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A global sensitivity analysis approach for identifying critical sources of uncertainty in non-identifiable, spatially distributed environmental models: A holistic analysis applied to SWAT for input datasets and model parameters

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A R T I C L E I N F O

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A B S T R A C T S

Environmental models have a key role to play in understanding complex environmental phenomena in space and time. Although their inherent uncertainty and non-identifiability are being increasingly recognized with the development and application of various methods, a more holistic analysis of all sources of model uncertainty is warranted. This paper addresses sources of uncertainty from various types of input datasets and model parameters, including those related to model structure assumptions, using a Soil and Water Assessment Tool (SWAT) application for the Minjiang River watershed, China. The holistic uncertainty sources in the SWAT application are summarized, and a sensitivity analysis (SA) is applied to examine the relative importance of the uncertainty sources influencing average streamflow and the load of nitrate. The analysis reveals that uncertainties related to the stream network precision and certain SWAT parameters are the most critical factors. Furthermore, building upon our SA framework to consider uncertainty sources more holistically would provide a good starting point for subsequent SA of spatially distributed environmental models in general.

1. Introduction

Deterministic environmental models offer useful methods for exploring problems, providing predictions, and supporting decisions that involve complex environmental phenomena evolving in space and time. It has become increasingly recognized, however, that these models are almost always non-identifiable (Guillaume et al., 2019), in the sense that the quantity and quality of data are insufficient to parameterize the models uniquely, and that the associated modelling must address a wide range of uncertainties, especially those related to predicting the impact of possible management actions. Accordingly, Uusitalo et al. (2015) review various methods that can be applied to evaluate uncertainty of deterministic model outputs. They cover expert assessment, model emulation, sensitivity analysis (SA) and use of multiple models, arguing that the best method for uncertainty evaluation is determined by the definition of a model, and the amount of available information. SA is an established approach to model assessment by quantitatively evaluating the change in model output(s) with respect to changes in model factors (usually parameters, forcing and other input data). A deterministic environmental model can be easily coupled with SA based on Monte Carlo type simulation (Farmer and Vogel, 2016). SA offers a quantitative evaluation for uncertainty in a model, rather than a qualitative evaluation which, for example, expert assessment does (Uusitalo et al., 2015), although qualitative evaluation could provide additional evidence to further support decision making and might be more efficient when a modeler is well-informed. In this paper we employ a global method of SA (Saltelli et al., 2008) as opposed to a local method. A global method allows one to compute the contribution to output sensitivity over a plausible range of factor values.

Global SA is undertaken here as a useful first step in addressing and understanding the criticality of uncertainty sources (see Norton, 2015 for an overview of methods, and Crosetto and Tarantola, 2001; Gan

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et al., 2014; Tong, 2015) by assessing those factors, and their plausible range of values, that dominate changes in model outputs. Understanding the criticalities can then be valuable for undertaking an uncertainty analysis in the traditional probabilistic sense, for example, where one assumes prior distributions of parameters and finds posterior distributions based on some measure of likelihood.

As indicated in the literature review of Section 2, previous approaches to SA tend to address only a modest set of the sources of uncertainty for spatially distributed environmental models. The aim of this article is to illustrate how a more holistic SA approach to spatially distributed environmental models can be used to identify their critical sources of uncertainty, which would subsequently allow focus on them for more specific uncertainty analysis and even its reduction. The Soil and Water Assessment Tool (SWAT) (Neitsch et al., 2011) is used as an archetypal example as it is the most frequently used water quantity-quality model (Fu et al., 2019; Ray, 2018). It is also a typical example of the type of uncertainties that need to be considered in a spatially distributed environmental model. The global SA approach undertaken is more complete than previous SA studies on spatially distributed environmental models in the sense that: it attempts to address model structure uncertainty in combination with the usual model parameter and data uncertainties; and examines impact on average streamflow as well as water quality outputs. Thus, this article addresses the uncertainty of model structure input parameters related to the submodels of a SWAT application [i.e., watershed delineation and hydrological response unit (HRU) characteristics]. It also explores the measurement uncertainty of the digital elevation model (DEM) (i.e., its vertical accuracy), and the uncertainty of boundaries of classes in land-use-land-cover (LULC) and soil datasets (Crosetto and Tarantola, 2001; Goodchild and Guoqing, 1992) because they have a profound effect on watershed delineation (Oksanen and Sarjakoski, 2005; Wu et al., 2008) and HRU creation, respectively. Another aspect investigated is the impact of measurement errors in meteorological information on model outputs. Finally, the SA is also applied to the model parameters investigated as has been the primary focus in the past (e.g., Setegn et al., 2010; Wu and Liu, 2012; Yang et al., 2018; Zhao et al., 2018), some of which relate to model structure assumptions. Clearly, while it is not possible to investigate all model structure assumptions as these can be innumerable in an environmental modelling exercise, it is acknowledged that expert assessment is a key, complementary and qualitative method that can be used to justify other model structure assumptions in relation to uncertainty (O'Hagan, 2012; Uusitalo et al., 2015). Our SA approach could therefore be followed up with a formal uncertainty analysis to help in setting the range of prior distributions and fixing unimportant factors, which is especially important when sampling needs to be limited because of high computational demands of the environmental model.

The remainder of this article is organized as follows. Section 2 contains a literature review and key qualitative findings of previous SA studies on the SWAT model. Section 3 briefly explains SWAT and the extended Fourier Amplitude Sensitivity Test (FAST) method which is the global SA method undertaken here. Then, in Section 4, the detailed holistic SA process is reported with our SWAT application to the Minjiang River watershed in Sichuan, China. This analysis follows a general process of SA (Cheng et al., 2014; Gan et al., 2014): identifying uncertainty sources associated with submodels in SWAT, and propagating the uncertainty from the identified source. Results of analyzing the uncertainty sources using SA appear in Section 5. Specifically, this article identifies uncertainty sources related to model structure input parameters and datasets, as well as general model parameters. Then, uncertainty propagation methods are utilized with respect to the corresponding uncertainty sources. For spatial input datasets, the measurement uncertainty of a DEM is propagated using a sequential Gaussian simulation to represent spatially autocorrelated uncertainty (Goovaerts, 1997; Pebesma, 2004), and the boundary uncertainties of LULC and soil datasets are simulated by adopting the epsilon band approach (Crosetto and Tarantola, 2001; Shi, 1998). The SA evaluates the relative importance of the uncertainty sources in the average streamflow (FLOW) and loads of nitrate (NO3). This article concludes in Section 6 with a discussion on future work that could profitably be conducted in relation to our analysis.

2. Previous SA studies on SWAT

There has been too little attention given to sensitivity analysis of spatially distributed models that focuses on a wide range of uncertainties, especially the influence of model structure assumptions. In illustration, this section explores limitations of previous SA studies for the water quantity-quality model known as SWAT, partly because it provides a typical example of the limitations of previous sensitivity studies with respect to a spatially distributed environmental model. SWAT requires various model input datasets and parameters. Some of these factors are related to model structure uncertainty, as in its sequential submodels for these prerequisite processes, including spatial input datasets (e.g., DEM, LULC, and soil datasets) for watershed delineation and HRU creation. Although the submodels for these prerequisite processes can be considered as important sources of uncertainty that have interactions with the uncertainty of other submodels, as well as impacts on SWAT outputs, SA related studies remain incomplete in terms of addressing all sources of uncertainty, especially those related to spatial input datasets and parameters for the submodels.

Thus, in SWAT applications, SA has primarily been conducted with respect to SWAT parameters (e.g., Setegn et al., 2010; Yang et al., 2018). In general, they have found that only a few parameters have been identified in applications to be the major sources of uncertainty, with other parameters having minor influence (Kumar and Merwade, 2009; Li et al., 2010; Shen et al., 2008). However, model input parameters related to other submodels (e.g., watershed delineation and HRU creation) have received relatively less sensitivity and uncertainty attention, although the potential impacts of the parameters of these submodels have been recognized (Fitzhugh and Mackay, 2000; Rouhani et al., 2009). Fitzhugh and Mackay (2000), for example with an application in the Pheasant Branch watershed in Dane County, Wisconsin, reported that the size of a watershed has no critical impact on streamflow and outlet sediment estimation. Conversely, another study (Rouhani et al., 2009) involving a SWAT application in the Grote Nete River watershed in Belgium revealed that streamflow estimation is more accurate with respect to its observed value when a larger watershed size is employed. These uncertainties of the parameters can be partially related to the model structure uncertainty (Matott et al., 2009), which is caused by the inability of the model structure to represent watersheds and HRUs. In particular, investigating the uncertainty of the parameters related to subwatershed sizes helps to address a scale issue in the model, which is one major aspect of the model structure uncertainty (Butts et al., 2004), by exploring the different levels of abstracting and generalizing of process levels.

Uncertainty related to meteorological input datasets has been considered an important uncertainty source in SWAT modelling (e.g., Aouissi et al., 2013; Strauch et al., 2012; Tasdighi et al., 2018), with respect to both sampling (Villarini et al., 2008) and measurement errors (Ciach, 2002). Among the uncertainties related to meteorological information, the impact of the density of meteorological monitoring stations on SWAT predictions has received some attention, which is related to sampling uncertainty. The uncertainty of SWAT predictions has been shown to substantially increase with an excessive reduction in the number of meteorological monitoring stations until a certain threshold value (Bárdossy and Das, 2008; Chaplot et al., 2005). Correspondingly, Cho et al. (2009) reported an exponential increase in the uncertainty of SWAT predictions with a decreasing number of meteorological monitoring stations. In addition, SWAT allocates meteorological information from the nearest station to the center of subwatersheds (Aouissi et al., 2013; Masih et al., 2011; Scherer et al., 2015), which can be also considered a source of uncertainty in SWAT output estimation. Thus, advanced interpolation methods for meteorological information allocation have been developed to increase the accuracy of SWAT estimations (Masih et al., 2011; Strauch et al., 2012). However, the impact of measurement uncertainty in meteorological information on SWAT output estimation is rarely investigated, although measurement uncertainty has also been recognized as a source of uncertainty (Shen et al., 2015a).

Spatial input datasets (e.g., DEM, LULC, and soil datasets), which tend to be static over time, should also be investigated for their effects on uncertainty. Although these spatial input datasets are the most important inputs to delineate watersheds and are critical in describing underlying watershed characteristics (Ray, 2018; Shen et al., 2015a), their uncertainty has been only partially examined. The resolutions of spatial input datasets have been the main focus of previous studies (e.g., Chaubey et al., 2005; Dixon and Earls, 2009; Lin et al., 2013; Shen et al., 2013). Specifically, Dixon and Earls (2009) showed that the resolution of a DEM has a significant impact on streamflow volume estimation and watershed delineation (e.g., size and number of subwatersheds, and average slopes) with three different DEM resolutions (i.e., 30, 90, and 300 m). Similarly, Chaubey et al. (2005) found that a coarser DEM resolution, in a comparison of seven different DEM resolutions, yields decreased streamflow and nitrate load estimations due to a decrease in subwatershed sizes and slopes. Lin et al. (2013) also reported decreasing total phosphorus and nitrogen load accuracy with coarser DEM resolutions.

In addition, the resolutions of LULC and soil datasets affect HRU creation in SWAT, which can yield uncertainty in watershed attribute properties and streamflow estimation (Kumar and Merwade, 2009). Shen et al. (2013) demonstrated the existence of a threshold resolution of spatial input datasets (i.e., DEM and LULC), where a finer resolution did not benefit the accuracy of SWAT predictions. Furthermore, the resolutions of the spatial input datasets can balance each other. For example, when the DEM in a finer resolution than a threshold value is provided in SWAT, the resolution of LULC becomes less important (Shen et al., 2015a).

We contend that previous SA approaches have tended to evaluate only a modest set of the uncertainty sources in spatially distributed environmental models, especially in hydrology as illustrated above for the widely used SWAT model. A more holistic SA approach for SWAT would therefore be conducted with a focus on the following aspects. Firstly, although the uncertainty of model input parameters related to the submodels of a SWAT application (e.g., watershed delineation and HRU creation) have been partially addressed, their impacts on SWAT predictions are rarely examined. Secondly, the impact of measurement errors in meteorological information (e.g., precipitation, wind speed, solar radiation, relative humidity, and temperature) has been poorly evaluated in SWAT estimations even though meteorological information is considered as a critical source of uncertainty. Finally, the uncertainty of spatial input datasets has several strands that warrant investigation in SA exercises. One is the uncertainty of spatial data due to lineage, positional accuracy, attribute accuracy, logical consistency, and completeness (ANSI, 1998; Koo et al., 2017). Only the impact of spatial dataset resolution has been examined in SWAT applications. Other main sources of uncertainty in spatial datasets, due to positional (e.g., boundary uncertainty) and attribute (e.g., measurement uncertainty) accuracy, should also be considered in SWAT estimations.

3. Methods

3.1. SWAT

SWAT is a watershed model that was developed by the Agricultural Research Service of the U.S. Department of Agriculture (USDA) (Neitsch et al., 2011). SWAT has been extensively applied in various sectors, including water management, hydrology, climate change, land use impact, and pollution, to predict the environmental impacts (e.g., land use and climate change) on water quantity and quality. To implement SA for SWAT applications (Bastin et al., 2013), this paper uses a tool for automated SWAT preparation (Zhang et al., 2019), which is based on an open source Geographic Information System (GIS) interface for SWAT (MWSWAT) (George and Leon, 2008), and implements the SA based on the sensitivity analysis package in R (Pujol et al., 2018).

3.2. The extended FAST method

SA methods are broadly classified as screening, local and global methods (Saltelli et al., 2004). Our analysis applies the extended FAST method (Saltelli et al., 1999) to evaluate the uncertainties associated with model parameters and input datasets (i.e., factors), and their interactions, because the factors are not independent and typically interact with one another.

The extended FAST is one of the SA variance decomposition methods. The variance decomposition method evaluates the sensitivity of the model output using sensitivity indices (Sobol, 2001) which compute the fractional contributions of input uncertainty (X_i) to the variance in the model output (Y). This variance is defined as:

$$V = \sum_{i-1} V_i + \sum_{i<j} V_{ij} + \cdots + V_{1\ 2 \ldots d} \tag{1}$$

where

$$V_i = V[E(Y|X_i)]$$

$$V_{ij} = V\left[E\left(Y\middle|X_i,\ X_j\right)\right] - V_i - V_j$$

$E(Y|X_i)$ denotes the conditional expected value of Y on X_i, and $V[\cdot]$ represents a conditional variance. The main effect index (S_i) and the first-order interaction effect (S_{ij}) can be represented as follows:

$$S_i = V_i / V \tag{2}$$

$$S_{ij} = V_{ij} / V \tag{3}$$

The main effect index quantifies the effect of only X_i over the averaged variations in other factors and is scaled by the total variance to represent the fractional contribution. The total effect index (S_{Tj}) can be defined as:

$$S_{Tj} = 1 - V[E(Y|X_{-i})] / V \tag{4}$$

where X_{-i} is the subset of all elements (X) except X_i. The main and the total effect indices are generally used to determine critical factors and to screen out uncritical factors, respectively (Yang et al., 2018). This study explores the uncertainty caused by each factor (i.e., model input datasets and parameters, as shown in Table 1) on SWAT estimations and their interactions to understand the uncertainty effects across its submodels. However, an alternative solution is necessary to quantify interaction effects because a vast number of indices, which is $2^n - 1$ with n factors, needs to be estimated to represent all interaction effects among factors. The extended FAST can be an alternative (Saltelli et al., 1999) because it furnishes only the estimates of both the main and total effects. Because the total effect indices include a main effect and all higher-order interaction effects related to specific factors, an interaction effect can be

Table 1
Uncertainty sources of SWAT.

Submodel	Source
Watershed delineation	DEM, precision of stream networks (MinStream)
HRU creation	LULC, Soil dataset, MinLU, MinSoil, MinSlope, and IntSlope
SWAT execution	Meteorological input datasets (e.g., UPREC) and SWAT parameters

distinguished by subtracting the main effect index from the total effect index. Additionally, the extended FAST is known to show better efficiency than the Sobol method, which is another extensively employed sensitivity method (Gómez-Delgado and Tarantola, 2006).

The sampling technique for the extended FAST method is fixed, which converts a multi-dimensional integral to a one dimension integral (Gan et al., 2014). After the number of factors is determined, the minimum sample size (N_s) for the extended FAST is not changeable (Gan et al., 2014), and is calculated by the following (Saltelli et al., 1999):

$$N_s = \ N_r(2M\omega_i + 1) \tag{5}$$

where M denotes the interference factor (set to 4 in this analysis), ω_i represents the frequency assigned to the factor of interest, and N_r is the number of resamplings. For 15 factors, the ω_i and N_r are set to 143 and 3 in order to keep the ratio ω_i/N_r within 16 and 64, which is an optimal region for convergence of SA indices (Saltelli et al., 1999). Following this recommendation, the sample size in this analysis is determined as 3, 435.

4. Application

4.1. Study area and datasets

This study illustrates a more holistic SA approach to spatially distributed environmental models with a SWAT example in a subset of the Minjiang River watershed. The Minjiang River watershed is located in the upper part of the Yangtze River basin, and the subset of the watershed in this analysis covers approximately 12,893 km^2 (Fig. 1). The Minjiang River is the largest tributary of the Upper Yangtze River and supplies water to downstream regions for agriculture (e.g., Chengdu and its neighbors). This watershed is highly vulnerable to climate change due to its high elevation, which ranges from 1,627 to 5,419 m. Thus, the Minjiang River watershed has been a high priority for developing and conserving the Yangtze River regions (Cui et al., 2012).

As previously indicated, SWAT requires spatial input datasets (e.g., DEM, LULC, and a soil dataset) and meteorological input datasets (e.g., precipitation, wind speed, relative humidity, and solar radiance) for its execution. This study has conducted analyses using commonly available

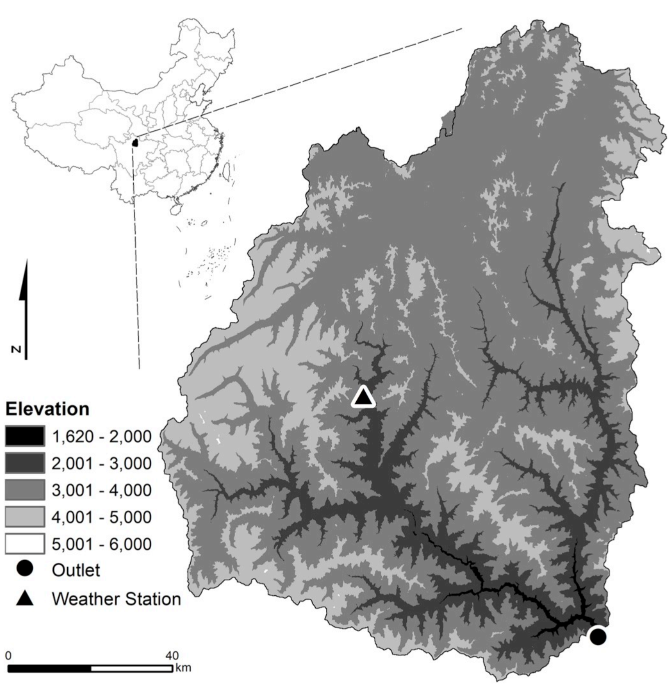

Fig. 1. Minjiang River watershed and a meteorological monitoring station.

spatial input datasets and meteorological input datasets (George and Leon, 2008) to ensure that its findings are readily applicable to other studies. The DEM was obtained from the NASA SRTM version 4.1, which was published by the Consultative Group on International Agriculture Research-Consortium for Spatial Information (CGIAR-CSI), with a spatial resolution of 3 arc-second (approximately 90 m) (Jarvis et al., 2008). The source of the LULC is based on the Global Land Cover Characterization (GLCC) database (Loveland et al., 2000), and the soil dataset was obtained from the Food and Agriculture Organization of the United Nations (FAO/UNESCO, 2003). Both the LULC dataset and the soil dataset are published in WaterBase (George and Leon, 2008) with spatial resolutions of 500 m and 600 m, respectively. The meteorological dataset was obtained using the National Center for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) (Fuka et al., 2014) in 2013. This study utilizes meteorological information from only one monitoring station to focus on the measurement uncertainty of meteorological information and avoid uncertainty produced by the numbers and locations of monitoring stations (Strauch et al., 2012).

4.2. Identifying sources of uncertainty

A SWAT application consists of three sequential submodels: watershed delineation, HRU creation, and SWAT execution. Each model requires separate model input datasets and parameters, which can be considered sources of uncertainty (Table 1). First, in the watershed delineation, a minimum threshold value is necessary for this analysis to designate drainage to a stream network (*MinStream*). Although a predefined stream network dataset can be superimposed on a DEM for accurate stream network delineation (e.g., Setegn et al., 2010), the predefined dataset should have a different precision depending on its target scale and/or scale of its source map. Thus, this analysis directly generates a stream network from the DEM to consider the uncertainty of the stream network precision. This stream network precision is directly related to the overall sizes of subwatersheds, which can partially address a scale issue in spatial datasets (Chrisman, 1991). Second, the DEM is required to delineate watersheds as a model input dataset. Previous studies have primarily addressed the impact of DEM resolution on SWAT estimations (e.g., Chaubey et al., 2005; Dixon and Earls, 2009; Shen et al., 2013). A DEM also contains systematic and random errors due to an inherent elevation measurement error, whose impact on watershed delineation has been investigated (Hengl et al., 2010; Oksanen and Sarjakoski, 2005; Wu et al., 2008). Thus, the measurement error of DEM (*UDEM*) can have an influence on SWAT estimations.

Second, the HRU creation model requires additional model input datasets, i.e., LULC and soil datasets, because HRUs are generally formed as a combination of LULC, soil, and slope ranges. These datasets can be considered sources of uncertainty in this submodel. SWAT classifies slope range on an ordinal scale. For simplification of this analysis, the slope range is divided into two groups based on the intermediate value of slope as a percentage. Then, the intermediate value of the two groups (*IntSlope*) is used as a model input parameter, which can be a source of uncertainty. However, a slope dataset itself is not considered a source of uncertainty in this analysis because a slope dataset is directly generated from the uncertainty propagated DEM. Additionally, input parameters of three models are required to define multiple HRUs in a watershed. The model parameters are used to eliminate small HRUs by considering minimum percentages for the categories of LULC (*MinLU*), soil (*MinSoil*), and slope (*MinSlope*).

Lastly, the meteorological input dataset and SWAT parameters can be sources of uncertainty. The meteorological input dataset includes precipitation, temperature, wind speed and solar radiation, as well as information about meteorological monitoring station locations. For simplicity, this analysis considers only uncertainty in precipitation (*UPREC*) because the uncertainty of precipitation is known to generally have a greater influence on SWAT estimations than any other meteorological input datasets (Chaplot et al., 2005; Strauch et al., 2012).

Specifically, a measurement error in precipitation is the main interest in this analysis, and the positional uncertainty of monitoring stations for precipitation measurement is not evaluated because previous studies have adequately addressed this aspect (e.g., Bárdossy and Das, 2008; Chaplot et al., 2005; Fu et al., 2011). With regard to SWAT parameter uncertainty, only a few significant parameters (see the Appendix) are selected and applied here in the SA to reduce the computational cost and to concentrate on other factors (e.g., *MinStream* and *UPREC*), although SWAT applications typically consist of hundreds of model parameters (Neitsch et al., 2011, pp. 567–595).

4.3. Propagating the identified uncertainty sources

Obtaining a proper uncertainty propagation model, especially with plausible range and distributional assumptions, is a crucial process in SA. The propagation model primarily reflects the degree of uncertainty in model inputs and determines the impact on the uncertainty of model output. Generally, a scalar random variable (e.g., model input parameters) can be simply represented using a probability density function. However, complex types of model inputs (e.g., spatial input datasets) require a more complex uncertainty propagation model by simultaneously considering various components of uncertainty (Crosetto and Tarantola, 2001). This study introduces various propagation models for the corresponding uncertainty sources with their justification.

For watershed delineation, two sources of uncertainty were identified in the previous section: *UDEM* and *MinStream*. Generating the uncertainty propagation model for *UDEM* is a challenge due to the complexity of the DEM and the existence of spatial autocorrelation in the DEM measurement errors (Temme et al., 2009). Thus, a limited number of relevant studies have been conducted (e.g., Fisher, 1998; Hengl et al., 2010; Holmes et al., 2000). To describe the spatially correlated structure of *UDEM*, this study constructs its uncertainty propagation model based on a sequential Gaussian simulation (Goovaerts, 1997; Pebesma, 2004). Then, the propagated values of *UDEM* are scaled based on a normal distribution to reflect the realistic range of measurement uncertainty in *UDEM*. The value of the scale parameter, which indicates the accuracy (i.e., difference to the true value) at a 95% confidence level, determines the level of uncertainty in *UDEM*. The scale parameters are uniformly distributed in the range between 0 and 16 because the total vertical accuracy in an SRTM v4.1 dataset with a 3 arc-second resolution is ±16 m at a 95% confidence level (Mukul et al., 2017). Lastly, the generated values of *UDEM* are added to the original DEM. Fig. 2 shows examples of the uncertainty propagation model of *UDEM* with the scale parameter values of 4, 8 and 16.

Another source of uncertainty in watershed delineation is *MinStream*, which is a critical parameter for determining the precision of a stream network. *MinStream* is simply modelled here based on a uniform distribution because it is represented as a scalar random variable. Because *MinStream* parameter uncertainties have not been fully considered in previous SA studies and is the critical parameter to determine spatial scales of a subwatershed, this parameter is examined with two different ranges. The uncertainty associated with *MinStream* is modelled by changing its uniformly distributed values in the range between 5,000 and 15,000 and 10,000–15,000 by considering widely available spatial datasets for stream networks. Specifically, the generated stream network from the *MinStream* value of 15,000 approximately corresponds to the stream network in the 1:1,000,000 Vector Map (i.e., VMAP0), and that from the value of 5,000 shows slightly coarser stream network than the 1:250,000 topographic map [i.e., Joint Operations Graphic (JOG)]. Fig. 3 illustrates examples of the stream network generation with *MinStream* values of 5,000, 10,000, and 15,000. In Fig. 3, the precision of the generated stream network tends to decrease when *MinStream* is increased. For instance, by increasing *MinStream,* an exponential decrease in the line feature counts of the generated stream networks (Fig. 3), which are 189, 89, 51 features for MinStream values of 5,000, 10,000, and 15,000, respectively, is observed. *MinStream* also relates strongly to overall size and number of subwatersheds. An increase in *MinStream* would lead to an increase in the number of subwatersheds, and a decrease in the overall size.

In the HRU creation submodel, uncertainty propagation models were generated for the following uncertainty sources, which have associated model input datasets, i.e., LULU (*ULUCL*) and soil datasets (*USOIL*), and model input parameters, i.e., *MinLU*, *MinSoil*, *MinSlope*, and *IntSlope*. *ULULC* and *USOIL* require an uncertainty propagation model that differs from the previous uncertainty propagation model for *UDEM*. It is noted, however, that LULC, soil datasets, and DEM are the same as raster datasets because they are represented on a different measurement scale (i.e., LULC and soil datasets are categorical raster datasets but the DEM is a quantitative raster dataset) (Heuvelink, 1998). This study constructs the uncertainty propagation models for *ULUCL* and *USOIL* by adopting the concept of the epsilon band, which was originally developed for vector data to represent boundary uncertainty (Crosetto and Tarantola, 2001; Shi, 1998). *ULUCL* is modelled using a uniformly distributed band within 2,000 m on both sides because LULC is generated based on a 1 km

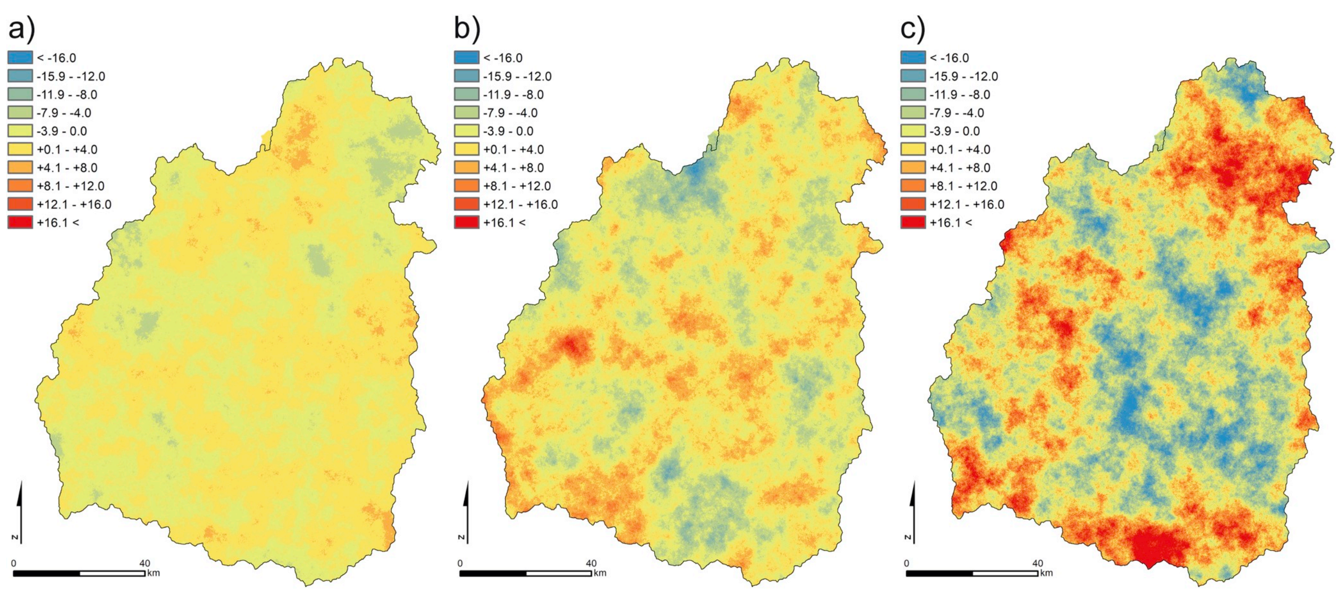

Fig. 2. Examples of DEM measurement error to be used for uncertainty propagation.

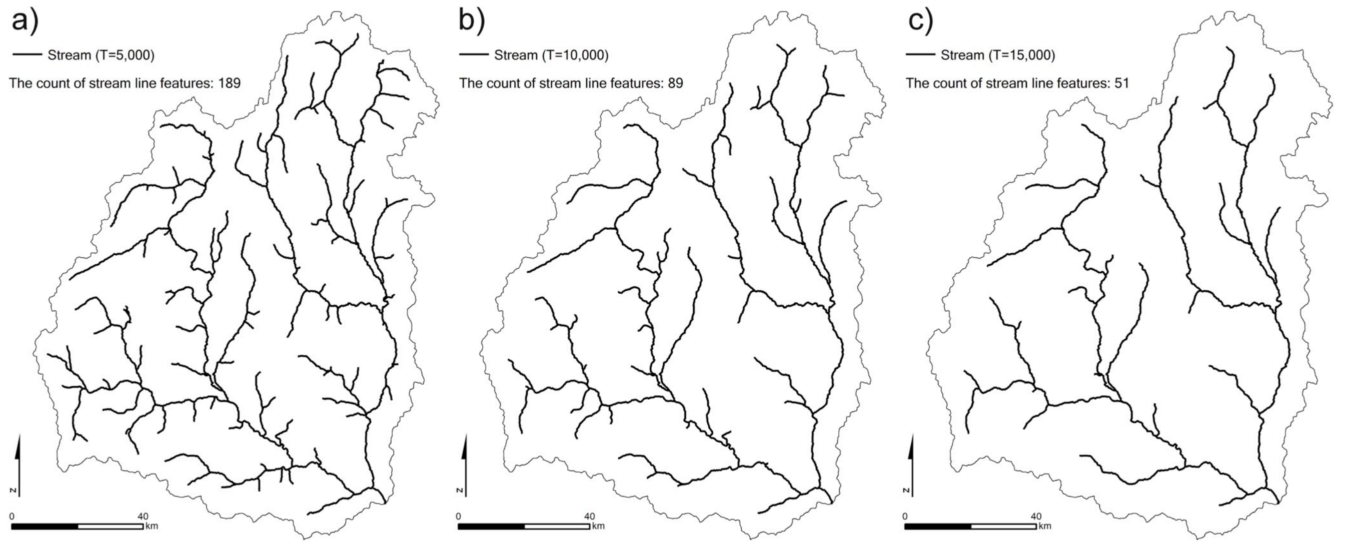

Fig. 3. Examples of the uncertainty propagation model for stream network precision.

monthly Advanced Very High Resolution Radiometer (AVHRR) satellite image. Similarly, *USOIL* is modelled within 2,500 m on both sides by adopting the rule of thumb for the positional uncertainty from maps (Longley et al., 2011), which represents the maximum uncertainty of 0.5 mm at the sources of the soil dataset (i.e., Soil Map of the World at 1:5 million). Because the uncertainty propagation models of *MinLU*, *MinSoil*, *MinSlope*, and *IntSlope* have not been fully investigated in previous research, all possible ranges of the parameters are examined here by assuming a uniform distribution. *MinLU*, *MinSoil*, *MinSlope*, and *IntSlope* were given the ranges of [5, 42], [5, 50], [5, 50], and [0.05, 0.8], respectively (Table 2).

We now address the uncertainty propagation models used for *UPREC* and the SWAT parameters for SWAT execution. Firstly, the uncertainty propagation model for *UPREC* is constructed based on a uniform distribution in the range [-15.2, 15.2] with a relative change to its observed precipitation. This range reflects the maximum measurement error of precipitation in China, which varies from ±4.34% to ±15.2% with a mean of ±6.52% in China according to the State Meteorological Administration (Ren et al., 2003; Shen et al., 2015b).

For the SWAT parameters, we chose the more sensitive SWAT parameters using the Morris screening method (Morris, 1991) among the candidate SWAT parameters acquired from the SWAT model calibration literature (e.g., Abbaspour, 2015; Abbaspour et al., 2007; Yang et al., 2018) (Appendix). Also, the ranges of the SWAT parameters (Table A-1) follow standard levels in SWAT model calibrations and SA studies, in the absence of better information. The selected parameters, in accordance with their SWAT parameter names, are the following: *ALPHA_BF*, *GW_DELAY*, *CN2*, *ESCO*, *RCN*, and *NPERCO*. Briefly, *ALPHA_BF* and GW_DELAY are used to describe the properties of groundwater, and *CN2* is the type of HRU management option, which includes land and water management practices. *ESCO* is related to the HRU general input file and describes diverse features within HRUs. *RCN* and *NPERCO* are utilized to define general watershed attributes, which are expected to be sensitive factors for nitrate outputs (*NO3*). Finally, Table 2 describes all selected parameters and their uncertainty propagation models that are used in the following sensitivity analyses (Refer Table A-1 for further detail of SWAT parameters).

5. Results of analyzing the uncertainty sources through SA

This analysis evaluates the impacts of the fifteen factors on variations in the two SWAT output estimates considered; i.e., *FLOW* and *NO3* at the

Table 2
The corresponding uncertainty propagation models of the identified uncertainty sources in SWAT.

Submodel	Source	Description	Model
Watershed delineation	UDEM	Spatially autocorrelated measurement errors of elevations	Sequential Gaussian simulation with the uniformly distributed scale parameters [0, 16]
	MinStream	Uncertainty with the minimum threshold value to designate drainage to a stream	U [5,000, 15,000]
HRU creation	ULUCL	Boundary uncertainty of landuse categories (m)	Epsilon bands between [-2,000, 2,000]
	USOIL	Boundary uncertainty of soil categories (m)	Epsilon bands between [-2,500, 2,500]
	MinLU	Uncertainty with the minimum percentage for a landuse category in HRU (%)	U [5, 42]
	MinSoil	Uncertainty with the minimum percentage for a soil category in HRU (%)	U [5, 50]
	MinSlope	Uncertainty with the minimum percentage for a slope category in HRU (%)	U [5, 50]
	IntSlope	Uncertainty with the intermediate slope percentage (%)	U [0.05, 0.8]
SWAT execution	UPREC	Percentage of measurement errors to observed precipitation (%)	U [-15.2, 15.2]
	ALPHA_BF	Uncertainty of the baseflow alpha constant	U [0, 1]
	CN2	Uncertainty of SCS run off curve number for moisture condition	U [-0.15, 0.15]
	ESCO	Uncertainty of soil evaporation compensation factor	U [0, 500]
	GW_DELAY	Uncertainty of ground water delay time (day)	U[0, 500]
	NPRECO	Uncertainty of nitrate percolation coefficient	U [0.01, 1.00]
	RCN	Uncertainty of nitrogen in rain (mg N/L)	U [0, 2.5]

*U denotes a uniform distribution model.

outlet of the Minjiang River watershed (refer to Fig. 1). Firstly, the impacts of the fifteen factors on *FLOW* are evaluated in terms of the main and total effect indices using the extended FAST (Fig. 4). As we discussed in Section 4.3, two different ranges of *MinStream* [i.e., the wide range (W-SA) between 5,000 and 15,000 and the narrow range (N-SA) between 10,000 and 15,000] are applied in the SA for further exploration of this factor. For both SA results, the main effect shows that five factors have a larger influence than others on the variation in *FLOW*: *MinStream*, *CN2*, *UPREC*, *GW_DELAY* and *ESCO*. Although in comparing N-SA (Fig. 4-b) to W-SA (Fig. 4-a), the main effect of *MinStream* decreases [i.e., *MinStream* (65.8%–54.7%)] and those of other four factors increase [i.e., *CN2* (6.2%–12.5%), *UPREC* (5.0%–9.4%), *GW_DELAY* (3.3%–6.6%) and *ESCO* (1.8%–2.7%)], the order of their main effects are still consistent. The range of generated stream feature counts in N-SA is much narrower than those in W-SA (i.e., 51–89 and 51–189, respectively. see Fig. 3), but *MinStream* still has the largest influence on *FLOW*. The main effects of other factors are less than 1%. In the total effects for both SA results, *MinStream* (77.3% and 64.8%), the three SWAT parameters [i.e., *CN2* (18.9% and 25.3%), *GW_DELAY* (8.2% and 10.4%), *ESCO* (9.1% and 10.2%)], and *UPREC* (12.4% and 14.5%) have the greatest influence on *FLOW*. The difference between the total and main effect indices provides the interaction effect between a factor and other factors. Comparing N-SA (Fig. 4-b) to W-SA (Fig. 4-a), the overall interaction effects, especially of the factors related to the HRU creation submodel, decreases, which could suggest that *MinStream* highly interacts with the factors.

The SA results for *NO3* show a slightly different relative importance among the fifteen factors compared with the previous results for *FLOW* (Fig. 4). With main effect indices, *MinStream* (22.0%) is still the most critical factor in the W-SA result (Fig. 5-a), but in the N-SA result (Fig. 5-b), the SWAT parameters, i.e., *RCN* (20.5%), *NPERCO* (16.7%), *CN2* (14.8%), have a larger influence on the *NO3* variation than *MinStream* (14.7%). *UPREC* shows a relatively high value for the main effect index (0.9% and 1.5% in W-SA and N-SA results, respectively), whilst the main effects of other factors have still much smaller impacts, less than 1%. With the interaction effect, the *NO3* results show a similar trend with the previous *FLOW* results, which is an overall decrease in the interaction effects compared to N-SA (Fig. 5-b) with W-SA (Fig. 5-a). In the N-SA result, the interaction effects for all factors, except for the five critical factors, are less than 1%. We suspect that a decrease in the impact of *MinStream* leads to this decrease in the interaction effects.

These SA results suggest the following findings. Firstly, the precision of a stream network (*MinStream*) in the watershed delineation submodel generally has the largest impact on variations in *FLOW* and *NO3*. Fig. 6 shows the relationships among *MinStream*, subwatershed count, and the estimations of *FLOW* and *NO3* over the wide range of *MinStream* (W-SA). In this analysis, *MinStream* shows a significantly negative relationship with the number of generated subwatersheds, with a correlation coefficient of -0.975 (p-value < 0.001) (Fig. 6-a), which indicates that the number of subwatersheds and the watershed delineation model can substantially affect SWAT estimations. This result is consistent with a previous study (Chaubey et al., 2005), in which as the number of watersheds increases (i.e., the subwatershed size decreases), the average streamflow and nitrate load decreases (Fig. 6-b and c). Also, by comparing SA in its narrow range with its wide range (W-SA), *MinStream* could contribute to increases in the overall total effects due to its high interaction with other factors.

Secondly, the uncertainties of input datasets and parameters for the HRU creation (i.e., *ULUCL*, *USOIL*, *MinSoil*, *MinSlope*, *MinSlope*, and *IntSlope*) have small impacts on the SWAT estimations with the ranges of the factors selected. Thus, this application shows that uncertainty in the HRU creation has a lesser effect on variations in the SWAT outputs than any other submodels. Thirdly, the total effects results show that *UPREC* addresses 12.4% and 14.5% of the *FLOW,* and 5.1% and 3.2% of the *NO3* variations in the case of the W-SA and N-SA results, respectively, which could require stronger consideration of measurement uncertainty of precipitation in SWAT applications.

Finally, this analysis reconfirms that certain SWAT parameters are the other important uncertainty sources in SWAT outputs according to high values in their main and total effects indices. As known in previous studies (e.g., Abbaspour et al., 2007), *CN2* (SCS runoff curve number for moisture condition) has an influence on both *FLOW* and *NO3*, and *RCN* and *NPERCO* have impacts on *NO3* only. However, the HRU management option, for example, fertilizer management including types and amount of fertilizers, may have considerable impacts on *NO3* output but this analysis did not specify the related management options.

6. Conclusion

A wide range of sources of uncertainty and their relative importance were examined in the context of an integrated, spatially distributed environmental model based on a SWAT application in the Minjiang River watershed in Sichuan, China. This paper identified the strength of uncertainty sources with respect to watershed delineation, HRU creation, and SWAT execution, thereby addressing the uncertainty of model structure through uncertainties of the input parameters and datasets in these submodels. With the ranges of the factors explored, results of our analysis show that the uncertainty of the stream network precision (*MinStream*) and certain SWAT parameters, [e.g., *CN2* (SCS runoff curve number for moisture condition), *GW_DELAY* (Ground water delay time) and *ESCO* (Soil evaporation compensation factor)] for the *FLOW* output,

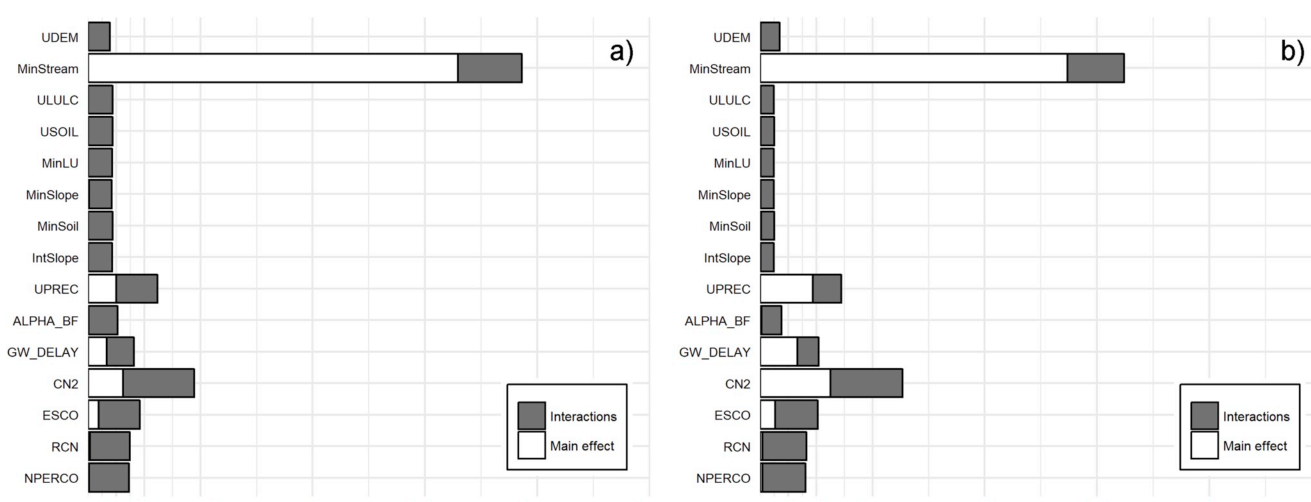

Fig. 4. SA results for estimation of *FLOW*: a) the wide range of *MinStream* (W-SA), and b) the narrow range of *MinStream* (N-SA).

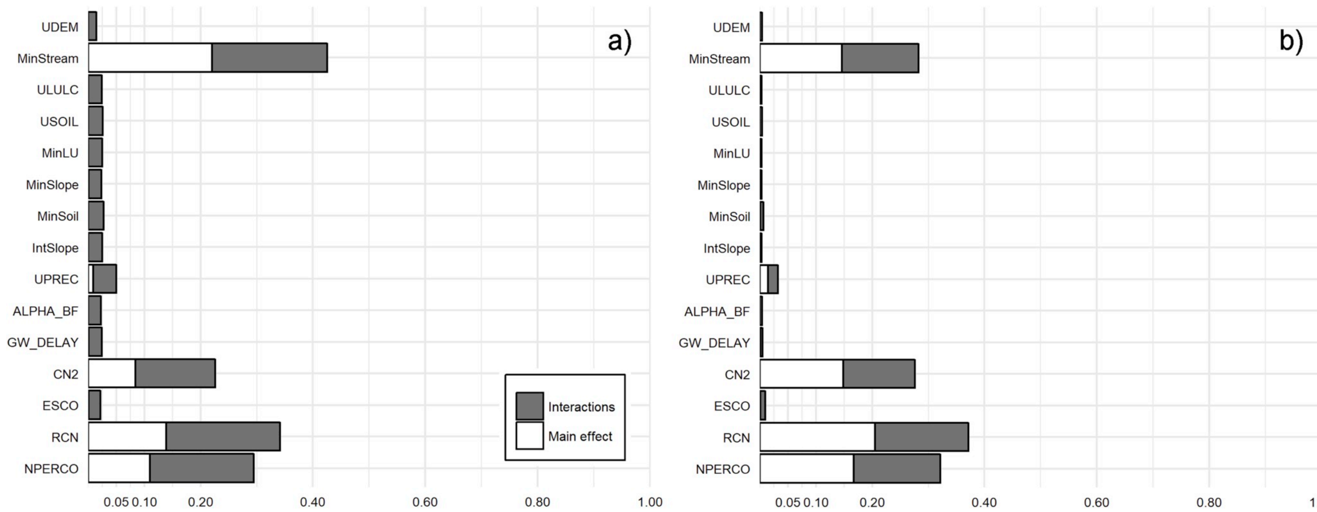

Fig. 5. SA results for NO3: a) the wide range of *MinStream* (W-SA), and b) the narrow range of *MinStream* (N-SA).

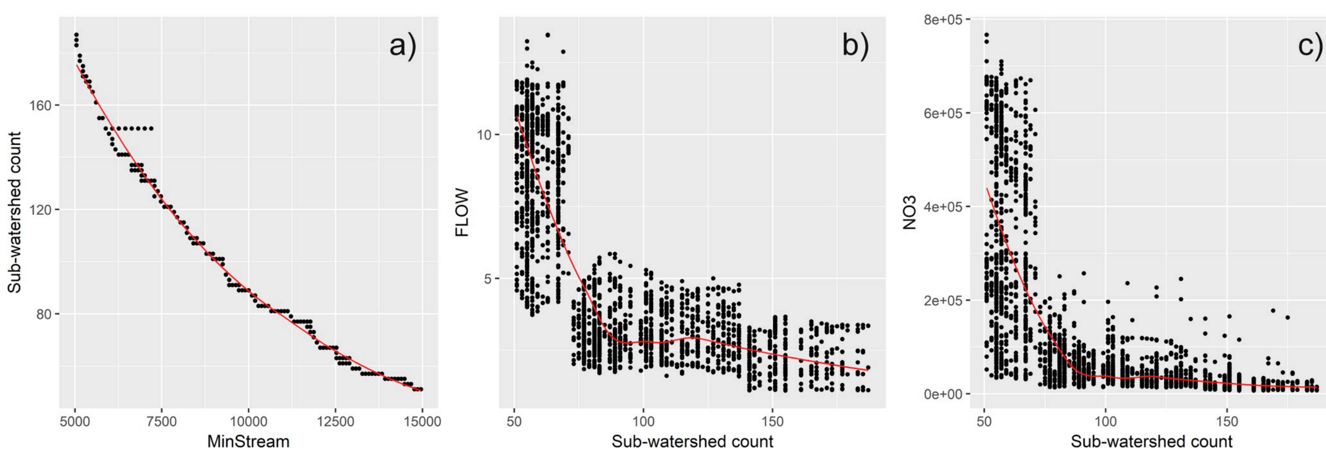

Fig. 6. Relationships among *MinStream*, subwatershed count, *FLOW* and *NO3*.

and *RCN* (Nitrogen in rain), *NPERCO* (Nitrate percolation coefficient), and *CN2* for *NO3*, as well as the measurement uncertainty of precipitation are the most critical factors for the SWAT predictions.

Importantly, among various uncertainty sources related to the submodels, the stream network precision has a strong influence on both the variations of water quantity and quality estimations, because it has a profound effect on watershed delineation and specifically determines the overall sizes of subwatersheds. In addition, the stream network precision propagates influences on factors in subsequent submodels. Thus, this analysis shows that selecting an appropriate spatial scale to describe underlying subwatersheds can be a fundamentally important step for SWAT modelling. Furthermore, this study illustrates the inherent spatial scale of a spatial input dataset in spatially distributed environmental models needs to be considered as a source of uncertainty (i.e., a factor of in the SA analysis).

This article aims to contribute to SA practice considerations more widely, beyond SWAT to the implications for spatially distributed environmental models. Specifically, the framework of SA examined in this paper provides a solid starting point for subsequent analyses of various spatially distributed integrated watershed models. Although this analysis was conducted specifically using a SWAT application, other environmental models [e.g., Storm Water Management Model (SWMM) (Rossman, 2010)] may contain similar kinds of uncertainty sources, for example, model input datasets and parameters. In particular, the uncertainty propagation methods used in this analysis, for example, a propagation model for measurement uncertainty considering its reported accuracy (e.g., SRTM and precipitation) and for positional uncertainty incorporating the rule of thumb for the positional uncertainty from maps (Longley et al., 2011), would be easily applicable to other spatially distributed environmental models.

This study has illustrated a more holistic SA process applied to a single geographic region. Therefore, the specific results may not be applicable to other geographical regions; that is, the uncertainty sources may show different relative importance in other study areas. Also, similar to other SA studies, SA results should be carefully interpreted with only selected ranges of prior distributions for corresponding factors. The criticality of a factor is determined with the selected ranges of all related factors, which should be explained in regard to only the selected ranges. However, the SA process in this paper is expected to offer guidance for more general SWAT applications and other spatially distributed environmental model applications.

Another proposed extension relates to achieving more realistic and credible uncertainty propagation models for model input parameters. Although an uncertainty propagation model has a significant effect on the results of SA, the models of the input parameters in the HRU creation submodel (i.e., *MinLU*, *MinSoil*, *MinSlope*, and *IntSlope*) might not be realistic. The complete possible ranges under a uniform distribution were evaluated here due to the lack of findings from previous studies. Although they have a small impact on the SWAT estimations in this application within the complete available ranges, an additional evaluation of the impact of the different ranges and/or probability distributions on the uncertainty analysis results may be profitable. One approach is to apply model emulation to SWAT, which would yield sensitivities to factors throughout their entire range, as undertaken in Yang et al. (2018).

This analysis has used a traditional global SA based on spatio-temporally aggregated measures (e.g., yearly average streamflow and *NO3* loads), which neglects spatio-temporally dynamical behaviors of environmental models (Gupta and Razavi, 2018). Specifically, spatio-temporal variations of SA for stream flow can vary under different conditions, such as higher precipitation in summer in the study area, and thus the use of aggregated measures can provide a limited perspective for SA. Incorporating spatio-temporally varying SA [e.g., generalized global sensitivity matrix approach (Razavi and Gupta, 2019)] into our SA approach would be helpful to support a better understanding of the dynamic behavior.

Some relatively well-known uncertainty sources (e.g., spatial distribution and the number of meteorological monitoring stations, resolutions of input spatial datasets) were not addressed here. Although their main effects on SWAT estimations are relatively well explained, the interaction effects of the missing sources with the identified uncertainty sources in this analysis should be investigated.

Finally, reliability and convergence tests might be necessary for SA results. Conducting analysis with different SA methods [e.g., McKay main and two-way interaction effect analysis (McKay, 1995)] applied to the current holistic set of factors might be helpful in enhancing the reliability of the results. Multiple methods help to provide a more complete and robust understanding of critical sources because different SA methods might yield somewhat different results as to the relative importance of factors (Pappenberger et al., 2008; Teng et al., 2017) due to the fact they either measure different effects or evaluate them in different ways. Additionally, although the extended FAST provides guidance on the minimum sample size for its convergence (Saltelli et al., 1999), it would be worth conducting a convergence analysis to enhance the credibility of the SA results (e.g., Vanrolleghem et al., 2015).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

The Morris screening method (Morris, 1991) was applied to SWAT parameters to select critical uncertainty sources on streamflow (designated as FLOW) and nitrate (NO3). Based on the Morris screening results (i.e., the absolute mean and standard deviation of their elementary effects), these following six SWAT parameters were chosen for the subsequent extended FAST analyses: v_ALPHA_BF.gw, v_GW_DELAY.gw, r_CN2.mgt, v_ESCO.hru, v_RCN.bsn, and v_NPERCO.bsn (Fig. A-1). Table A-1 lists the candidate SWAT parameters and their ranges. The candidate parameters are relative well known to be sensitive to streamflow and nitrate loads (Abbaspour et al., 2007), and their ranges follow standard levels of SWAT model parameterization (Abbaspour, 2015; Yang et al., 2018). The notation 'v_' or 'r_' in the factor names denotes a replacement or a relative change, respectively, to their initial values. All parameters are globally applied into replacement and change into the entire study area (Yang et al., 2007). Refer to the SWAT documentation for additional descriptions of the SWAT parameters (Neitsch et al., 2011).

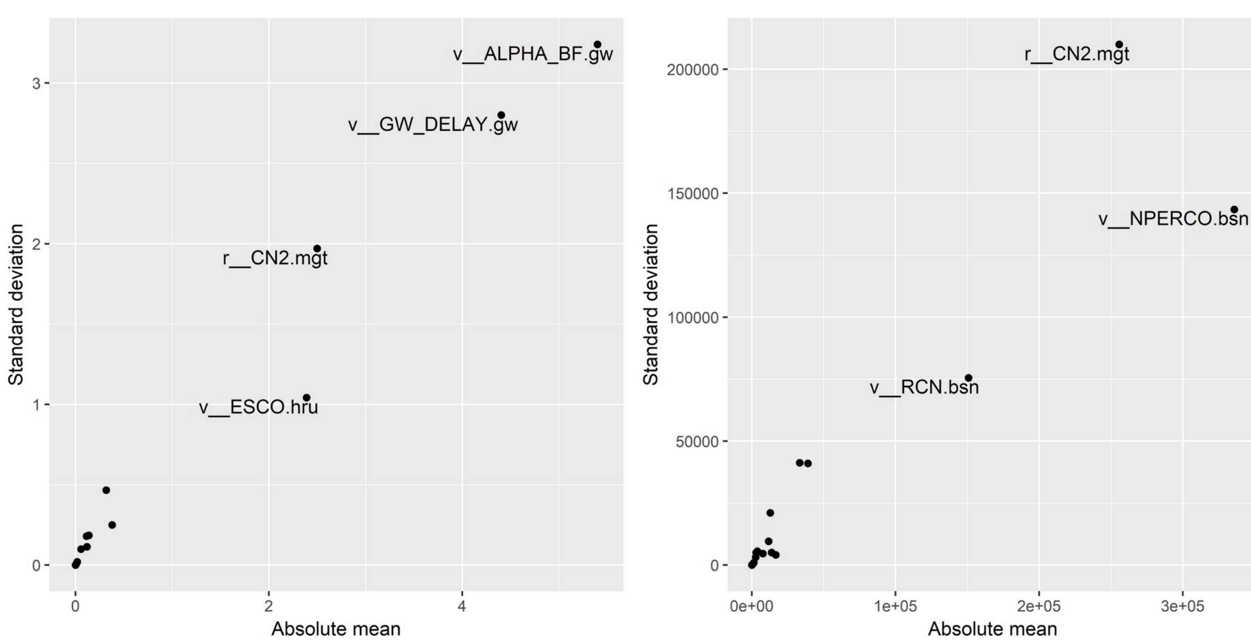

Fig. A-1. The Morris screening results: a) FLOW and b) NO3

Table A-1
Candidate SWAT parameters and their ranges

No.	Factor	Range	SWAT parameter
1.	v_ALPHA_BF.gw	[0, 1]	ALPHA_BF: Baseflow alpha factor
2	v_CANMX.hru	[0.1, 1]	CANMX: Maximum canopy storage (mm H_2O)
3	v_CH_K2.rte	[0, 500]	CH_K(2): Effective hydraulic conductivity in the main channel alluvium (mm/hr)
4	v_CH_N2.rte	[0, 0.3]	CH_N(2): Manning's 'n' value for the main channel
5	r_CN2.mgt	[-0.15, 0.15]	CN2: SCS runoff curve number for moisture condition
6	v_ERORGN.hru	[0, 5]	ERORGN: Organic N enrichment for sediment
7	v_ESCO.hru	[0, 1]	ESCO: Soil evaporation compensation factor
8	v_GW_DELAY.gw	[0, 500]	GW_DELAY: Ground water delay time (day)
9	v_GWQMN.gw	[0, 1000]	GWQMN: Threshold water level in shallow aquifer for baseflow (mm)
10	v_NPERCO.bsn	[0.01, 1]	NPERCO: Nitrate percolation coefficient
11	v_RCN.bsn	[0, 2.5]	RCN: Nitrogen in rain (mg N/L)
12	v_REVAPMN.gw	[0, 500]	REVAPMN: Threshold depth of water in shallow aquifer for 'revap' (mm)
13	v_SFTMP.bsn	[-1, 1]	SFTMP: Snowfall temperature (°C)
14	v_SMTMP.bsn	[-1, 1]	SMTMP: Snow melt base temperature (°C)
15	r_SOL_AWC.sol	[-0.25, 0.25]	SOL_AWC: Soil available water storage capacity (mm H_2O/mm soil)
16	v_SURLAG.bsn	[0, 24]	SURLAG: Surface runoff lag time (day)

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