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IMPLICATIONS OF CONCEPTUAL CHANNEL REPRESENTATION ON SWAT STREAMFLOW AND SEDIMENT MODELING[1]

Younggu Her, Jaehak Jeong, Katrin Bieger, Hendrik Rathjens, Jeffrey Arnold, and Raghavan Srinivasan[2]

ABSTRACT: Hydrologic modeling outputs are influenced by how a watershed system is represented. Channel routing is a typical example of the mathematical conceptualization of watershed landscape and processes in hydrologic modeling. We investigated the sensitivity of accuracy, equifinality, and uncertainty of Soil and Water Assessment Tool (SWAT) modeling to channel dimensions to demonstrate how a conceptual representation of a watershed system affects streamflow and sediment modeling. Results showed the amount of uncertainty and equifinality strongly responded to channel dimensions. On the other hand, the model performance did not significantly vary with the changes in the channel representation due to the degree of freedom allowed by the conceptual nature of hydrologic modeling in the parameter calibration. Such findings demonstrated good modeling performance statistics do not necessarily mean small output uncertainty, and partial improvements in the watershed representation may neither increase modeling accuracy nor reduce uncertainty. We also showed the equifinality and uncertainty of hydrologic modeling are case-dependent rather than specific to models or regions, suggesting great caution should be used when attempting to transfer uncertainty analysis results to other modeling studies, especially for ungauged watersheds. ***Editor's note:*** *This paper is part of the featured series on SWAT Applications for Emerging Hydrologic and Water Quality Challenges. See the February 2017 issue for the introduction and background to the series.*

(KEY TERMS: channel dimension; SWAT; equifinality; uncertainty; hydrology; sediment.)

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INTRODUCTION

The definition of channel geometry is essential for watershed modeling because the shape and dimensions of channels affect streamflow hydraulics, including depth and velocity, determining the shape of hydrographs (Stewardson, 2005). In conventional modeling practice, channel geometry is usually simplified with predefined geometric shapes such as rectangular or trapezoidal and predetermined dimensions expressed as a function of watershed features such as upstream drainage area (Richards, 1977; Zhang *et al.*, 2009; Neitsch *et al.*, 2011). From hydrological point of view, channel geometry is determined by channel-forming discharge, often represented by

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[2]Assistant Professor (Her), Department of Agricultural and Biological Engineering, University of Florida, 18905 SW 280th St., Homestead, Florida 33031; Associate Professor (Jeong) and Assistant Research Scientist (Bieger), Blackland Research and Extension Center, Texas A&M University, Temple, Texas 76502; Environmental Modeler (Rathjens), Stone Environmental, Montpelier, Vermont 05602; Research Agricultural Engineer (Arnold), Grassland Soil and Water Research Laboratory, USDA Agricultural Research Service, Temple, Texas 76502; and Professor (Srinivasan), Department of Ecosystem Science and Management, Texas A&M University, College Station, Texas 77843 (E-Mail/Her: yher@ufl.edu).

bankfull discharge, which can be approximated in different ways, such as surveying the bankfull stage, estimating flow discharge of one to two-year frequencies, or calculating effective discharge that conveys the largest fraction of the annual sediment load (Copeland *et al.*, 2000; Castro and Jackson, 2001; Powell *et al.*, 2006). As it is much more convenient and easier to estimate bankfull discharge than to survey channel geometry at field, many studies tried to relate the dimension of a channel to its upstream drainage area via the bankfull discharge so that geospatial analysis and hydrologic modeling may benefit from the relationship (Leopold and Maddock, 1953; Richards, 1977; Allen *et al.*, 1994; Bieger *et al.*, 2015).

A power regression model approach introduced by Leopold and Maddock (1953) has been popularly used to estimate channel dimensions from characteristic discharges (Stewardson, 2005; Johnson and Fecko, 2008). Once the characteristic discharge is statistically related to drainage areas, the channel dimension becomes a mathematical function of the upstream drainage areas as a surrogate for discharge. In reality, however, there are many other factors influencing the channel forming processes, such as climate, geology, groundwater, topography, land cover, soil, and materials and slopes of streambed and bank. Thus, the regression equations based on drainage area only are likely to include a substantial amount of uncertainty (Doll *et al.*, 2002; Johnson and Fecko, 2008). Many studies showed that physiographic regions have their own unique relationships between drainage areas and channel dimensions (Leopold and Maddock, 1953; Dury, 1976; Park, 1977; Doll *et al.*, 2002; Stewardson, 2005; Johnson and Fecko, 2008; Bieger *et al.*, 2015). Fenneman (1946) divided the United States (U.S.) into 86 physiographic areas by divisions, provinces, and sections. For some physiographic areas, regional hydraulic geometry curves were developed by federal, state, and local agencies and compiled by the National Water Management Center (NWMC) of the U.S. Department of Agriculture-Natural Resources Conservation Service (USDA-NRCS, 2008). Bieger *et al.* (2015) compiled a large dataset of measured channel dimensions from the literature and derived representative regression equations describing the relationship between drainage area and bankfull width and depth for eight physiographic divisions and the entire conterminous U.S., which is expected to provide information that is useful in estimating channel dimensions based on topography in hydrologic modeling.

All hydrological models represent the features and processes of a watershed system in conceptual manners while the main functions of the system can still be effectively considered, using simulation strategies and mechanisms designed appropriately (Beven, 1989, 2001). When hydrological processes of a watershed are conceptualized in a mathematical model, some of watershed's physical (or measurable) properties may not be directly represented in the model due to differences in the spatiotemporal scales at which the conceptualization and measurements of the physical properties are made. The conceptualization involves lumping of known details of physical processes both spatially and temporally. Model parameters link the physical system of interest to mathematical representations of mechanisms controlling the system by characterizing the properties of the systems at a certain spatiotemporal scale. Determination of model parameter values often takes advantage of calibration or inverse modeling due to the lack of direct observations of the parameters and/or inconsistency between spatiotemporal scales for which the parameters were originally intended and actually applied (Yeh, 1986; Vrugt *et al.*, 2008). A calibration practice can identify multiple parameter sets providing equally good or acceptable model performance statistics, and a modeler may fail to select the most representative parameter set without additional observations, information, and/or criteria that can further screen the multiple sets. Such issue is called equifinality (Beven, 2006). The use of sampling-based heuristic search algorithm is likely to expose (rather than creating) the equifinality issue by aggressively exploring the parameter space in calibration (Her and Chaubey, 2015; Seong *et al.*, 2015). Although many studies were carried out to quantify equifinality and uncertainty, it has not been clearly understood how a conceptual watershed representation affects model performance, equifinality, and uncertainty in watershed modeling.

The Soil and Water Assessment Tool (SWAT) has been employed as a tool to address a range of water quantity and quality problems, such as assessment of climate and land use change impacts on hydrology and water quality, evaluation of best management practice effectiveness, total maximum daily load (TMDL) development, and critical source area identification (Srinivasan *et al.*, 2005; Kang *et al.*, 2006; Ficklin *et al.*, 2009; Douglas-Mankin *et al.*, 2010; Her *et al.*, 2016). In SWAT, once the volume of runoff coming from a subbasin into a channel segment in a time interval (*i.e.*, day) is calculated using the curve number (CN) and unit hydrograph methods, the rate and velocity of streamflow are calculated considering channel geometry predefined by ArcSWAT, a graphical user input interface and preprocessor for SWAT, based on upstream drainage area of the segment. Then the calculated streamflow rate and velocity are used to estimate travel time of the streamflow and to route runoff, sediment, and nutrients along the channel networks. Thus, the channel geometry definition is expected to influence water quality as well as hydrology simulations of SWAT. ArcSWAT employs a regression equation to define the dimensions of a trapezoidal channel based on drainage area estimated from watershed topography (Allen *et al.*, 1994; Muttiah *et al.*, 1997; Ames *et al.*, 2009; Neitsch *et al.*, 2011). Although the model has been extensively applied to simulate hydrologic processes of many watersheds in different landscapes, countries, and continents, the applicability of the regression equations has not been evaluated yet (*c.f.*, Staley *et al.*, 2006; Zhang *et al.*, 2009).

We demonstrate the conceptual nature of channel dimension definition and discuss its implications in watershed modeling, using SWAT. For this, we investigated the relationships of the accuracy, equifinality, and uncertainty of the model with respect to channel dimensions defined using regression equations linking channel width and depth to drainage area. Ten different regression equations derived by Bieger *et al.* (2015) were incorporated into the SWAT model for the St. Joseph River watershed, which served as a set of example models in this study. Streamflow and sediment simulations of each model equipped with unique channel dimensions were calibrated, using a sampling-based automatic optimization algorithm. The model performance, uncertainty, equifinality, and posterior distributions of calibration parameters were quantified using a Generalized Likelihood Uncertainty Estimator (GLUE) framework (Beven and Freer, 2001) and compared across different regression equations to figure out the impacts of the conceptual representation of channel geometry on streamflow and sediment simulations of the SWAT model.

METHODOLOGY

Study Watershed

The St. Joseph River watershed was used as the study area for showing channel representation impacts on model outputs. The watershed is located across Indiana, Ohio, and Michigan, draining 2,800 km^2 of gently rolling drainage areas on flat plains into Lake Erie (Figure 1). The local relief (the difference between the maximum and minimum elevations) of the watershed is 152 m (380-228 m), and land slopes range from 0% to 48.8% with an average of 2.3% according to the National Elevation Dataset (NED) (Figure 1a). The main channel of the St. Joseph River is 165.7 km long, and its average slope is 1/2,500. The river is alluvial, and its bed mainly consists of materials transported with overland flow from the hills to the streams (Kirschner and Zachary, 1969). According to the USDA National Agricultural Statistics Service-Cropland Data Layer (NASS-CDL), the watershed land uses are mostly croplands (53%) including corn, soybeans, and others distributed on relatively flat areas along the stream networks. According to the Soil Survey Geographic (SSURGO) database, the soils of the watershed are characterized as moderately fine or fine and overall poorly drained. Annual average precipitation is 1,000 mm, and 40% of the precipitation occurs from May to Aug (Figure 1b). A hydrologic analysis suggests that 360 mm of the annual precipitation reach the watershed outlet in the form of streamflow. Baseflow contribution to the total runoff ranges between 156 and 213 mm (Arnold and Allen, 1999). Hydrology and water quality of the St. Joseph watershed have been extensively investigated because of its contribution to the water quality of Lake Erie (USDA-NRCS, 2005). Using the ArcSWAT program, we divided the watershed into 39 subbasins based on its topography and stream networks. Then, we broke the subbasins into 498 hydrologic response units (HRUs) according to combinations of watershed land uses, soils, and slopes. The baseline watershed representation of the SWAT model was directly adopted from the previous study, Her *et al.* (2015).

Characterization of Open Channel Geometry and Hydraulics in SWAT

In SWAT, the bankfull channel width and depth are used to calculate the channel cross-sectional area of the corresponding bankfull streamflow, which is the criterion to decide if floodplain inundation occurs (Equations 1-5). When streamflow is less than the bankfull discharge rate, the streamflow velocity in a channel segment is calculated, using Manning's equation (Equations 6-11), and the travel time for the streamflow to pass through the segment is calculated based on the segment length and the calculated velocity (Equation 12). Then, the storage coefficient is determined for the variable storage routing method based on the travel time, which eventually determines the shapes of streamflow hydrographs in the channel segment (Equations 13 and 14) (Neitsch *et al.*, 2011). Floodplain inundation occurs when the estimated streamflow is greater than the bankfull flow, for which the SWAT model incorporates floodplain geometry into the channel routing simulation (Neitsch *et al.*, 2011).

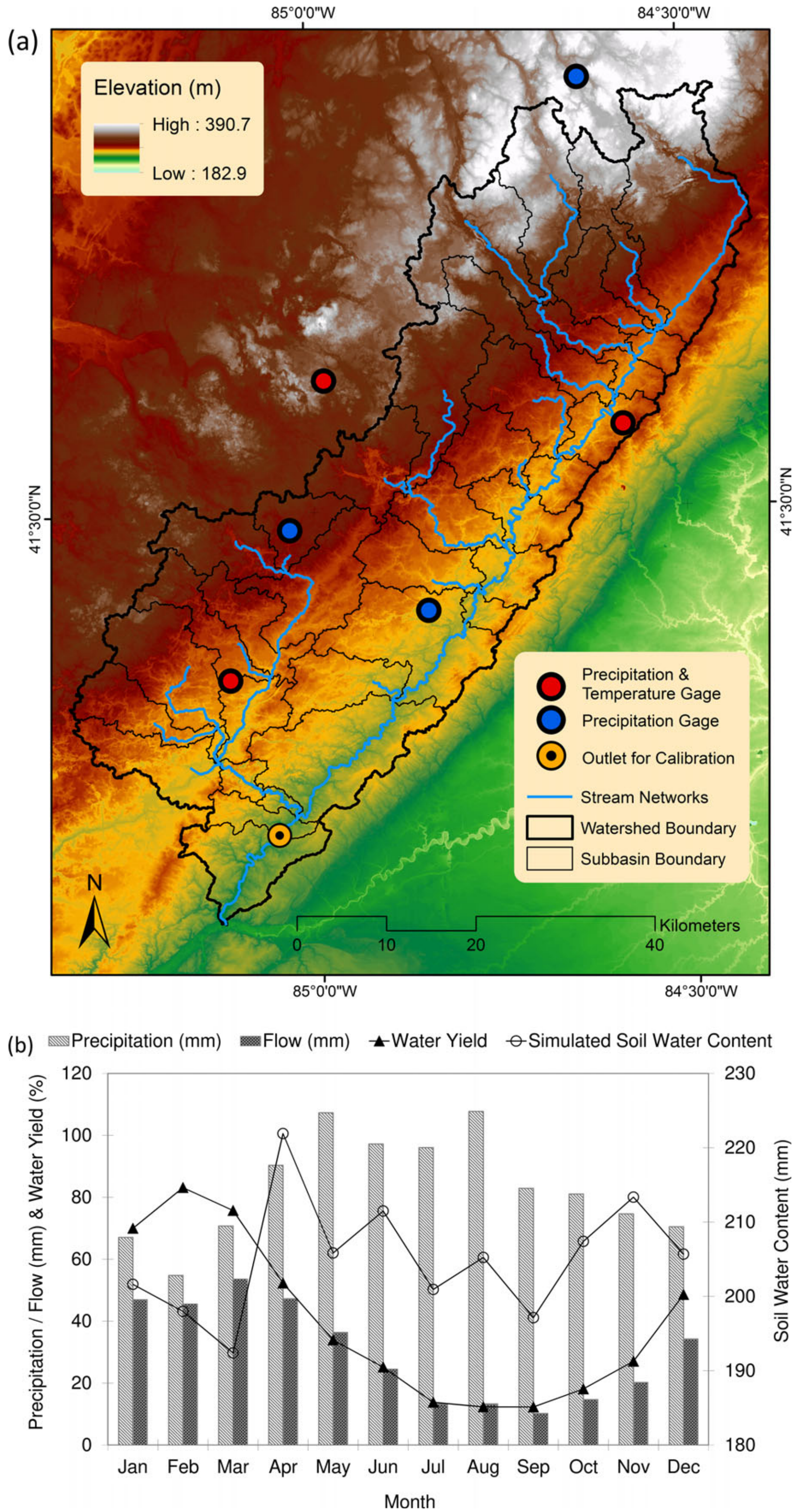

FIGURE 1. Hydrologic Characteristics of the St. Joseph River Watershed. (a) Topography, stream networks, weather and flow gage stations and (b) average monthly variations of the observed precipitation, streamflow, water yield, and simulated soil water content.

$$P_{\text{bankfull}} = W_{\text{bottom}} + 2 \cdot D_{\text{bankfull}} \cdot \sqrt{1 + z_{\text{ch}}^2} \tag{1}$$

$$W_{\text{bottom}} = W_{\text{bankfull}} - 2 \cdot z_{\text{ch}} \cdot D_{\text{bankfull}} \tag{2}$$

$$R_{\text{bankfull}} = \frac{A_{\text{bankfull}}}{P_{\text{bankfull}}} \tag{3}$$

$$A_{\text{bankfull}} = (W_{\text{bottom}} + Z_{\text{ch}} \cdot D_{\text{bankfull}}) \cdot D_{\text{bankfull}} \tag{4}$$

$$\begin{aligned} Q_{\text{bankfull}} &= A_{\text{bankfull}} \cdot v_{\text{bankfull}} \\ &= A_{\text{bankfull}} \cdot \frac{R_{\text{bankfull}}^{2/3} \cdot \text{slp}_{\text{ch}}^{1/2}}{n} \end{aligned} \tag{5}$$

$$A_{\text{ch}} = (W_{\text{bottom}} + z_{\text{ch}} \cdot D_{\text{ch}}), \text{when}(Q_{\text{ch}} < Q_{\text{bankfull}}) \tag{6}$$

$$P_{\text{ch}} = W_{\text{bottom}} + 2 \cdot D_{\text{ch}} \cdot \sqrt{1 + z_{\text{ch}}^2} \tag{7}$$

$$R_{\text{ch}} = \frac{A_{\text{ch}}}{P_{\text{ch}}} \tag{8}$$

$$Q_{\text{ch}} = A_{\text{ch}} \cdot v_{\text{ch}} = A_{\text{ch}} \cdot \frac{R_{\text{ch}}^{2/3} \cdot slp_{\text{ch}}^{1/2}}{n} \tag{9}$$

$$W_{\text{ch}} = W_{\text{bottom}} + 2 \cdot z_{\text{ch}} \cdot D_{\text{ch}} \tag{10}$$

$$v_{\text{ch}} = \frac{Q_{\text{ch}}}{A_{\text{ch}}} \tag{11}$$

$$\text{TT}_{\text{ch}} = \frac{L_{\text{ch}}}{v_{\text{ch}}} \tag{12}$$

$$C_{\text{storage}} = \frac{2 \cdot \Delta t}{2 \cdot TT_{\text{ch}} + \Delta t} \tag{13}$$

$$V_{\text{out}} = C_{\text{storage}} \cdot (V_{\text{in}} + V_{\text{stored}}), \tag{14}$$

where P_{bankfull} is the wetted perimeter of bankfull discharge (m), W_{bottom} is the bottom width of a channel segment (m), D_{bankfull} is the bankfull depth (m), z_{ch} is the inverse of the channel slope (m/m), W_{bankfull} is the bankfull width (m), R_{bankfull} is the hydraulic depth of bankfull discharge (m), A_{bankfull} is the cross-sectional area of bankfull discharge (m), Q_{bankfull} is the bankfull discharge (m^3/s), A_{ch} is the cross-sectional area of flow for a given volume of water (m^2), P_{ch} is the wetted perimeter for a given depth of flow (m), R_{ch} is the hydraulic radius for a given depth of flow (m), Q_{ch} is the discharge for a given volume of water (m^3/s), v_{ch} is the velocity of flow for a given volume of water (m/s), slp_{ch} is the slope of a channel segment (m/m), n is Manning's roughness coefficient for the channel segment (s/m$^{1/3}$), W_{ch} is the width for a given depth of flow (m), D_{ch} is the depth for a given depth of flow (m), TT_{ch} is time for flow to travel through a channel segment (travel time of streamflow; s), L_{ch} is the length of a channel segment (m), C_{storage} is the storage coefficient of the variable storage routing method, Δt is a simulation interval (s), V_{out} is the volume of water going out of a channel segment in a time interval (m^3), V_{in} is the volume of water coming into a channel segment in a time interval (m^3), and V_{stored} is the volume of water stored in a channel segment in a time interval (m^3).

The SWAT model employs stream power equations to determine the amount of sediment transported, called transport capacity, by streamflow through a channel segment under the sediment transport capacity concepts. For estimating the maximum concentration of sediment that can be transported by streamflow, the equations refer to hydraulic features of streamflow such as average or peak streamflow velocity and discharge (Neitsch *et al.*, 2011). When the concentration of sediment is greater (or smaller) than the maximum concentration that flow can hold, the net amount of sediment is considered to be deposited (or detached) in the segment. Thus, the definition of channel dimension influences streamflow velocity, streambed and bank erosion, sediment transport in the channel, and other constituents such as nutrients, pesticide, and bacteria.

Incorporation of Channel Geometry into SWAT

In ArcSWAT, the shape of a channel is assumed to have a trapezoidal shape, and the width and depth of each channel segment are calculated using a regression equation that relates channel cross-sectional geometry to the upstream drainage area of the segment as summarized in Table 1 (Ames *et al.*, 2009; Neitsch *et al.*, 2011; Bieger *et al.*, 2015). Therefore, unique values of channel depth and width are assigned to each segment depending on the stream network and watershed topography. For the purpose of clarification, it is worth noting that channel dimension is defined using the regression equation in ArcSWAT, and then channel dimension is used in calculating streamflow hydraulics (Equations 1-14) in SWAT. According to the physiographic map, the St. Joseph River watershed belongs to the Central Lowland of the Interior Plains (IPL) (Table 1). In this study, modeling experiments were set up so that all equations listed in Table 1 were incorporated into the SWAT model by modifying the channel input files (*.rte) for all 39 subbasins. Thus, a total of 10 different SWAT models with unique representations of channel dimensions were prepared for the study watershed, using the regional regression equations proposed by Bieger *et al.* (2015). The equations implicitly assume that bankfull discharge is identical to channel-forming discharge. Consequently, floodplain flow is not considered with the regression equations.

Model Calibration and Uncertainty Analysis

We calibrated the SWAT models that were prepared with different channel dimensions determined using the regression equations while adopting the baseline watershed representation from Her *et al.* (2015). In the calibration, daily streamflow and sediment yield measured at the watershed outlet for seven years between 1993 and 1999 were used as references. Stream gauge data were obtained from the U.S. Geological Survey and the Indiana Department of Environment Management for flow and sediment, respectively. Sediment data were assimilated using the LOADEST program (Runkel *et al.*, 2004) and converted from concentration to mass loads. Fifteen parameters were calibrated for streamflow calibration, and three basin-scale parameters associated with peak rate and sediment transport capacity of flow were additionally considered for sediment calibration. The SWAT parameters calibrated for this study are listed in Table 2. In summary, a set of fifteen parameters and another set of eighteen parameters were independently and concurrently calibrated for hydrology and sediment yield prediction, respectively, so that the sediment calibration would not be limited by the hydrology calibration, which enables a fair comparison between the hydrology and sediment calibration results. In the calibration, the parameter space was explored by a heuristic sampling-based optimization algorithm named AMALGAM (Vrugt and Robinson, 2007), and a total of 960 parameter sets were sampled in each calibration trial.

Equifinality, parameter and output uncertainty of the calibrated model were quantified using a framework of the Generalized Likelihood Uncertainty Estimator (Beven, 2006; Her and Chaubey, 2015), which constructs the posterior distributions of parameters based on behavioral parameter value sets identified using a predefined threshold and performance statistics (or values of generalized likelihood function) of the corresponding model runs. Then, uncertainty bands of outputs were developed from likelihood-weighted model predictions (Beven and Freer, 2001). Since behavioral parameter values are regarded as equally acceptable or good for simulation in the GLUE framework, selection of a single parameter set providing the best performance statistics (*e.g.*, Nash-Sutcliffe efficiency, NSE) does not deliver a meaningful message. In this study, the NSE coefficient (Nash and Sutcliffe, 1970) was used as a generalized likelihood function in the GLUE framework, and a relative threshold of the best 5% model performance was applied to screen behavioral parameter sets (Her and Chaubey, 2015). The relative level of equifinality was measured with the number of behavioral parameter sets identified in the calibration.

TABLE 1. Regression Equations Selected for the Study Watersheds Based on the Physiographic Regions (Bieger *et al.*, 2015).

Physiographic Division	Width (*W*, m)	Depth (*D*, m)
Appalachian Highlands (AHI)	$W = 3.12\text{DA}^{0.415}$	$D = 0.26\text{DA}^{0.287}$
Atlantic Plain (APL)	$W = 2.22\text{DA}^{0.363}$	$D = 0.24\text{DA}^{0.323}$
Interior Highlands (IHI)	$W = 23.23\text{DA}^{0.121}$	$D = 0.27\text{DA}^{0.267}$
Intermontane Plateau (IMP)	$W = 1.11\text{DA}^{0.415}$	$D = 0.07\text{DA}^{0.329}$
Interior Plains (IPL)	$W = 2.56\text{DA}^{0.351}$	$D = 0.38\text{DA}^{0.191}$
Laurentian Upland (LUP)	$W = 4.15\text{DA}^{0.306}$	$D = 0.31\text{DA}^{0.202}$
Pacific Mountain System (PMS)	$\text{W} = 2.76\text{DA}^{0.399}$	$D = 0.23\text{DA}^{0.294}$
Rocky Mountain System (RMS)	$W = 1.24\text{DA}^{0.435}$	$D = 0.23\text{DA}^{0.225}$
United States of America (USA)	$W = 2.70\text{DA}^{0.352}$	$D = 0.30\text{DA}^{0.213}$
SWAT Default (DFT)	$W = 1.29\text{DA}^{0.600}$	$D = 0.13\text{DA}^{0.400}$

Note: DA, drainage area (km^2); SWAT, Soil and Water Assessment Tool.

RESULTS AND DISCUSSION

Compared to the default regression equation used in the ArcSWAT program, the regression equations proposed by Bieger *et al.* (2015) provided smaller widths and depths of the 39 channel segments of the St. Joseph stream network, except for the equation used to estimate the width of channels in the Interior Highlands (IHI) region (Figure 2). The Appalachian Highlands equations estimated channel widths closest to those of the default equation on average. Among the regression equations, the USA equations provided the largest averaged differences and variations across the subbasins in the channel

TABLE 2. Sensitivity (coefficient of variation) of Parameter Values and Their Uncertainty to Channel Dimension Representations.

Parameter	Descriptions	Hydrology Simulation	Sediment Simulation
SURLAG	Surface runoff lag time (days)	**1.22**[1]	0.97
TIMP	Snow pack temp. lag factor	0.38	1.10
PRF	Peak rate adjustment factor for sediment routing in the main channel	—	0.92
SPCON	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	—	**1.30**
SPEXP	Exponent parameter for calculating sediment reentrained in channel sediment routing	—	**1.22**
ESCO	Soil evaporation compensation factor	0.38	**1.18**
OVN	Manning's n for overland	0.37	1.13
SLOPE	Average slope steepness (SF[2])	**0.44**	0.89
DEPIMP	Depth of the impervious layer (mm)	0.20	0.52
ALPBF	Baseflow alpha factor	**0.46**	0.67
GWQMN	Threshold depth of shallow aquifer (mm)	0.40	0.68
CNF	Curve number (SF)	0.18	0.77
CHN2	Manning's n for the main channels	0.36	**1.14**
CHS2	Average slope of the main channel (SF)	**0.68**	**1.32**
SOLAWC	Available water capacity (mm/mm, SF)	**0.51**	0.97
SOLZ	Depth of the soil layers (SF)	0.36	0.93
CHN1	Manning's n for the tributary channels	0.30	0.95
CHS1	Average slope of the tributary channels (SF)	0.37	0.63

[1]Bold face indicates five most sensitive parameters.
[2]SF: Scale factor that proportionally increases and decreases values of calibration parameters spatially distributed over hydrologic response units (HRUs) and subbasins of the study watershed.

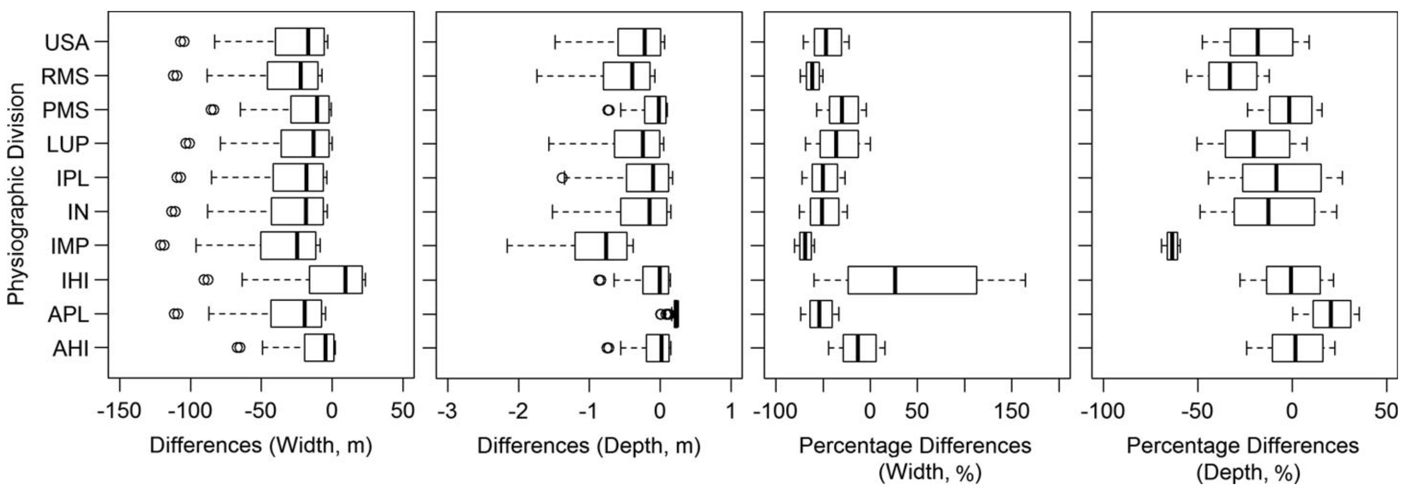

FIGURE 2. Differences between Channel Width and Depth Defined Using the Default Equations and the Regression Equations Proposed by Bieger *et al.* (2015) across 39 Subbasins of the St. Joseph Watershed. See Table 1 for full physiographic division names.

width and depth estimations. The comparison in Figure 2 clearly demonstrates that use of a single (or default) regression equation may lead to large errors in channel dimension estimation.

Parameter Uncertainty

The posterior distributions of calibration parameters were responsive to the channel dimensions in the SWAT modeling, showing significant differences to each other across the regression equations (Figures 3 and 4). Compared to the hydrologic calibration, the posterior distributions of the parameters (*e.g.*, SURLAG) have relatively narrow and clear modes when used for sediment calibration, indicating that the sediment calibration more restrictively screened parameter values even though three more parameters were evaluated. This may in part be attributable to the general

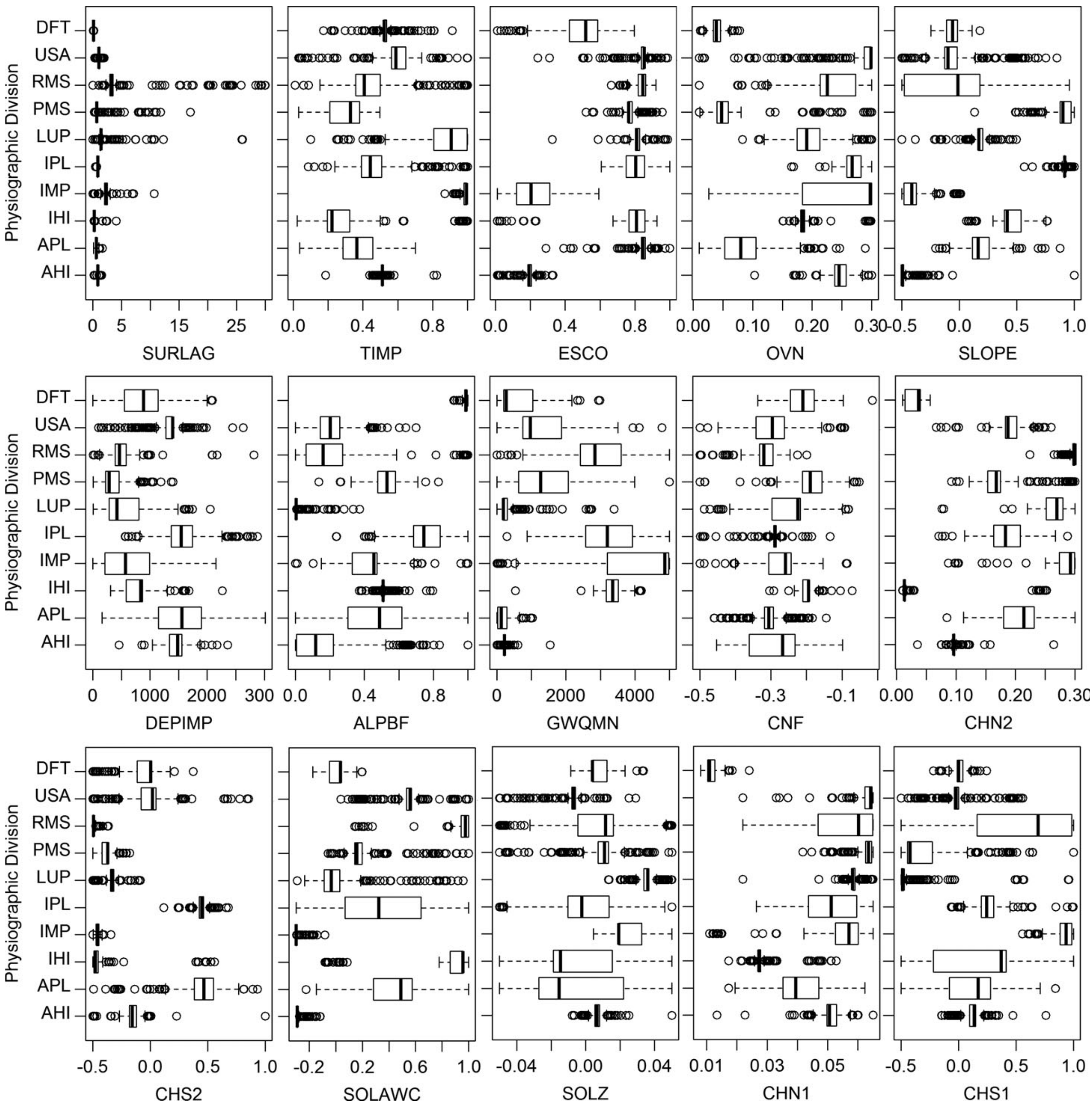

FIGURE 3. Posterior Distributions of Calibration Parameters for Hydrology Simulation of SWAT. See Table 1 for full physiographic division names and Table 2 for parameter descriptions.

principle that sediment transport processes are more selective to storm events, hydrodynamic conditions of the watershed including soil water content (affecting direct runoff volume), and anthropogenic factors such as conservation practices occurring in the watershed. Therefore, sediment measurement data implicitly contain more information about hydrological processes of a watershed. No statistically significant relationship was found between the channel dimensions and the means or medians of the posterior distributions, confirming that selecting a single value out of behavioral parameter values is not meaningful within the GLUE framework.

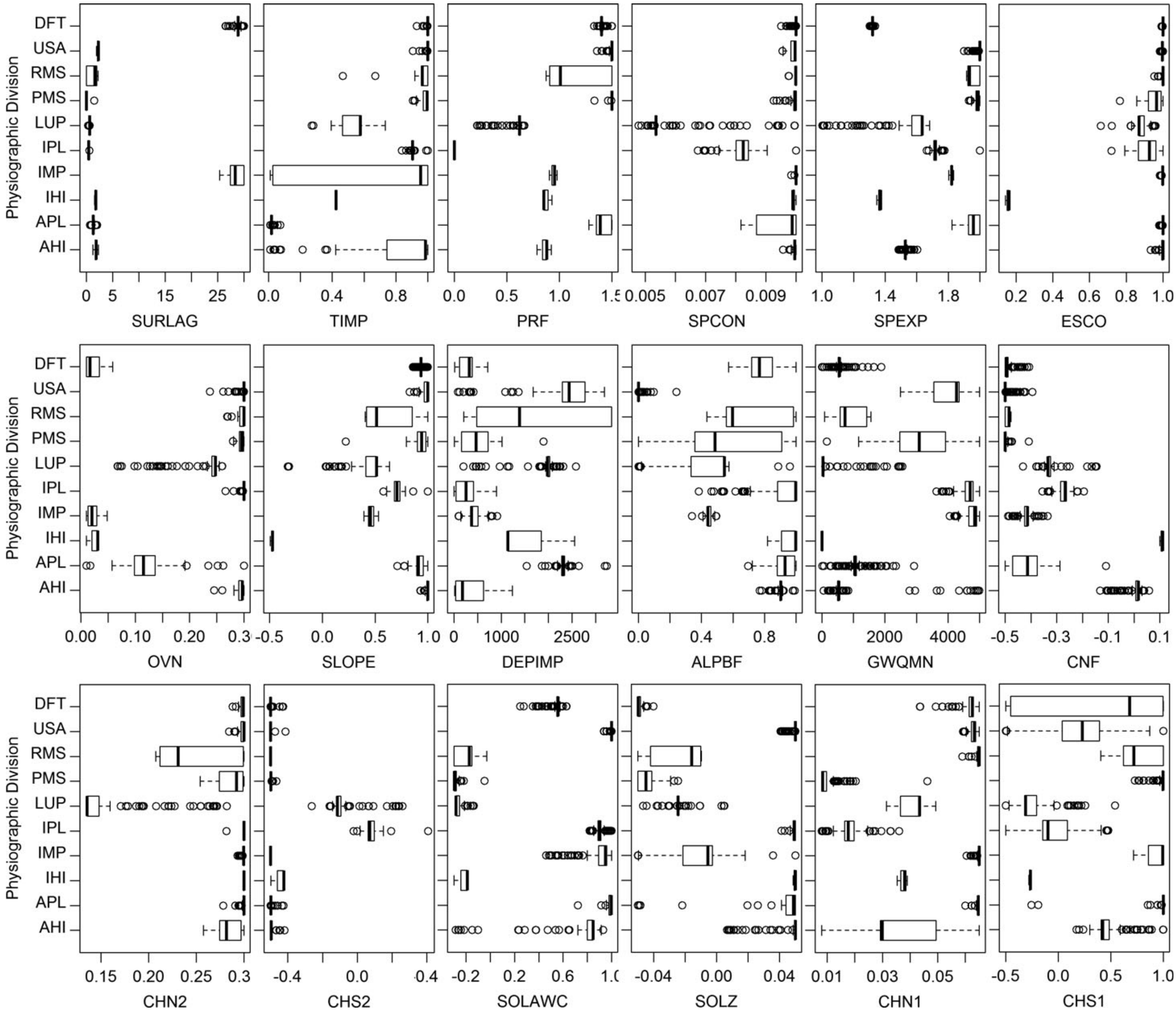

FIGURE 4. Posterior Distributions of Calibration Parameters for Sediment Simulation of SWAT. See Table 1 for full physiographic division names and Table 2 for parameter descriptions.

A strong correlation between the behavioral values of two parameters means that one parameter can be expressed as a predictive function of the other one. Thus, one of the parameters does not have to be included in calibration, which indicates there is over-parameterization. Figure 5 shows the correlation structure between the behavioral values of each possible pair of parameters across the regional equations. Overall, the behavioral values of the parameters were not significantly correlated with each other, which indicated that the model was not over-fitted or over-parameterized (Figure 5).

However, strong correlations between the behavioral parameter values varied by the channel dimensions incorporated were also found in some of the cases. For instance, it turned out that the behavioral values of hydrologic parameters such as SURLAG, OVN, CHN1, and CHN2 are strongly correlated (R^2 > 0.85; Devore, 2015) to each other in the cases of the IHI, Intermontane Plateau (IMP), and Pacific Mountain System regions (Figures 5a, 5b, and 5c). Also, the behavioral values of PRF were closely associated (R^2 > 0.85) with those of SPCON (negatively) and SPEXP (positively) in the sediment calibration for the Atlantic Plain (APL) and Laurentian Upland (LUP) regions (Figure 5b, 5d, and 5f). In the LUP region, it was found that the behavioral values of hydrologic parameters (*e.g.*, CHN2, SLOPE, and OVN) are highly

(a)

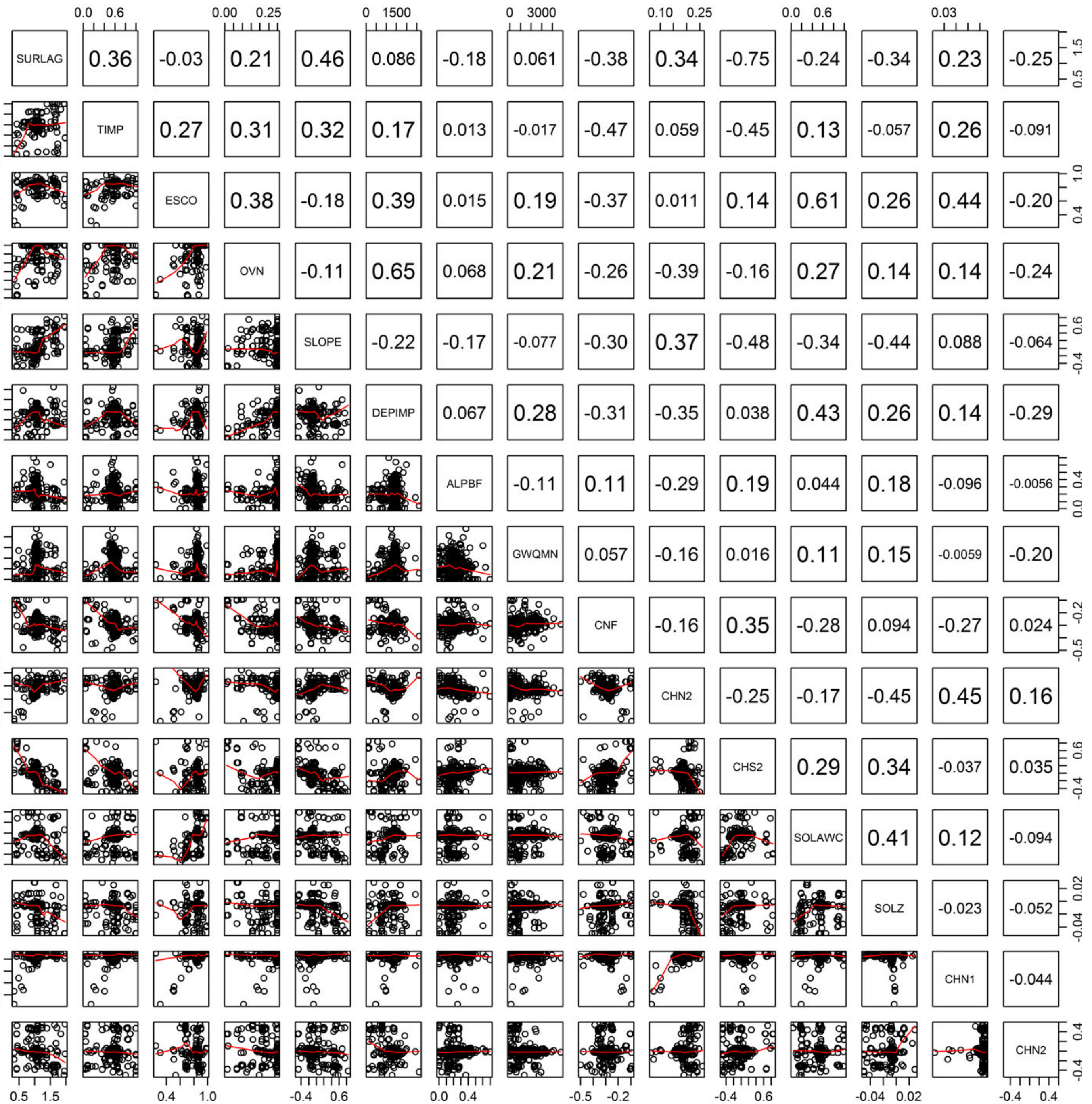

FIGURE 5. Correlation between Behavioral Values of the Calibration Parameters for Streamflow and Sediment Simulation of SWAT. (a) and (d): USA, (b) and (e): DFT, and (c) and (f): LUP; (a), (b), and (c): Streamflow and (d), (e), and (f): Sediment. The numbers represent the Pearson correlation coefficient measuring the strengh of the linear relationship between two variables. A large correlation coefficient means that values of a parameter are dependent on values of another parameter and thus one of the parameters does not have to be included in calibration, indicating overfitting or overcalibration. Each dot in the cloud plots signifies a pair of behavioral parameter values. See Table 1 for full physiographic division names and Table 2 for parameter descriptions.

correlated ($R^2 > 0.75$) to each other and those of sediment parameters (*e.g.*, PRF, SPCON, and SPEXP) (Figure 5f). Such results show that the occurrence and severity of over-parameterization are dependent on ways how the physical characteristics of a watershed are represented in a model, implying that they are case-dependent rather than specific to models.

The variations in the amount of parameter uncertainty across the different regression equations were quantified using the coefficient of variation (CV) of the

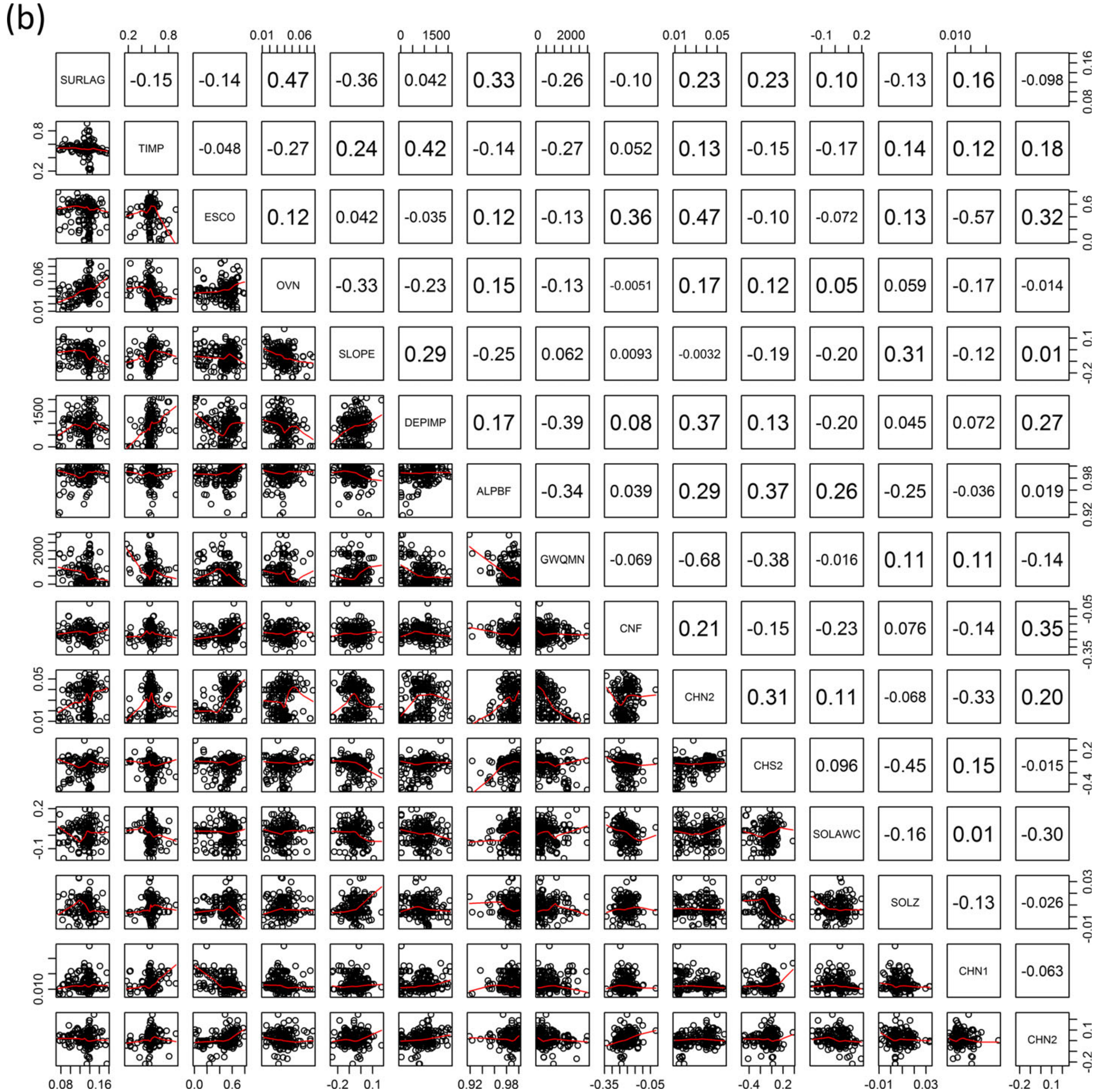

FIGURE 5. (Continued).

behavioral parameter value ranges (Table 2). In the hydrology simulation of SWAT, the uncertainty of SURLAG was found to be the most sensitive to channel dimensions, followed by those of CHS2, SOLAWC, ALPHABF, and SLOPE (Table 2). As ALPHABF and SOLAWC control baseflow between rainfall events, their values would be closely associated with the channel dimensions. As expected, the channel dimensions were found to greatly impact the uncertainty of parameters related to the travel time of runoff such as SURLAG, CHS2, and SLOPE. In the sediment simulation, the uncertainty of SPCON and SPEXP were strongly influenced by the channel dimensions (Table 2). In addition, CHN2 and CHS2 were responsive to the channel representation as these properties control streamflow velocity and thus sediment transport.

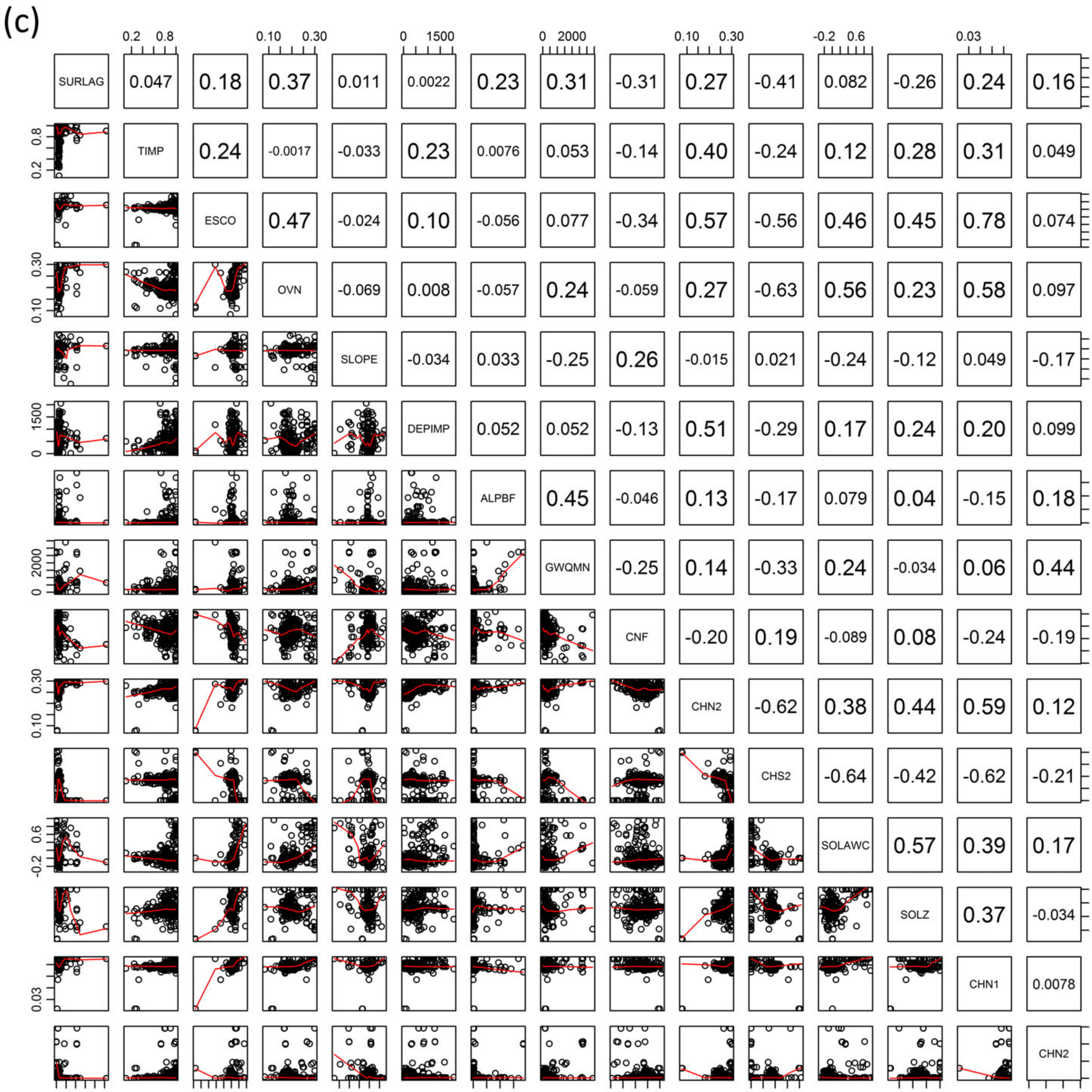

FIGURE 5. (Continued).

Interestingly, ESCO controlling soil evaporation in SWAT was also found to be sensitive to the channel dimensions in the sediment calibration (Table 2). In the literature, ESCO is also identified as a parameter largely affecting the sediment simulation of SWAT (White and Chaubey, 2005). In SWAT, the depth of direct runoff is calculated using a modified CN method relating CNs to soil water content for continuous daily simulations. ESCO can influence on the calculation of direct runoff depth through controlling the soil water distributions in the soil profile and thus the rate of soil water evaporation. Since the study watershed is mainly covered by row crops such as corn and soybean, there is no large variation in CN values across the watershed; then ESCO can have more influence on direct runoff generation and

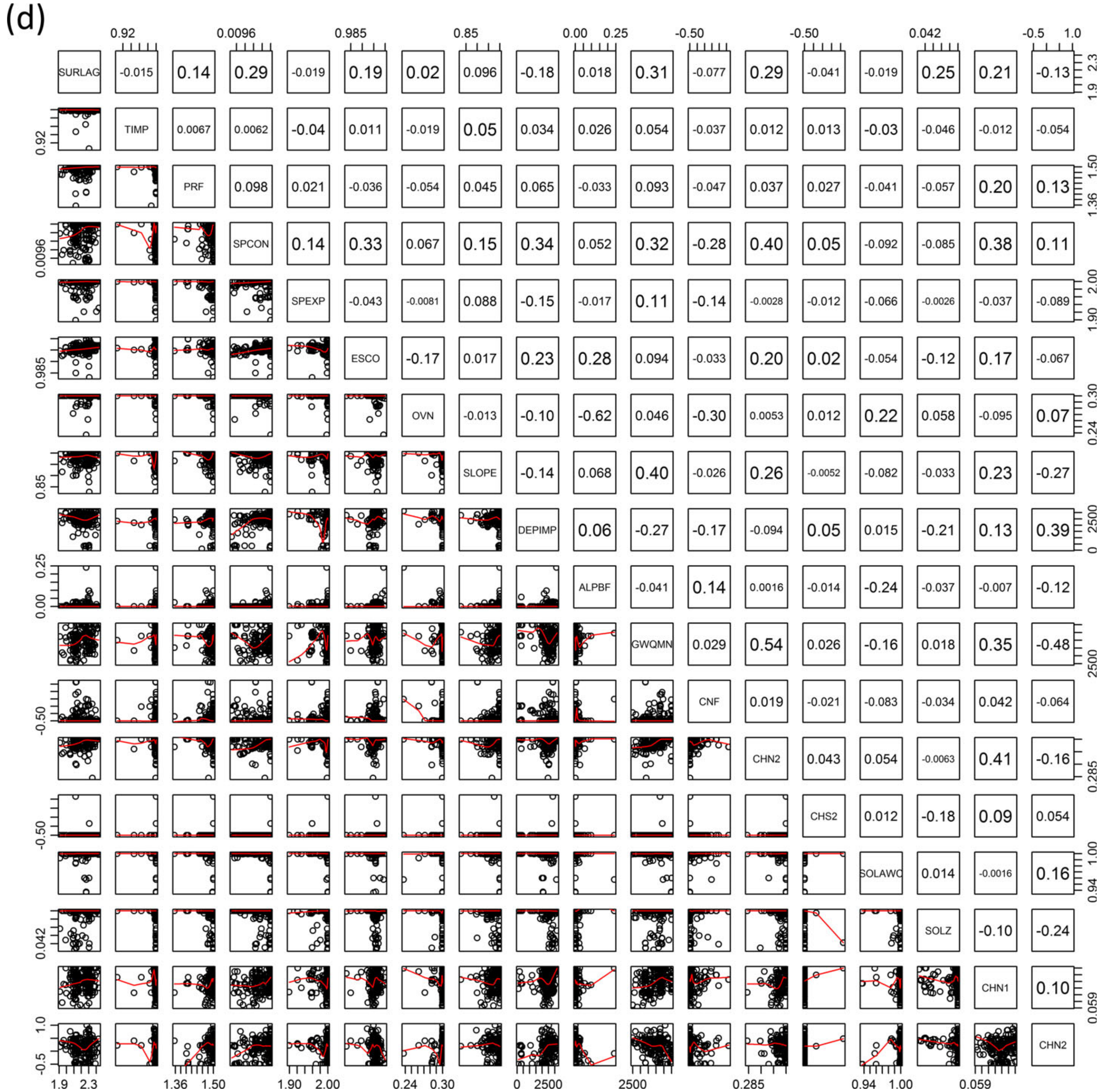

FIGURE 5. (Continued).

sediment transport processes than other parameters like CNF as demonstrated in Table 2.

There was no strong correlation between the amount of parameter uncertainty and the channel dimensions. The amount of uncertainty only in CHN2 was found moderately and also inversely correlated ($R^2 = -0.62$) to the channel areas defined using the regression equations. Such results imply that the Manning's roughness coefficient was actively compensated for varied channel areas. The values of the parameters and the amount of their uncertainty did not present a notable trend across the regression equations, which can be attributed to the highly complicated interaction between parameters and channel dimensions in the calibration. The conceptual nature of parameters or the lumped representation of watershed processes, such as SURLAG, may add vagueness to parameter determination. For instance, the peak

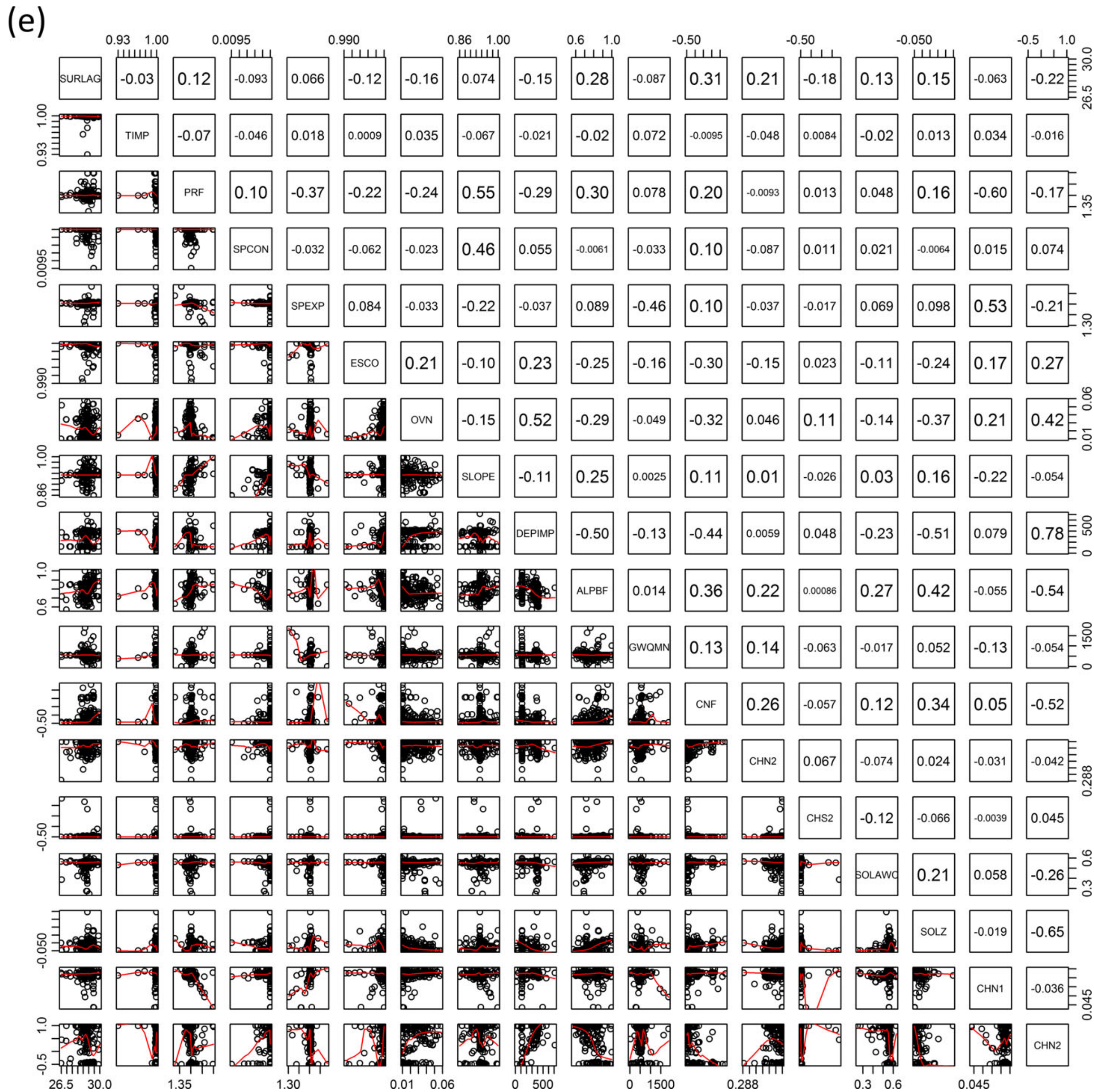

FIGURE 5. (Continued).

times and rates of streamflow to which the objective function, NSE, is sensitive are controlled by several parameters including SURLAG, OVN, CHN1, CHS1, CHN2, and CHS2, and the various combinations of their values would give similar peak time and rates leading to equally good (or acceptable) NSE values. In this case, soft data, such as the proportions of surface runoff and baseflow in the overall annual runoff and tile drainage contribution, that were made for similar landscapes, can be used to further screen parameter values so as to improve parameter identifiability (Arnold *et al.*, 2015).

Output Uncertainty

Variations in streamflow hydrographs simulated using the behavioral parameter sets of the SWAT

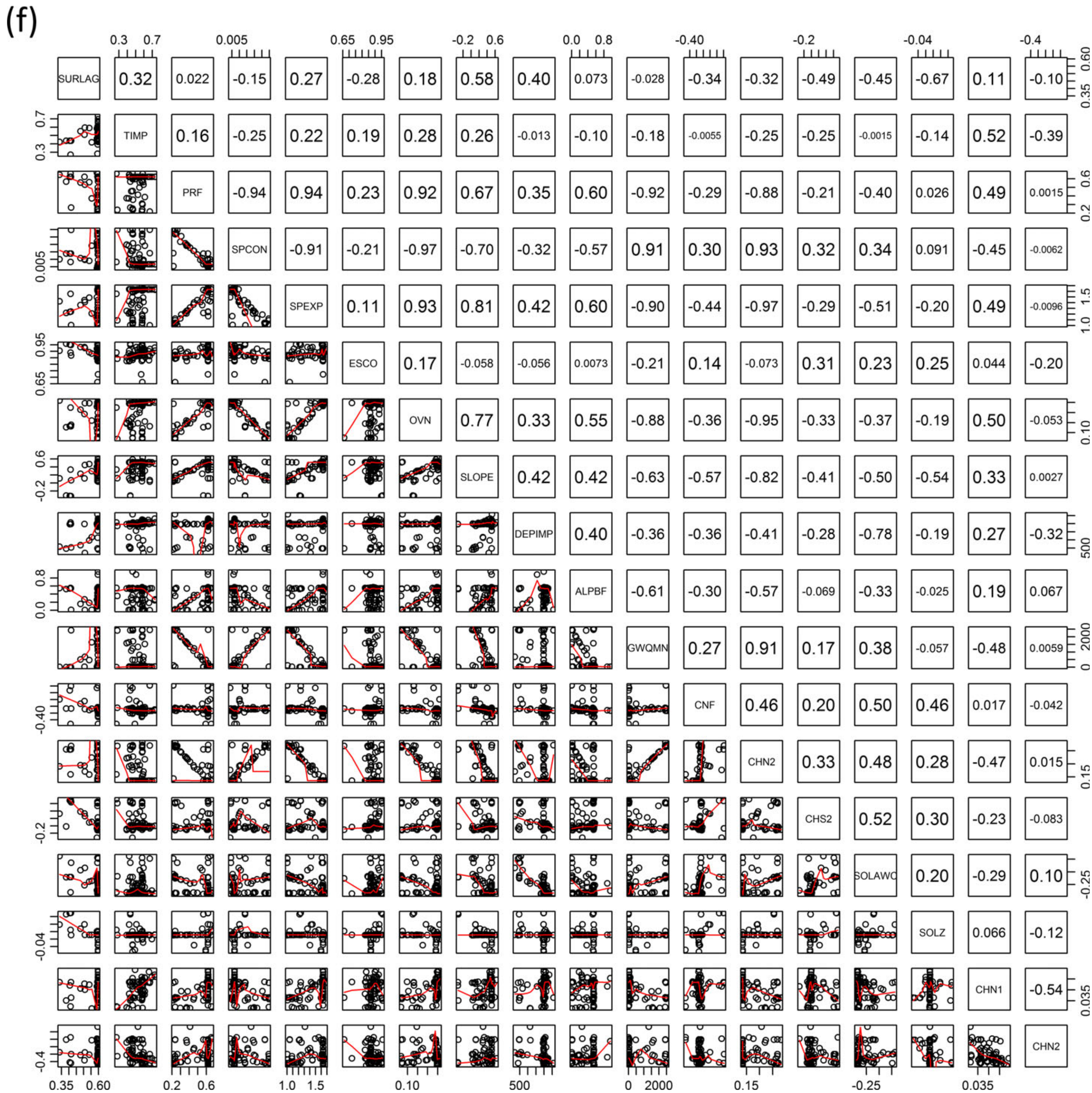

FIGURE 5. (Continued).

model were quantified by calculating an average bandwidth of the upper and lower limits of simulated streamflow hydrograph (Figures 6 and 7 and Table 3). In the study watershed, the IHI equations gave the greatest output uncertainty, followed by IPL, USA, APL, and Default (DFT) (Table 3). As the watershed is located within the IPL region, the IPL equations were expected to provide the most accurate estimates of channel dimensions. However, IPL yielded relatively large uncertainty compared to other equations, suggesting two possible interpretations. First, the regression equations inherently contain errors and uncertainty. In the case of IPL equations, for instance, the prediction interval of the cross-sectional areas of a channel that drains 100 km^2 ranges from 1.075 to 61.67 m^2 at 95%

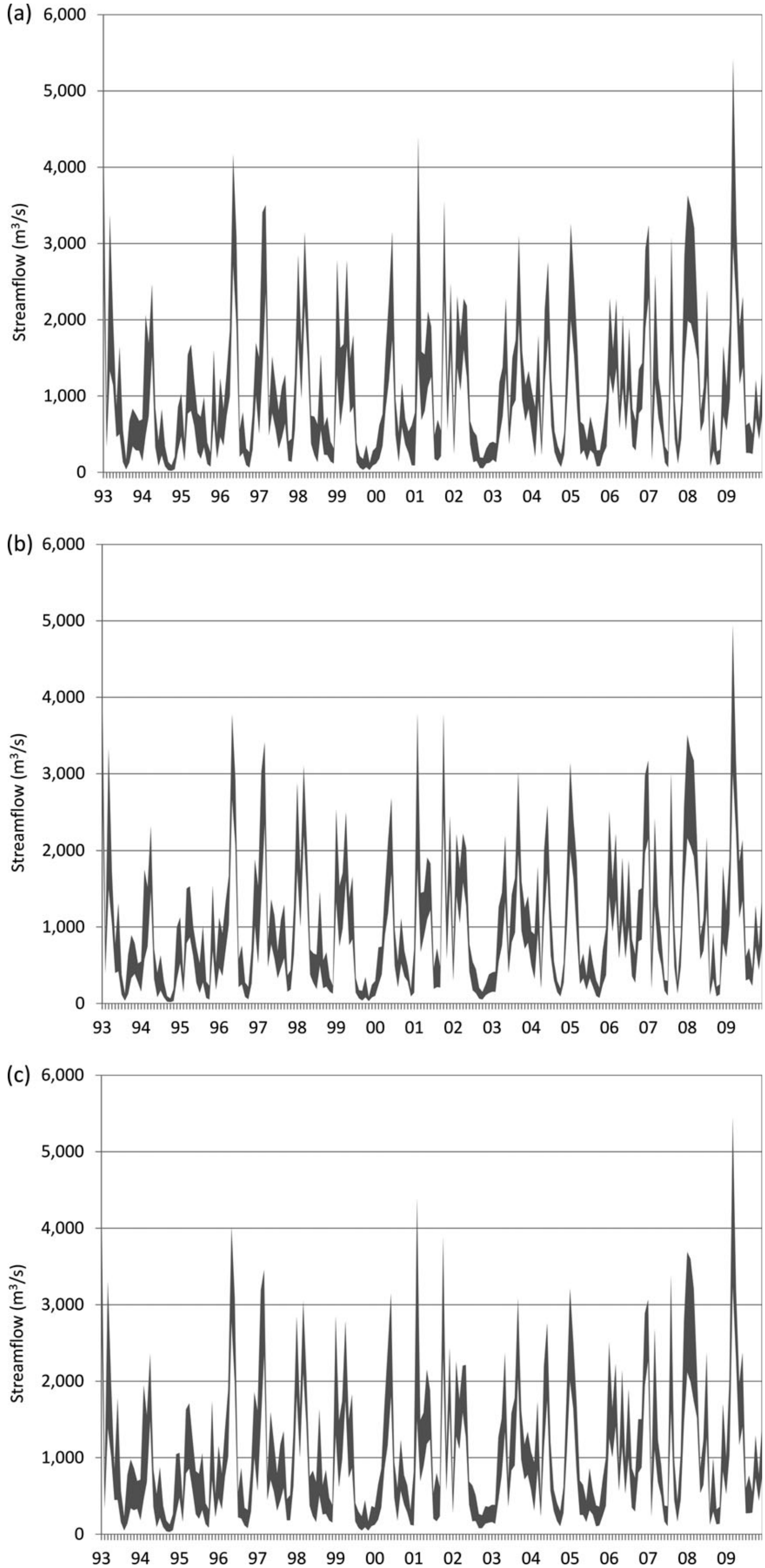

FIGURE 6. Uncertainty Bands of Monthly Streamflow and Sediment Hydrographs Simulated with Behavioral Parameter Sets. (a) and (d): USA, (b) and (e): DFT, and (c) and (f): IPL; (a), (b), and (c): Streamflow and (d), (e), and (f): Sediment. See Table 1 for full physiographic division names.

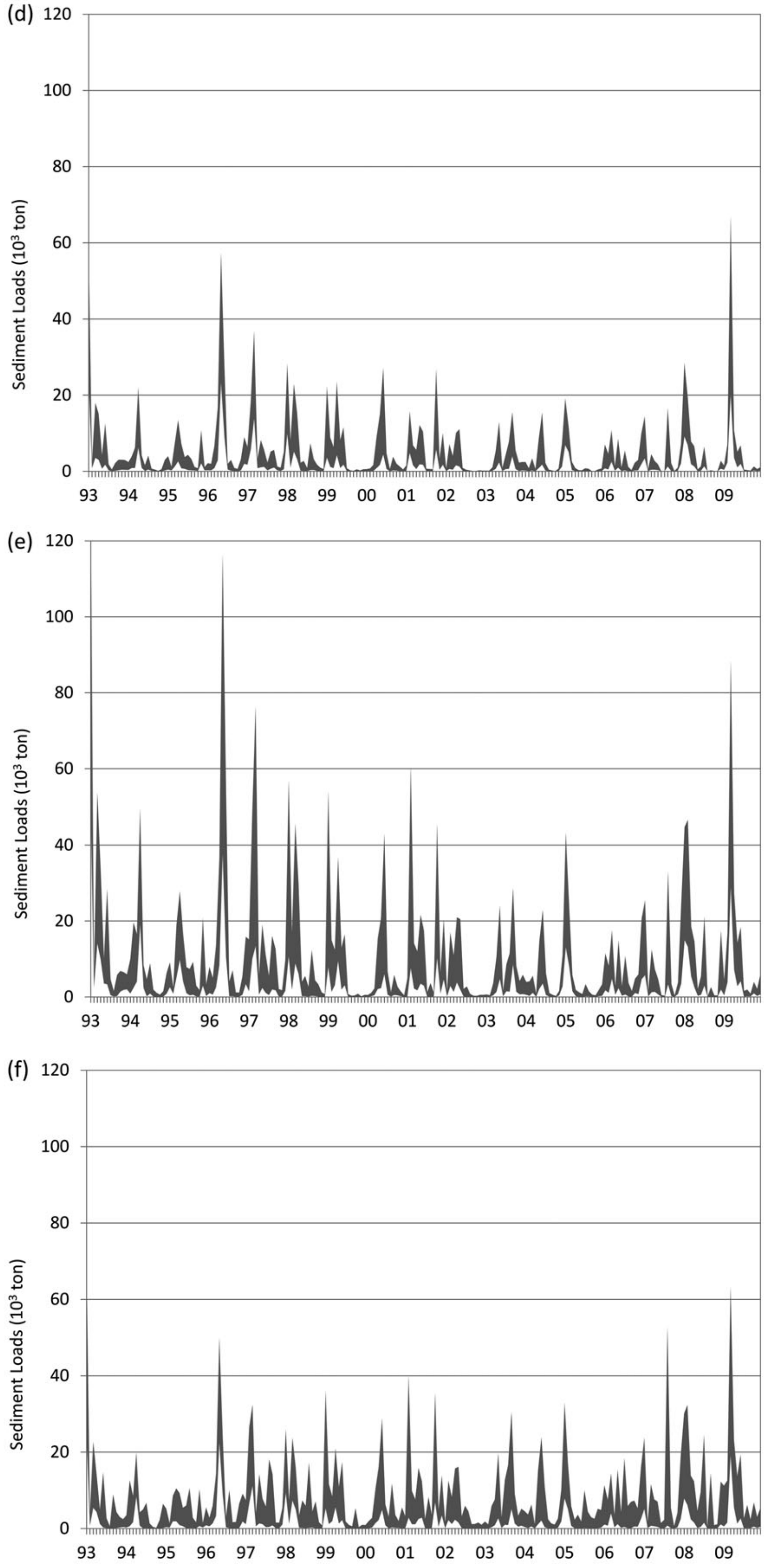

FIGURE 6. (Continued).

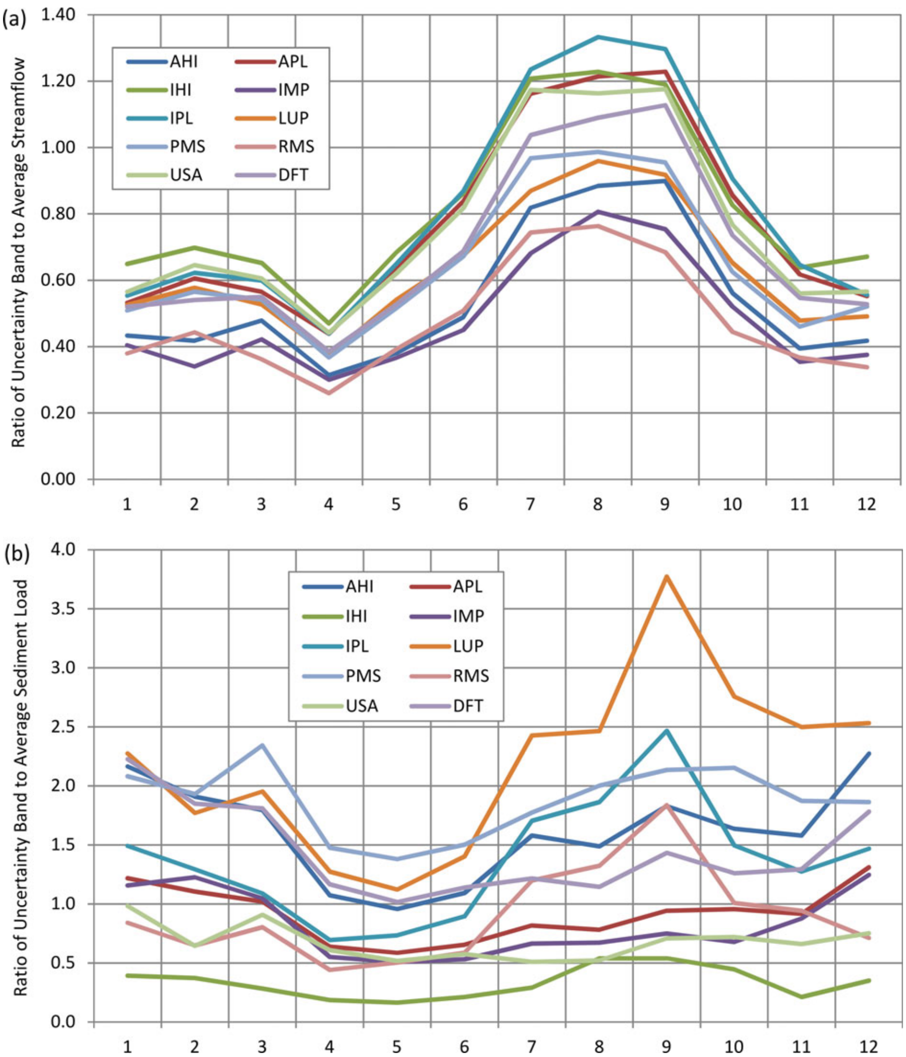

FIGURE 7. Relative Amount of Uncertainty Bands of Monthly Streamflow and Sediment Hydrographs Simulated with Behavioral Parameter Sets to the Observed. (a) Streamflow and (b) sediment. See Table 1 for full physiographic division names.

TABLE 3. The Amount of Uncertainty in Daily Streamflow and Sediment Load Hydrographs Simulated Using the Behavioral Parameter Sets.

	Uncertainty Measures			
	Hydrology Simulation		Sediment Simulation	
Divisions	**Streamflow (m^3/s)**	**Percentage to Average[1]**	**Sediment Load (tons/day)**	**Percentage to Average**
AHI	14.9	70	349	185
APL	20.9	80	200	165
IHI	22.9	79	67	50
IMP	13.4	59	184	125
IPL	21.7	79	272	172
LUP	18.0	65	431	186
PMS	18.0	63	419	168
RMS	13.2	59	176	140
USA	21.0	82	157	160
DFT	18.8	73	334	161

Notes: AHI, Appalachian Highlands; APL, Atlantic Plain; IHI, Interior Highlands; IMP, Intermontane Plateau; IPL, Interior Plains; LUP, Laurentian Upland; PMS, Pacific Mountain System; RMS, Rocky Mountain System; USA, United States of America; DFT, SWAT Default.
[1]Percentage of the uncertainty measures to the average streamflow and sediment load.

confidence level. The estimated large range implies that substantial uncertainty is inherently contained in the channel dimension estimations. Second, the finding may indicate that a watershed landscape representation close to the reality does not necessarily guarantee small modeling output uncertainty due to the conceptual nature of hydrological models (Beven, 1989, 2001, 2006). In the streamflow routing simulation of SWAT, the channel is assumed to be trapezoidal in shape, and its dimension is hypothesized to be constant along the channel segment of a sub-basin. In addition, there are other parts conceptually representing hydrological processes in SWAT, such as SURLAG regulating the contribution of direct runoff to streamflow, REVAP controlling upward movement of soil water, and HRUs representing homogeneous hillslope areas (Krysanova and Arnold, 2008; Neitsch *et al.*, 2011). Thus, more accurate and precise representation of only a part of the watershed landscape and/or processes may not substantially reduce the overall uncertainty and/or increase the accuracy of hydrologic modeling, as depicted in Figure 8.

Seasonal patterns of uncertainty in the simulated streamflow were similar to each other across the regions (Figure 7a). Compared to measured streamflow, the amount of uncertainty in the simulated streamflow hydrographs was relatively large in July, August, and September when the flow rate was low (Figures 1b and 7a). In the cases of APL, IHI, IPL, USA, and DFT, the amount of uncertainty was greater than the measured streamflow (*i.e.*, ratio of uncertainty to average streamflow is >1.0) in the summer months (Figure 7a and Table 3). While it was large in dry months, the relative amount of uncertainty to streamflow was small in April and November when soils were relatively wet, implying a connection of uncertainty to simulated soil water content (Figures 1b and 7a). Relative amounts of uncertainty in simulated monthly sediment loads showed larger variations across the regions than did those of the streamflow uncertainty (Figure 7b). When using the IHI and USA equations, the amount of uncertainty was as low as the measured sediment for all seasons, whereas it increased to 430% of the measured sediment in the LUP region. The relative amount of uncertainty to sediment loads was minimal in May when the maximum sediment load was observed at the watershed outlet. The estimated uncertainty was the greatest in September when observed sediment load was minimal (Figure 7b).

The output uncertainty analysis results demonstrate that the occurrence and degree of over-parameterization are significantly dependent on ways how watershed features such as channel geometry are represented in a simulation as well as the structure of a model, implying the degree of overfitting is case-dependent rather than specific to models.

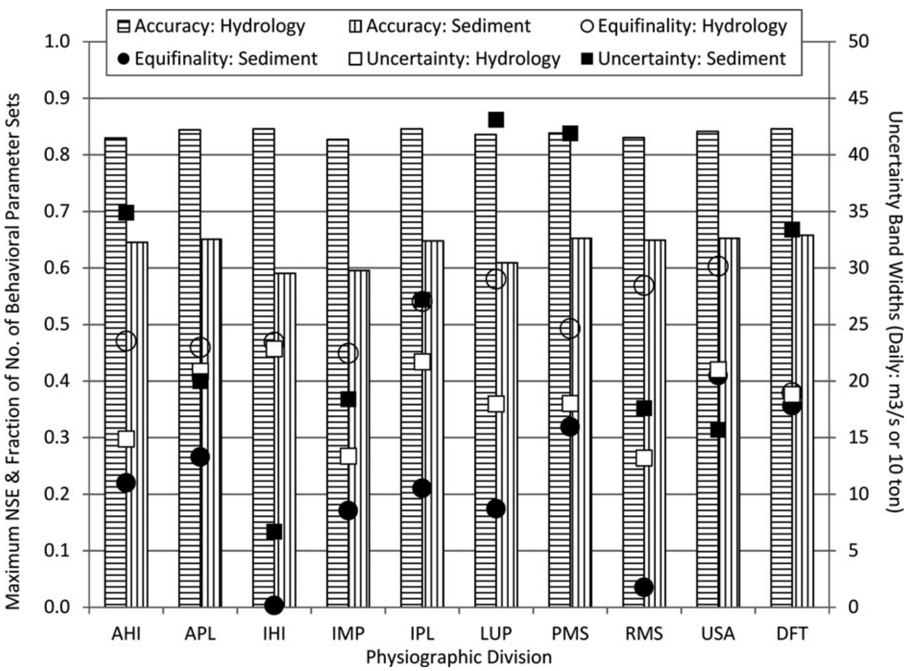

FIGURE 8. Sensitivity of Accuracy, Equifinality, and Uncertainty to the Regression Equations. Maximum Nash-Sutcliffe efficiency (NSE) is used as a surrogate of modeling accuracy, fraction of no. of behavioral parameter sets is used as a quantitative measure of equifinality, and uncertainty band width represents the amount of output uncertainty. See Table 1 for full physiographic division names.

Relationship between Accuracy, Equifinality, and Uncertainty through Channel Geometry

The overall accuracy, equifinality, and uncertainty of SWAT modeling implemented with different regression equations predicting channel width and depth were quantified and presented in Figure 8. The best performance or accuracy the model could achieve did not vary significantly with the channel dimensions defined using the regression equations for both the streamflow and sediment yield simulations. In contrast, parameter equifinality and model output uncertainty were highly sensitive to the channel dimensions, indicating that equifinality and uncertainty are closely associated with the representation of watershed features. In the calibration, parameters were automatically adjusted by the optimization algorithm to values maximizing an objective function (*i.e.*, NSE) as demonstrated in Figures 3 and 4, so model accuracy would not be greatly deteriorated as long as parameter search spaces were set to ranges wide enough to accommodate combinations of parameter values providing equally good performance measures.

A positive correlation between accuracy and equifinality was found (correlation coefficient of 0.62) in the case of the sediment simulation of SWAT, which well agrees with previous research (Her and Chaubey, 2015). In the case of the hydrologic simulation, the difference between the maximum and minimum NSEs across the regions was 0.02, which was not large enough to detect statistical significance in the relationship between accuracy and equifinality. The positive correlation is caused by the characteristics of the optimization algorithm, AMALGAM, used to identify more behavioral parameter sets while maximizing the model performance in the parameter calibration. In contrast to a simple Monte Carlo method, a "heuristically guided probabilistic search" algorithm such as AMALGAM samples values of parameters based on model performance statistics provided by parameter values sampled in the previous iteration (or generation). Thus, a sampling of AMALGAM is not purely random but is rather conditional. As iteration progresses, parameter sets located in the vicinity of the global optimum get a higher probability of being sampled than other sets, which contributes to increasing the measure of equifinality (or the number of parameter sets providing equally good or acceptable model performance statistics). In parameter calibration of a hydrologic model, therefore, the use of optimization algorithms rather than a simple (or purely random) Monte Carlo sampling shows a proportional relationship between the degrees of accuracy and equifinality. It is interesting to find that output uncertainty of the sediment simulation was relatively large compared to that of the hydrologic simulation even though the amount of uncertainty in sediment parameters was smaller than that of hydrologic parameters. Consequently, large parameter uncertainty did not necessarily involve large output uncertainty (Figures 3-6). This is consistent with the findings reported by Her and Chaubey (2015).

Temporal lumping and abstraction contribute to modeling error and uncertainty. In hydrologic modeling, watershed processes are simplified at a temporal scale where known empirical relationships between variables and mechanisms controlling variables can be applied. Thus, variables of a hydrologic model represent the averaged behavior of the corresponding system or process varying within a simulation time interval. In the SWAT model, hydrologic and water quality processes are simulated on a daily basis for large-scale basin modeling (Srinivasan and Arnold, 1994; Gassman *et al.*, 2007). Although recent improvements enabled the model to describe subdaily processes occurring during a storm event (Jeong *et al.*, 2011, 2012), the model has been more commonly utilized for daily-scale simulations. The large temporal scale can improve simulation efficiency especially for large-scale modeling, but may not be able to describe temporal processes of interest in detail. In a SWAT modeling, for instance, subbasins are often delineated small enough to have streamflow travel time shorter than a half of the simulation interval (*i.e.*, 12 h), in particular, steep watersheds that have rough topography. Then the storage coefficient of the variable storage routing is likely to become greater than one, the theoretical maximum (Williams, 1969). In this case, SWAT assumes that a combined amount of streamflow coming in during a simulation time interval and water stored at the beginning of the interval will leave the stream segment at the end of the interval, which is equivalent to a storage coefficient of one (Neitsch *et al.*, 2011). Thus, the channel routing effects (travel time delay and peak attenuation) are likely to be underestimated, which would lead to additional (or excessive) adjustment of parameters related to runoff velocity across all watershed processes, such as SURLAG, OVN, SLOPE, CHN1, CHN2, CHS1, and CHS2, to reproduce the routing effects in parameter calibration. The SWAT channel routing simulations implemented with the different channel dimensions exemplified the close and complicated relationship between the representation of watershed features and parameters, performance, and uncertainty through spatial and temporal scales of hydrologic modeling.

SUMMARY AND CONCLUSIONS

We investigated the effects of the conceptual representation of the channel geometry on the performance, equifinality, and uncertainty of hydrologic modeling using the SWAT model. Regional regression equations were used to define the widths and depths of channel segments along stream networks of the SWAT model prepared for the St. Joseph River watershed in the Midwest of the U.S. Each SWAT model was equipped with a unique representation of channel geometry and calibrated using streamflow and sediment loads observed at the watershed outlet. Multiple parameter sets providing equally good model performance were identified using a sampling-based heuristic optimization algorithm in the calibration. Then, the equifinality and uncertainty of the SWAT modeling that have different channel representations were quantified using a GLUE framework.

Results showed that the hydrology and sediment simulations of SWAT were sensitive to channel dimensions. However, the best model performance statistics did not greatly vary with changes in the channel dimensions, which was attributed to the conceptual nature of channel geometry representation in the SWAT model. In the calibration using an automatic optimization algorithm, an inadequate channel representation was compensated by adjusting parameter values. Overall, the behavioral values of the calibration parameters were not significantly correlated with each other, indicating that the SWAT models calibrated for the study watershed were not overfitted. When some of the regional regression equations were applied, however, a strong correlation was found between behavioral values of parameters controlling travel time of runoff and sediment transport capacity of streamflow such as CHN2, CHN1, OVN, SURLAG, PRF, SPCON, and SPEXP. Such a case-dependent correlation structure of parameters demonstrated that the relationship between parameters could be affected by the representation of watershed features including channel dimensions as well as the model structure and the types of parameters selected for calibration.

The accuracy of hydrologic modeling was not related to the amount of its output uncertainty. Thus, good modeling performance statistics do not necessarily mean small output uncertainty and vice versa. A positive correlation between accuracy and equifinality was found, which was caused by the sampling strategy of a heuristically guided probabilistic search algorithm used in the parameter calibration. Such findings agree with Her and Chaubey (2015). The amount of equifinality, uncertainty and the posterior distributions of the calibration parameters were responsive to the channel dimensions, but there was no statistical correlation found between them, implying a non-linear and complicated interaction between channel dimensions and modeling outputs via routing simulation.

We found that the conceptual nature of the channel geometry representation is closely related to the equifinality and uncertainty of hydrologic modeling, but at the same time, the model performance is not significantly affected by the channel geometric representation methods because compensating parameter values for best fitting can be found during calibration. Such findings suggest that improvements in only one part of the watershed representation neither increase the overall accuracy of hydrologic modeling nor reduce its uncertainty while significantly affecting parameter calibration. To improve the accuracy of hydrologic modeling and reducing its uncertainty, thus, a hydrologic modeler may want to spend great effort on collecting more observations that can further refine parameter values, rather than making a part of a hydrologic model “look” more realistic or accurate as long as the conceptual structure and watershed representation of the model adequately explain the mechanisms how a watershed system works. In addition, we demonstrated that calibrated parameter values, the equifinality, and uncertainty of hydrologic modeling are case-dependent rather than model- or region-specific, implying it would be difficult to make a generalization or transfer of calibration and uncertainty analysis results to hydrologic modeling for an ungaged watershed.

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