently revised (Saxton and Rawls, 2006; Nemes et al., 2009) because the original analysis included only 18 U.S. states from which soil samples were initially collected with little representation and sometimes exclusion of major U.S. cropland areas. These relationships can be useful in areas where characterization of soil hydraulic properties does not exist but soil textures are known. They also reflect the effect of organic matter, and thus of management, on these soil properties, as verified by other authors (Rachman et al., 2004; Seobi et al., 2005; Jiang et al., 2007; Mudgal et al., 2010). The Rosetta software (Schaap et al., 2001) has also been used to determine soil field capacity and wilting point based on more easily determined properties, such as bulk density and soil texture (e.g., Givi et al., 2004; Srivastava et al., 2013).

An alternative to these empirical relationships is the non-parametric *k*-nearest neighbor technique (Nemes et al., 2006, 2008). This technique consists of searching a soil database for a small number of soils that are most similar to the target soil, according to preselected soil attributes. The soil parameter value (field capacity or wilting point) is then calculated as a weighted average of the values for this small number of soils, each weight being a function of the degree of similarity between the target soil and the selected soil. This technique was implemented in APEX and EPIC (Wang et al., 2012), has the advantage that the soil database can be updated as additional data become available, and does not require any revision of the relationships between the soil properties.

Leaf Area Index

The leaf area index (LAI) is defined as the area of one side of leaves per unit soil surface area (Vose and Allen, 1988; Neitsch et al., 2005). LAI is a seasonal parameter, an indicator of crop growth, and it correlates well with evapotranspiration (ET) (Jensen et al., 1990; Sun et al., 2011), which is a major component of the hydrologic water balance. Once the maximum LAI is reached, LAI remains constant until leaf senescence begins to exceed leaf growth (Jensen et al., 1990; Amatya and Skaggs, 2001; Neitsch et al., 2005). LAI is an indication of the biophysical capacity for energy acquisition by the vegetation canopy (Jensen et al., 1990; Fisher et al., 2008) and is a key parameter of ecosystem structure (Sun et al., 2011). LAI is used for global and regional models of biosphere/atmosphere exchange of carbon dioxide and water vapor, including the energy balance of the land surface (Scurlock et al., 2001), and it is scalable as it correlates well with the normalized difference vegetation index (NDVI) derived from remote sensing images (Hwang et al., 2009). LAI is a widely used parameter in simulating potential evapotranspiration (PET) using physically based energy-balance models, as well as canopy and soil evaporation, transpiration, and plant growth (Monteith, 1965; Jensen et al., 1990; McKenney and Rosenberg, 1993; Amatya et al., 1996; Amatya et al., 1997; Watson et al., 1999; Amatya and Skaggs, 2001; Jonkheere et al., 2004; Neitsch et al., 2005; Rao et al., 2006; Irmak and Muttiba, 2010; Sun et al., 2011; Brauman et al., 2012; Domec et al., 2012; Hansen et al., 2012; Jaber and Shukla, 2012; Tian et al., 2012; Irmak et al., 2013a, 2013b). LAI is used in estimating vegetation or crop surface canopy resistance as a function of stomatal conductance in the physically based ET routines (Monteith, 1965; Jensen et al., 1990; Neitsch et al., 2005; Irmak and Mutiibwa, 2010; Domec et al., 2012; Irmak et al., 2013b) of hydrologic and water balance models (Amatya et al., 1996, 2002; Arnold et al., 2012; Caldwell et al., 2012). Canopy storage capacity and soil evaporation are frequently calculated as a function of LAI in water balance models (Jensen et al., 1990; Amatya et al., 1996; Gowda et al., 2012).

Of the models reported in the special collection (Moriasi et al., 2012), at least five (Hansen et al., 2012; Jaber and Shukla, 2012; Arnold et al., 2012; Ma et al., 2012; Gowda et al., 2012) can use LAI for the simulation of crops and vegetation. In DAISY (Hansen et al., 2012), LAI was an input for canopy interception and storage and also for plant growth and ET. Although Arnold et al. (2012) did not specify LAI explicitly in their article, other than noting it as a parameter in the case study, LAI is an input variable in SWAT if the Penman-Monteith PET option (Monteith, 1965) is used and for the plant growth component (Eckhardt and Arnold, 2001; Neitsche et al., 2005). LAI was mentioned as a time-series variable for estimating interception and ET and as a calibration parameter in MIKE SHE (Jaber and Shukla, 2012). Ma et al. (2012) reported that RZWQM2 simulates LAI rather than using it as an input variable to calibrate and validate crop growth. LAI was used in simulating evaporation and plant growth in ADAPT (Gowda et al., 2012). Although the standard version of DRAINMOD (Skaggs et al., 2012) does not use LAI, daily LAI was a direct input parameter in the physically based Penman-Monteith (P-M) canopy evaporation and transpiration modules of the extended forestry version of DRAINMOD (Amatya and Skaggs, 2001). Daily LAI was an input variable for estimating daily P-M-based PET input in the watershed-scale versions of DRAINMOD (Amatya et al., 1997, 2004; Kim et al., 2012, 2013). Most recently, LAI was simulated as a physically based daily input variable to simulate potential transpiration using the P-M method as well as tree growth within the comprehensive DRAINMOD-FOREST model integrated for simulating hydrology, nutrients, and productivity of forests (Tian et al., 2012).

LAI can be measured either using an LAI-2000 Plant Canopy Analyzer (Li-COR, Inc., Lincoln, Neb.) using two sensors simultaneously above and below the canopy during overcast sky conditions or using litter biomass and specific leaf area values (Amatya et al., 1996; Hwang et al., 2009; Behera et al., 2010; Brauman et al., 2012; Domec et al., 2012). In some cases, LAI is estimated as a modification of the LAI-2000 measurements. The LAI in matured vegetation (e.g., loblolly pine, *Pinus taeda* L.) was measured as total all-sided LAI of the pine needle and used for estimates of transpiration that required a conversion factor of 2.84 (Vose and Allen, 1988; Amatya et al., 1996). Similarly, Sampson et al. (2011) used a factor of 1.436 to represent the actual LAI of needles of young pine (one to four years old) from LAI obtained using the LAI-2000. LAI can also be estimated using the ground-measured reflectance of agricultural crops (Haboudene et al., 2004). Jensen et al. (1990) developed procedures for approximating LAI of grass and alfalfa reference crops as a function of canopy height. The authors recommended calculating LAI of 12 cm standard grass as 0.24 $\times$ canopy height and the LAI of alfalfa as 1.5 $\times$ ln(canopy height) $-$ 1.4. This procedure yields LAI values of approximately 2.9 m^2 m^{-2} for grass and 4.5 m^2 m^{-2} for alfalfa. An LAI of 2.9 is used for the standard grass within the standard FAO-Penman-Monteith method, yielding a canopy resistance of 70 s m^{-1} (Sumner and Jacobs, 2005). LAI was also calculated from total fractional vegetation cover by inverting Beer's law (Fisher et al., 2008). In other cases, LAI was estimated as a simple function of leaf biomass and specific leaf area obtained from litterfall data or destructive sampling and measuring leaf area (Amatya et al., 1996; Sampson et al., 2011; Domec et al., 2012). In SWAT, daily LAI is estimated as a function of the maximum LAI and fraction of potential heat units accumulated for a plant on a given day (Neitsch et al., 2005).

Haboudene et al. (2004) found good correlations between field-measured LAI and the LAI obtained from remote sensing based hyperspectral images over agricultural crops of corn, wheat, and soybean near Montreal in Canada. Rao et al. (2006) found that the narrow-band NDVI derived from Hyperion showed better results than those from the broadband LISS-III for crops such as cotton, sugarcane, and rice in India, although the potential to overfit models using the large number of Hyperion bands is a concern for future research. Similar approaches using the NDVI index from remote sensing data were used to obtain the LAI used for estimates of crop coefficients and ET for wheat crop (Duchemin et al., 2006) and more recently for managed pine forests (Panda et al., 2014).

Scurlock et al. (2001) compiled approximately 1000 published estimates of LAI from nearly 400 unique field sites covering the period 1932-2000. These data provided a benchmark of typical values and ranges of LAI for a variety of land cover types using nearly 300 original references that would be useful for estimates of PET and ET, and development of several other biophysical models. These data covered natural and managed ecosystems including some agricultural croplands. Mean LAI covering 15 different biomes and land cover types varied from 1.31 ±0.85 for deserts to 8.72 ±4.32 for tree plantations, with the highest values for evergreen forests. Sun et al. (2011) reported LAI values ranging from 7.1 (peak) for the coniferous Coweeta forest in western North Carolina with a temperate climate (precipitation >2000 mm) to as low as <0.4 for a poplar plantation site in a desert environment of China's Inner Mongolia (precipitation <300 mm).

Estimates of the net radiation parameters, P-M PE, crop coefficients, and water balance outputs such as drainage flows and ET are generally found to be sensitive to LAI (Amatya, 1993; Irmak and Mutiibwa, 2010; Tian et al., 2013).

Breda (2003) reviewed the direct and indirect methods for measuring LAI, the required instruments, their advantages and disadvantages, and the accuracy of the results. The authors noted that there was a significant underestimation of LAI associated with the latter techniques. This was particularly so in forest stands. The authors concluded that there was a need for quality assurance with regard to the accuracy, sampling strategy, and spatial validity of LAI measurements for both the measurement and modeling of all LAI-dependent ecosystems. Jonkheere at al. (2004) also reviewed various direct and indirect methods for *in situ* measurements of LAI using theories, sensors, and hemispherical photography. In a companion article, Weiss et al. (2004) discussed associated assumptions and limitations, such as the clumping effect and the distinction between green and non-green elements within the vegetation canopy.

Other Parameterization Considerations

Precipitation and Weather

The magnitude and variability of weather elements consist of deterministic and random components that drive runoff and chemical load responses in watersheds. Deterministic components are generally expected magnitudes that can be cyclical (e.g., seasonal, decadal) and vary in space horizontally and vertically. The two components are quantified by direct observation or by frequency distribution parameters of weather elements. Parameterization of models is affected by many factors including (1) assigning representative weather inputs that include components that are deterministic, random, and temporally and spatially representative, and (2) consideration of biases in measurements. The most spatially and temporally varying weather input is precipitation, which is subject to numerous measurement errors. These errors are embedded in existing long-term precipitation records and must be recognized and considered when parameterizing a model. For example, Malone et al. (2011) reported that actual historical weather records can show measurement errors in rain, solar radiation, and humidity of 10% or more. They then use RZWQM to show that data bias of 10% in humidity, rainfall, and solar radiation results in long-term simulation errors of more than 50% for drainage loss in tile drains, 30% of which was due to rainfall bias. Thus, this section discusses precipitation considerations, and to a lesser extent general weather inputs, for watershed modeling. Temporal and spatial variability of precipitation inputs to watershed modeling studies are discussed by Baffaut et al. (2015).

Precipitation plays an important role in water distribution in the hydrological cycle and thus in the parameterization of watershed models. Under natural conditions during passage of a storm over an area, the land surface receives precipitation that varies spatially and temporally depending on storm intensity, wind, topography, wind obstacles, air temperature, and aspect. Precipitation affects hydrological processes on the landscape during storms, recharging soil water and groundwater storage and producing runoff. Evapotranspiration is partially a function of weather variables (e.g., air temperature, dew point, wind speed, and solar radiation), all of which affect the soil-water state of the landscape between precipitation events. Precipitation has the added complexity of being in solid form (e.g., snow) at times, with more solid precipitation at higher latitudes and in mountainous areas (Marks et al., 2001; Hanson, 2001). Furthermore, amounts of snowfall and rainfall vary with elevation from the same storm passing over high and low relief areas. Even in areas of lower topographic relief, precipitation on leeward slopes is generally larger than on windward slopes (Lentz et al., 1995). Accumulated snow on the landscape stores water, acting as a reservoir for later release to soil water, groundwater, and runoff as the temperature increases. Clearly, if weather input biases and complexities to watershed models are not adequately considered, the distribution of water in the hydrological cycle, water quality, and the final set of "optimized" model parameters will be suboptimal and non-representative of the watershed.

Most historical precipitation data are point measurements; however, precipitation intensities within a storm are spatially and temporally correlated ("coherence," i.e., there is a tendency for precipitation amounts for a given time interval to have similar magnitudes at close distances; Baffaut et al., 2015). This temporal and spatial variability is only grossly met by our current spatially inconsistent distributed rain gauge networks (Cho et al., 2009; Sexton et al., 2010). This available network of gauges often inadequately represents ground-level precipitation. Even though NEXRAD radar data incorporate coherence, when rain-gauge networks are used for model input parameter optimization the model results can be influenced by the associated biases and errors (Sexton et al., 2010).

Standard procedures for accurate and representative measurement of weather elements are available from WMO (2008) and are not presented here. However, precipitation measurements have uncertainties and systemic biases in the data. It is well known that standard precipitation gauges typically underestimate true ground-level precipitation (e.g., McGuinness, 1966; Sieck et al., 2007; Kampf and Burges, 2010). McGuinness (1966) reported that a ground-level lysimeter in Ohio caught 1.09 times more annual precipitation than an adjacent recording rain gauge. Average monthly errors ranged from 1.02 times gauge catch during May through July to 1.20 times in February when snowfall was greatest. The largest ratio was underestimated due to blowing and drifting snow across the lysimeters. Gauge catch deficiencies can be as large as 100% (Goodison et al., 1998). The errors in precipitation measurements are due to wind diverting many smaller diameter raindrops over the top of the gauge orifice, and to vulnerable low-density snowflakes carried by the wind (Wagner, 2009). As wind speed increases, the ratio of ground-level precipitation to gauge catch increases. Terrain slope and other obstacles in the vicinity of precipitation gauges, gauge type (tipping vs. weighing bucket), and gauge shielding also affect the representativeness of measurements. Air temperatures are projected to increase over the 21st century due to global climate changes (IPCC, 2013), and thus winter temperatures may increase. This temperature increase suggests less snow and an increase in precipitation in the form of rain. However, future trends detected in annual and especially winter precipitation could be due to decreased bias of rain gauge measurements with less annual snow rather than an actual increase in ground-level precipitation.

Many studies have shown that rain gauge shielding increases the catch of precipitation to varying degrees (Goodison et al., 1998). Yang et al. (2001) noted that precipitation measurements across country borders can result in discontinuities, and Groisman et al. (2013) found that recording methods and measurement technology affect U.S.-Canada extreme precipitation measurements. Since about 2007, a network of 114 weather stations with improved ground-level, short-time-increment precipitation instrumentation has been installed in the U.S. (https://www.ncdc.noaa.gov/crn), which will deliver high-quality, representative, point, short-time-increment data.

The undercatch of precipitation and exposure of gauges is a major source of modeling input error that, if corrected, would improve model results. Groisman and Legates (1994) suggested that adjustments can be made to precipitation measurements to minimize bias in the data. Wagner (2009) reported that corrections for wind speed and precipitation-form effects are dependent on gauge type, temperature, and exposure; involve much empiricism; and are characterized by wide variability. In a Danish watershed study, Stisen et al. (2012) compared the hydrological performance of a model using an average monthly precipitation gauge correction and a dynamic (daily) correction based on air temperature and wind speed. Their study showed improved simulations by using dynamic correction for their watersheds with more realistic parameters representing rooting depths, groundwater recharge, and streamflows.

An alternative to measured precipitation inputs to models is the stochastic simulation of synthesized data. The measured precipitation data are statistically characterized without consideration of underlying meteorological processes by computing statistical parameters of frequency distributions from the measured data. The advantage of stochastically generated data is that a data sequence can be generated for as many years as required and can incorporate seasonal variability. The disadvantage is that statistics developed from a historical data set can include data that have measurement errors and biases, may be trending (e.g., climate change), or may include periods of changes in recording methods (Groisman et al., 2013). Data analyzed may also be weighted by periodic or decadal atmospheric forcings (e.g., El Nino-Southern Oscillation) that include periods of persistent weather in the form of drought or large precipitation (e.g., Garbrecht and Starks, 2009). If inappropriately characterized, a generated sequence will not be statistically representative of long-term ground-level characteristics, leading to misleading watershed model outputs. Although synthetic data may be representative of general weather conditions in a watershed, such data should not be used for calibration purposes as they lack direct temporal correspondence to observed data.

Weather data elements often exhibit serial and cross correlation and, if not accounted for, will yield non-representative model outputs. Serial correlation occurs when the weather on the current day is dependent on the weather of a previous day. Because model inputs often require daily data, serial correlation is quantified using a daily time step. Cross correlation between weather variables occurs when a weather element is dependent on another weather element. For example, precipitation days have reduced solar radiation compared to sunny days. Consequently, a stochastic weather generator must include conditional probability statistics for "wet" and "dry" days and other possible cross-element correlations. Two often-used weather generators for watershed modeling are GEM (Harmel et al., 2002) and CLIGEN (Nicks et al., 1995). GEM incorporates serial and cross correlations. Both models require parameters describing the frequency distributions of weather elements that are often based on biased precipitation data. The temporal and spatial coherence of weather data across a watershed should also be considered when generating weather data, but unfortunately rarely are (Baffaut et al., 2015). The PRISM data set shows promise (e.g., PRISM; Baffaut et al., 2015); however, these data sets include measured historical precipitation inaccuracies.

With the high likelihood of annual and seasonal underrepresentation of ground-level precipitation in measured historical data, watershed parameterization will be biased, suboptimal, and non-representative, resulting in modeling outputs that may be misleading. Future research is needed to develop promising methods to synthesize representative precipitation inputs to models. Dynamic adjustments to historical precipitation data show promise, but expansion of historical data sets and stochastic generation that includes temporal and spatial synthesis of records are in their infancy. Parameter optimization and use of "effective" parameters can compensate for temporal and spatial non-representativeness of precipitation over an area, but bias in precipitation measurements can still result in non-representative parameter values and simulated distribution of water in the hydrologic cycle.

MANAGEMENT

Long-term simulation requires land management information such as tillage and planting type and timing for the simulated production of crops, cattle, or wood. That information is critical when calibrating, validating, and applying a model because it includes details that strongly affect water balance, erosion, and transport of agro-chemicals. For example, crop distribution in a watershed affects evapotranspiration and the water balance, erosion caused by rainfall is affected by the timing and intensity of tillage operations, and nutrient or pesticide transport is affected by the timing of storms in relation to fertilizer or pesticide application. Management includes specifying successive crops and vegetation in the field (organized in a rotation or not), grazing intensities, and field operations (e.g., tillage, fertilization, herbicide application, planting, harvesting, thinning, irrigation, etc.). Field operations are typically defined by their characteristics (e.g., application rate or tillage/harvest intensity) and by their timing. Timing can be defined by fixed dates or, for some models, by the heat unit index, which allows spatial or temporal variation of operation timing according to temperature.

For research fields or plots, management is often predefined, follows a protocol, and is well recorded. For privately owned and managed fields, the characteristics of the cropping or grazing system (e.g., crop sequence, grazing intensity, type of tillage) are highly diverse and require consultation with individual producers. In the farm-scale watershed study by Gitau et al. (2008), for example, detailed management data were available on a field-by-field basis, allowing a fairly accurate representation of management during the simulation periods. There may be more uncertainty about the dates on which operations were performed if careful records were not kept. The best approach is to have a one-on-one conversation with the farm operator and obtain information that is as precise as possible (e.g., Pennington et al., 2008). Anticipation is best, and asking producers to record their management at the beginning of a study is recommended.

As the size of the simulated area or the length of the simulation period increases, uncertainties increase. Land management varies in space and time because the decision-making process varies from producer to producer and is typically based on many factors, including land suitability, weather, agricultural policy, economics, seed availability, conservation programs, and specific circumstances (Osmond et al., 2012). When detailed management records exist, using these records to their full extent might necessitate a finer watershed discretization (e.g., Gitau, 2003; Chaubey et al., 2010), which has implications on model computational efficiency. Because individual producers may not be willing to share detailed management records, existing management data are typically either aggregated or generalized for use with larger-scale model parameterization, or used indirectly to derive representative model parameters (e.g., Gitau, 2003; Tolson et al., 2007). When detailed management information is not available, data collected at local or national levels can provide useful information. In these cases, several strategies can be used alone or in combination to define crop distribution and land management in a watershed, including:

- U.S. Farm Service Agency data collected on crops planted in each field enrolled in a conservation program prior to 2000.
- Watershed inventories conducted by stakeholder groups can be used to define major cropping systems, grazing systems, and management scenarios. The groups should be composed of people familiar with farming practices, such as district conservationists, individual producers, extension personnel, etc. Although this strategy carries the risk for the results to be influenced by the committee members, if members are selected carefully this strategy has the advantage of increasing buy-in to the model results. This is especially true if the modelers are directly and actively

involved with these stakeholder groups, as this allows continuous dialog on the modeling process, parameter selection and/or determination, review of the preliminary results, etc., making the effort a stakeholder-guided process (e.g., Baffaut, 2004; Benham et al., 2006; Bryant et al., 2008; Pennington et al., 2008; Hoag et al., 2012).

- Use of dominant crop rotations and management systems.
- County statistics on crop distribution (no rotation information) (USDA-NASS, 2013).
- The USDA-NASS cropland data layer (Han et al., 2014), annual since 2008, contains 136 agricultural land use categories and sixteen 2006 NLCD categories of non-agricultural land uses.
- USDA-NASS county statistics on pastures, hay land, and number of cattle can be combined to estimate grazing densities. Local technical field personnel can then provide information to redistribute combined pasture/hay acreage into overgrazed (poor), non-managed (fair), and managed (good) subcategories.
- Total maximum daily load (TMDL) studies in the region often include detailed agricultural management data from a variety of sources (Baffaut, 2006; Benham et al., 2005).
- Annual National Survey Data (1989-2004) from the Conservation Tillage Information Center (CTIC) on tillage (www.ctic.purdue.edu/crm/).
- County statistics on fertilizer and pesticide sales.
- Surveys.
- Data on wildlife may be more difficult to obtain, yet they may be critical when assessing nutrient and bacterial loads in mostly forested watersheds (Benham et al., 2005).

Analysis of model sensitivity to management is difficult because changing one management input (e.g., crop grown) can affect a number of input variables. For example, crop parameters and the timing and type of field operations vary from one crop to another (corn requires fertilizer application but soybean does not, corn is often planted earlier than soybean and harvest is later, etc.). Crop-specific management, such as planting date, fertilization date and amount, herbicide type and amount, and harvest date, is generally not fully automated in models. Thus, automated sensitivity analysis methods cannot be applied. Manual methods have been applied, such as by Huang et al. (2009), who investigated SWIM model sensitivity to crop distribution and operation timing. They concluded that optimal agricultural land use and management are essential for reduction of excess nutrient loads and improvement in water quality.

CASE STUDIES ILLUSTRATING PARAMETERIZATION GUIDELINES

As discussed earlier, parameterization guidelines were extracted from the special collection of articles (Moriasi et al., 2012) and other relevant literature. Each guideline is illustrated with at least one example of a published model application case study (table 1). Guidelines from table 1 are specifically identified in each case study for the associated important parameters discussed earlier (e.g., bulk density, saturated hydraulic conductivity).

Santhi et al. (2001) parameterized SWAT for application at Hico and Valley Mills along the North Bosque River in Texas. A few important parameters that were not well defined physically, such as runoff curve number, were adjusted to fit the model output to observed data (Guideline 2). For flow calibration, the runoff curve numbers were maintained close to literature values by constraining adjustments to within 10% of tabulated curve numbers (Guideline 4). Flow-related parameters were optimized so that the simulated baseflow and total flow were both within 15% of observed flows at Hico and Valley Mills (Guideline 5). Saturated hydraulic conductivity and bulk density were estimated from USDA-NRCS databases (Guideline 1).

Thorp et al. (2007) parameterized RZWQM for application at Story City, Iowa. Multiple criteria were used by adjusting parameters to reduce the error in targets that included RZWQM-simulated nitrate concentrations in subsurface drain flow, evapotranspiration, denitrification, and net mineralization (Guideline 5). Adjusted parameters included the denitrification reaction rate coefficient, the rate coefficient for decay of the slow organic matter pool, and the water retention parameters. The final parameter values were reported as reasonable through comparison of the unmeasured denitrification, net mineralization, and ET with literature values (Guideline 6). The annual simulated denitrification was reported as between 3 and 17 kg ha^{-1} year^{-1}, which was similar to Svensson et al. (1991). The annual net N mineralization was between 69 and 149 kg N ha^{-1} year^{-1}, which was reasonable compared to values reported by Vigil et al. (2002). The annual simulated evapotranspiration was between 43 and 50 cm year^{-1}, comparable to values reported by Hatfield and Prueger (2004) for a nearby field. These techniques may be comparable to using soft data for parameter optimization to more fully utilize the information content from experimental sites (Seibert and McDonnell, 2002). The soil saturated hydraulic conductivity and bulk density were set equal to values from previous modeling research at the site (Guideline 1). Soil hydraulic parameters affecting the model-simulated field capacity and subsurface drainage were optimized within values reported by Rawls et al. (1982) (Guideline 4).

Thompson et al. (2004) reported a coupled MIKE SHE/MIKE 11 model application for a lowland wet grassland, the Elmley Marshes, in southeast England where the number of optimized parameters were minimized (Guideline 3). Relevant literature and previous research within the North Kent marshes supported the final optimized parameter values (Guideline 4). Seven parameters were optimized, including saturated hydraulic conductivity, maximum bypass ratio within the macropore and preferential flow component, and the Manning's roughness coefficient for overland flow.

Malone et al. (2004) used RZWQM to investigate pesticide transport near Frankfort, Kentucky. The most important and sensitive measured parameters for simulating pesticide transport through soil included saturated hydraulic conductivity, water retention parameters (affecting model-simulated field capacity and wilting point), and coefficients of pesticide sorption to soil (Guideline 1). Sensitive estimated parameters such as the number of macropore and preferential flow paths per unit area were derived from similar modeling efforts (Guideline 1). Sensitive optimized parameters were comparable to literature values, such as macropore radius and surface crust saturated hydraulic conductivity (Guideline 4). Soil bulk density was also directly measured using field soil samples, although this was not reported as part of the sensitivity analysis (Guideline 1).

Scorza et al. (2007) applied MACRO in a subsurface tile-drained cracked clay soil with measurements of water flow and bromide. Three parameters that were difficult to measure were optimized: the parameter controlling percolation to groundwater, the aggregate half-width, and the kinematic exponent (Guideline 2). The saturated hydraulic conductivity and the hydraulic conductivity of the micropores were optimized because of the large uncertainty from variable measured data (Guideline 2). In addition, multiple criteria were used for model optimization: soil moisture profiles, cumulative subsurface drain flow, soil bromide concentration profiles, and bromide concentrations in drain water (Guideline 5). The soil bulk density was directly measured (Guideline 1).

Tian et al. (2012) evaluated the performance of DRAINMOD-FOREST using a 21-year data set collected from an artificially drained loblolly pine plantation in eastern North Carolina. Optimized parameters were reported as reasonable compared to literature sources, and justification was provided for parameters not conforming to the expected range (Guideline 4). Many parameters were optimized, most of which were comparable to literature values (e.g., soil hydraulic conductivity, PET-related, Michaelis-Menten related, decomposition rates of soil organic matter pools, C allocation parameters). A few parameters that did not correspond to literature values were justified according to the physical characteristics of the site (distribution coefficients for C/N transformations). Drainable porosity, which is associated with field capacity and porosity, was optimized but not discussed in relation to expected values. Soil bulk density was measured at the site (Guideline 1).

Meng et al. (2010) tested SWAT for the Rappahannock River basin, which is one of the major components of the Chesapeake Bay watershed. They used available databases to determine the majority of watershed and management parameters related to elevation, land use/cover, and soils (Guideline 1). Additionally, reservoir data and point source data were obtained from national databases, while management data were obtained from a variety of federal, state, and local sources to characterize crop rotations and their planting, harvesting, and fertilization schedules (Guideline 1). Thirteen parameters were adjusted to balance the water budget during hydrologic calibration, while other parameters were adjusted by applying multipliers to the default values. The model was run for a two-year initialization (warm-up) period preceding the actual simulation periods for calibration, validation, and applications in order to stabilize internal storages (Guideline 7). Optimized parameters included saturated hydraulic conductivity, available water capacity of soil (related to wilting point and field capacity), Manning's "n", and curve number.

Abaci and Papanicolaou (2009) used WEPP to examine the effects of land management practices on soil erosion in the South Amana subwatershed (SASW), a catchment of about 26 km^2 that drains to Clear Creek in east central Iowa. Key optimized parameters such as soil hydraulic conductivity were constrained to within their physical ranges based on *in situ* measurements within SASW, critical literature review, and assessment by local USDA-NRCS personnel (Guideline 4). GIS was used to extract needed elevation and soils attributes from spatial data layers, while land use and management practices were obtained from local USDA-NRCS and SWCD representatives (Guideline 1).

SUMMARY

Despite more than five decades of hydrologic computer model development and application and the continuing difficulty and importance of parameterization, few articles have focused on developing general hydrologic parameterization guidelines. One persistent difficulty is that many different parameter sets may produce acceptable model predictions (equifinality). Each of the guidelines presented in table 1, discussed in the "Parameterization Guidelines" section, and illustrated in the "Case Studies" section can help reduce the acceptable parameter space. Use of multi-criteria model targets such as measured total streamflow, stream baseflow, nitrate concentrations, and soil water content at different depths tends to constrain the optimized range of parameter values. Likewise, including soft data (non-measured qualitative or estimated data such as evapotranspiration for model output comparison) can further constrain parameter values. Additionally, the range of acceptable parameter values is constrained through the use of measured values where possible, maintaining optimized parameter values to within justified ranges for the field or watershed conditions, and reducing the number of optimized parameters by optimizing only the most sensitive or uncertain parameters. Finally, including an initialization period can reduce the importance of accurately determining initial values of critical model storage variables, such as initial soil water and groundwater level.

Determining a set of parameter values that produce acceptable model predictions includes measurement and estimation of the most sensitive or uncertain parameters. Several soil parameters common to many hydrologic models are porosity or bulk density, saturated hydraulic conductivity, field capacity, and wilting point. These can all be determined in the laboratory from field samples and can be estimated based on more easily determined soil texture. Other model input parameters, such as curve number, Manning's "n", and leaf area index, can also be determined based on more easily determined field and watershed conditions. The spatial variability inherent in watershed-scale models is represented by readily available data in digital layers of land use, soils, and elevation using GIS techniques.

Parameterization includes imparting knowledge of the simulated field or watershed processes to the model and determining a set of acceptable parameter values for a model application, which is affected by the associated weather and management. Measurements of precipitation as an input variable from rain gauges are often lower than ground-level precipitation because of factors such as wind and snow, which must be considered in hydrologic model applications. Using "effective" model parameters can compensate for temporal and spatial physical characteristics such as precipitation over an area, but parameterization will be biased if precipitation measurements are biased, which can affect the simulated distribution of water in the hydrologic cycle. Management considerations include the timing and spatial distribution of crop or vegetation planting and harvesting, and operations such as tillage and fertilizer application, as well as structural hydrological controls such as filter strips and terracing, which can be determined through field notes from local operators or national and local databases.

In summary, parameterization guidelines for hydrologic model application were extracted from reviewing the special collection of 22 articles previously assembled along with other relevant literature. Common soil and hydrology related parameters were briefly described along with discussion of measurement and estimation methods and parameter sensitivity. Weather and management considerations were also discussed because they are critical to model parameterization. Finally, case studies were used to illustrate the hydrologic model parameterization guidelines and the determination of a few important parameters. The model parameterization guidelines will help model users more consistently parameterize agricultural system hydrologic models, which will result in more accurate model simulations that are more representative of the field or watershed conditions.

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