Research papers

Uncertainty in simulation of land-use change impacts on catchment runoff with multi-timescales based on the comparison of the HSPF and SWAT models

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\textbf{A R T I C L E  I N F O}

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\textbf{A B S T R A C T}

Hydrological modeling has provided key insights into the mechanisms of land-use change impacts on runoff. However, the uncertainty of this impact is poorly understood. This paper examines the uncertainty originated from hydrological models' parameters and structure in simulating hydrological responses to land use change on daily, monthly and annual time scales. Two hydrological models, SWAT and HSPF, were applied to simulate the runoff response in the Xitaixiao basin of eastern China. The effects of three land use scenarios (in 1985, 2002 and 2014) were analyzed with respect to the expansion of urban areas and reduction of cropland and forests. The changes in streamflow with multi-timescales between two models were compared at the whole basin and the sub-basin scales. The parameter uncertainty was estimated based on a sequential uncertainty analysis method (SUFI-2). The results indicate that the two models (SWAT and HSPF) could reproduce the observed daily and seasonal flows well, but they cannot accurately reconstruct the extreme flows (such as annual 7-day minimum discharge, R\textsubscript{7dMIN}). The effect of parameter uncertainty on streamflow varies over time scales. The simulated annual and monthly runoff change values show large discrepancies but with same trends. The simulated changes for annual maximum discharge (R\textsubscript{1dMAX}) and R\textsubscript{7dMIN} often show different signs. The average width of the predictive interval in the relative change of different flow characteristics exceeded 100\% of the average relative changes for both models. HSPF tends to present larger relative changes for the annual and monthly runoffs compared to SWAT. Moreover, the model choice could affect the direction change in R\textsubscript{1dMAX} and R\textsubscript{7dMIN}. However, when land use change was significant to a certain degree, both models simulated increased R\textsubscript{1dMAX} and decreased R\textsubscript{7dMIN}, but with different significance levels. The study suggests that the model structure represents an additional uncertainty, which should be accounted for in the land-use change impact assessment.

\textbf{1. Introduction}

Land use change caused by human activities is an important driver that alters the hydrological and ecological processes over a range of temporal and spatial scales. It influences canopy interception, infiltration and evaporation, thus causing flood-drought disasters and ecological complications (e.g., Chang, 2007; Chen et al., 2009; Chu et al., 2013; Lin et al., 2015; Zhang et al., 2018). Therefore, a comprehensive understanding and assessment of land-use change impacts on hydrological processes is essential for environmental policies and decisions, which should provide managerial options that focus on water resource allocations, riparian ecosystem protection and river restoration, etc. (Chu et al., 2013; Sharifi et al., 2017).

In the last two decades, many efforts were made to better understand the impacts of land use change on hydrological processes. The spatially distributed hydrological models were widely employed to predict the hydrological responses to land use change (Singh et al., 2015; Li et al., 2018b). Conventionally, this is done by setting up a
hydrological model for a baseline land use scenario (LUS). After calibrating and validating the model, it is then re-processed for different LUSs using the same meteorological inputs. Subsequently, the differences between these simulations are compared. However, it is widely acknowledged that hydrological modelling is subject to a wide range of uncertainties, which are commonly from the measured input data, model parameters and model structure (Xu et al., 2007; Ma et al., 2018). Considering these sources of uncertainty, it seems reasonable to doubt the reliability of the estimated hydrological responses to land use change, especially when minor or moderate responses were observed (Brath et al., 2006; Huisman et al., 2009; Yin et al., 2017).

Although much attention has been paid to the model predictive uncertainties, less for uncertainties in the context of impact assessment of land-use change. Model structural and parameter uncertainties can generally be considered as the two main sources in the hydrological modeling process (Brigode et al., 2013). Parameter uncertainty represents the prediction uncertainty derived from parameter non-unicity due to parameter interactions and model complexity (Jiang et al., 2015). Eckhardt et al. (2003) and Breuer et al. (2006) examined the parameter uncertainty in the hydrological response to land use change based on a Monte Carlo simulation, and their results suggest a significant output uncertainty due to the uncertainty in the model parameterization. In a recent study, Niraula et al. (2015) found that the values for both absolute and relative changes in runoff due to land use change were significantly different for different calibration approaches (i.e., an uncalibrated, a single outlet calibrated, and a spatially calibrated model). These varied calibration approaches reflect the impacts of the different parameter sets to some extent. Previous studies show that the uncertainty related to the hydrological model parameters could be significant and it should not be overlooked in land use change impact studies.

In terms of structural uncertainty, it is generally caused by the limited understanding and simplification of real hydrological systems. All model structures contain errors to some extent (Athira et al., 2018). However, most of the studies employ a single hydrological model in impact assessment of land use change and disregard any structural uncertainty therein. The selected hydrological model might strongly affect the hydrological response to land use change. The LUICHEM (Assessing the impact of Land Use Change on Hydrology by Ensemble Modeling) project (Breuer and Huisman, 2009; Huisman et al., 2009) applied an ensemble of 10 hydrological models in the Dill catchment of Germany, to address the impact of land-use change. The results indicated that there was a general agreement between the direction change in the mean annual discharge. Similarly, Cornelissen et al. (2013) and Morán-Tejeda et al. (2015) addressed the model structural uncertainty in the evaluation of hydrological sensitivity to land use and climate changes based on different hydrological model types and different process-based hydrological models. The results from both studies indicated that the model choice could exert a significant influence on hydrological response to land use change. However, these studies have employed different calibration techniques or various objective functions to calibrate the hydrological models. The differences in calibration schemes may affect the simulated hydrological responses between the models (Niraula et al., 2015).

Although all the above studies indicated that the uncertainty stemming from the model parameters or model structure has significant influence on the impact assessment of land use change, they mainly focused on the impacts of model uncertainty in annual or monthly runoff, rather than daily scale or extreme conditions. Until now, how the uncertainty stemming from the model parameters and model structure affects the land-use change impacts on a daily scale remains unknown. Thus, the main objective of this study is to assess (1) the influence of parameter uncertainty and (2) the effects of model structure uncertainty in simulation of land-use change impacts on catchment runoff at annual, monthly and daily time scales at the Xitiaoxi basin, which is one of the most important catchments in the Taihu Lake basin, China. It has been undergoing intensive land use change due to rapid economic growth and urbanization in the past decades (Zhang et al., 2014a). Runoff change characteristics due to land use change in the Xitiaoxi basin are therefore important in helping to manage the Taihu Lake in a sustainable healthy manner (Zhou et al., 2013). To this end, two watershed models, the Soil and Water Assessment Tool (SWAT) and the Hydrological Simulation Program-Fortran (HSPF), and three historical LUSs were used to simulate the hydrological response at annual, monthly and daily time scales, in the Xitiaoxi basin.

The structure of this paper is as follows. Section 2 introduces the study area and land use change. Then, the details about the two hydrological models, the model calibration method and the uncertainty estimation methods for impact assessment of land use change are given in Section 3. In Section 4, the model calibration results as well as the results to the two objectives of the study are demonstrated and analyzed. These results are discussed and compared to those of other studies in Section 5. Finally, major conclusions are drawn in Section 6.

2. Study area

2.1. Geographical overview

The Xitiaoxi River is one of the most important tributaries of the Taihu Lake basin, and it contributes 27.7% of the lake’s water volume. The drainage area controlled by the Hengtangcun streamflow gauge is 1273 km². There are two large multipurpose reservoirs established (i.e., Fushi and Laoshikan reservoirs) in the upstream region of the Xitiaoxi basin, serving the main function of flood control. Due to the great disturbance posed on the streamflow, the area between the Hengtangcun stream gauge and the two reservoirs is chosen for the current study with the total area of 727 km² (Fig. 1). The climate in the study area is subtropical monsoon climate, with an average annual temperature and precipitation of 15.5 °C and 1465.8 mm, respectively. More than 75% of the annual precipitation occurs during the wet season (from April to October). The major land use types are forest (mainly including mixed forest and broadleaf forest with high fractional vegetation cover), cropland (including rice and dryland), and urban areas. Major soil types in the watershed are yellowish red soil, paddy soil, red soil and yellow soil.

2.2. Land use change

In the past decades, considerable land use changes have occurred within the study area, and three historical LUSs, referring to the years 1985, 2002 and 2014, were used to investigate the land use changes. The 1985 and 2002 land use maps were acquired by digitizing the land use maps (1:100,000) in 1985 and 2002. The 2014 map was obtained from Landsat Enhanced Thematic Mapper (ETM +) image based on supervised classification and manual interpretation as well as ground truthing, and the overall accuracy of land cover classification was about 89.8%. The land use was categorized into five major types: forest, cropland, urban, water and bare land. The land use changes are summarized in Fig. 2. It is seen from the figure that the major change in the past 30 years is a rapid expansion of the urban areas at the expense of cropland and forest. The urban area has increased from 35.43 km² (4.9%) in 1985 to 60.96 km² (8.4%) in 2002 and to 124.12 km² (17.0%) in 2014. It has significantly increased by 250% from 1985 to 2014. The increase was counterbalanced by the decrease in cropland and forest by 40.2% and 5.8% respectively from 1985 to 2014. The forest area decreased from 522.01 km² (71.7%) in 1985 to 509.73 km² (70.0%) in 2002 and 491.65 km² (67.5%) in 2014, while the cropland area decreased from 150.04 km² (20.6%) in 1985 to 135.80 km² (18.6%) in 2002 and to 89.99 km² (12.3%) in 2014. Water and bare land areas both increased/decreased slightly, during 1985 to 2014. In addition, compared to the land use change between 1985 and 2002, the watershed experienced a more significant change from 2002 to 2014.
3. Material and methods

3.1. Description of the HSPF and SWAT models

In this study, HSPF and SWAT were both applied for assessing the impacts of land use change on hydrological processes. Both models are semi-distributed and widely used by the hydrology community. The two models differ in model structures and process representations as well as complexity. The models’ basic characteristics and inputs are summarized in Table 1, while the text presents detailed descriptions of the most important differences in process representation between HSPF and SWAT.

HSPF is based on the original Stanford Watershed Model IV (Crawford and Linsley, 1966; Johnson et al., 2003). It is a comprehensive, continuous, semi-distributed, conceptual model that simulates the various hydrological processes and water quality components of a watershed (Bicknell et al., 2001). HSPF consists of three main modules: PERLND, IMPLND and RCHRES. The PERLND module simulates water quantity in a pervious land including interception, ET, surface detention, surface runoff, infiltration, interflow, base flow, and deep percolation (Donigian et al., 1995). The IMPLND module simulates hydrological processes in impervious land, and only the surface detention and surface runoff components are simulated. The RCHRES module simulates the processes which occur in the stream reaches and reservoirs in a watershed.

SWAT is a physically-based and semi-distributed hydrological model that was designed to predict continuous long-time runoff, sediment and agricultural chemical yields in a watershed. SWAT divides the hydrological processes into a land phase and a routing phase. The land phase calculates the input of water, sediment, nutrients and pesticides...
Table 1
General summary of selected model attributes.

<table>
<thead>
<tr>
<th>Feature</th>
<th>HSPF</th>
<th>SWAT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model type</td>
<td>Semi-distributed</td>
<td>Semi-distributed</td>
</tr>
<tr>
<td>Time step</td>
<td>Subdaily to daily</td>
<td>Subdaily to daily</td>
</tr>
<tr>
<td>Weather input</td>
<td>Hourly precipitation, air temperature (maximum and minimum), solar radiation, cloud cover, wind speed, dew point, potential ET</td>
<td>Daily precipitation, air temperature (maximum and minimum), solar radiation, relative humidity, wind speed</td>
</tr>
<tr>
<td>Calibration module</td>
<td>SUFI-2</td>
<td>SUFI-2</td>
</tr>
<tr>
<td>Spatial division</td>
<td>Land use and climate stations- based lumped land segments</td>
<td>Land use, soil, and slope-based Hydrological response units (HRUs)</td>
</tr>
<tr>
<td>Potential Evapotranspiration</td>
<td>Penman-Monteith (1965)</td>
<td>Penman-Monteith (1965)</td>
</tr>
<tr>
<td>Actual Evapotranspiration</td>
<td>Computed as a function of moisture storage and PET</td>
<td>Calculated separately for evaporation and transpiration, reduction of PET by soil water content</td>
</tr>
<tr>
<td>Infiltration and overland flow</td>
<td>Infiltration is computed with Philip's equation for infiltration, and overland flow is calculated using Chezy-Manning equation</td>
<td>SCS curve number method with daily precipitation or Green-Ampt Mein-Larson infiltration equation with sub-daily time step precipitation</td>
</tr>
<tr>
<td>Water routing</td>
<td>Storage routing (kinematic wave) method</td>
<td>Variable storage or the Muskingum</td>
</tr>
</tbody>
</table>

Table 2
Description of input data for HSPF and SWAT models in the Xitaixiao basin.

<table>
<thead>
<tr>
<th>Data</th>
<th>Source</th>
<th>Resolution/scale and the period of the data</th>
<th>Station number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topography</td>
<td>Anji Department of Hydrology</td>
<td>1:10,000 topographic contour data (2001)</td>
<td>–</td>
</tr>
<tr>
<td>Soil map</td>
<td>Anji Bureau of Agriculture</td>
<td>1:100,000 (1985)</td>
<td>–</td>
</tr>
<tr>
<td>Climate</td>
<td>Anji Department of Meteorology</td>
<td>Daily (1977–2014)</td>
<td>6 stations for daily, and 1 station for hourly</td>
</tr>
<tr>
<td>Precipitation</td>
<td>Anji Department of Hydrology</td>
<td>Daily and hourly (1977–2014)</td>
<td>1</td>
</tr>
<tr>
<td>Discharge</td>
<td>Anji Department of Hydrology</td>
<td>Daily (1977–2014)</td>
<td>3</td>
</tr>
</tbody>
</table>

to the main channel in each sub-basin (Cibin et al., 2010). This is performed based on the water balance concept that considers the most important processes, such as precipitation, ET, interception, surface runoff, lateral flow, and groundwater flow. The routing phase connects all sub-basins by means of the main channel and simulates the movement of water, sediment to the basin outlet.

HSPF and SWAT subdivide the watershed into a number of sub-basins based on the digital elevation model (DEM), and subsequently the sub-basins are delineated into hydrological response units (HRUs). SWAT creates HRUs based on a homogeneous combination of land use, soil type and slope class (Arnold et al., 1993), while HSPF partitions the sub-basins to pervious and impervious land segments based on land use and meteorological conditions (Gebremariam et al., 2014).

Whereas SWAT divides the soil into numerical layers, HSPF divides the soil into two storage components, i.e., upper and lower zones. Upper zone storage is filled by rainfall that is not captured by interception and runoff, while lower zone storage is filled by infiltration or percolation, which was determined by the water level in upper zone storage and its nominal storage (LZSN). HSPF and SWAT differ in their representation of infiltration. In SWAT, infiltration is calculated using a linear function that consists of slope length and angle, saturated conductivity, drainable porosity and the amount of water that is stored in the saturated zone (Cornelissen et al., 2013). In HSPF, infiltration is calculated on the basis of a linear relation between the conceptual infiltration-storage volume and lateral flow as a function of the infiltration-recession coefficient (IRC). In addition, HSPF and SWAT adopt a linear storage approach to calculate baseflow. They simulate one inactive groundwater storage and one active groundwater storage. The inactive groundwater storage does not contribute to baseflow, while the active groundwater storage is linked to the river system.

3.2. Data sources

The input data required by SWAT and HSPF are summarized in Table 2. The climate, precipitation and discharge data were collected as daily total or averages for the period 1977–2014. Identical climate and precipitation data (Fig. 1) were used to run the models, while the periodicity of the data for the HSPF model was disaggregated into hourly intervals in contrast to the daily data used for SWAT. The disaggregation was done at the reference station that has hourly precipitation data based on the Data Disaggregation Tool in the Watershed Data Management Utility (WDMUtil) of HSPF (Fig. 1).

3.3. Model setup and calibration

3.3.1. Model setup

HSPF and SWAT were run on the same sub-watershed delineation data. SWAT application was set up using ArcSWAT. The study area was divided into 23 sub-basins, with 178, 209 and 206 HRUs for 1985, 2002 and 2014 LUSs, respectively. The sub-basin delineation was based on land uses, soil types and slope classes that contributed more than 5%, 10% and 20% to each sub-basin, respectively. Land use codes such as AGRR, FRST, URMD, and WATR refer to cropland, forest, urban, and water, respectively. HSPF was set up using the BASINS interface (version 4.0). To maintain similarity, the sub-basins and stream reaches from SWAT were imported into BASINS by manually editing the user control input (UCI) file of HSPF generated using the WinHSPF interface. The same land use codes of SWAT were adopted for HSPF.

3.3.2. Model calibration

Sensitivity analysis and calibration were performed for SWAT and HSPF using the same methods. Sensitivity analysis was conducted using the Morris (1991) method, which perturbed one parameter and measured the change in the model output. The method proposed two sensitivity measures to analyze the data: 𝛾̂ which estimates the overall effect of each input on the output, and σ which estimates the higher order effects such as nonlinearity and interactions between inputs. The Morris suggests evaluating a graphical representation of 𝛾̂ vs. σ to determine the most important factors. The details of the Morris method can be referred to Campolongo et al. (2007) and Tong (2008).

A sequential uncertainty fitting program (SUFI-2) was used for auto-calibration (Abbaspour et al., 2004). The SUFI-2 is a combined
optimization approach that uses a global search method along with the Latin hypercube sampling technique (LHS) (Iman and Conover, 1980) to examine the behavior of objective functions (Abbaspour et al., 2004). SUFI-2 is a model-independent calibration approach, it changes the related model input files for the model during the calibration process. The details of SUFI-2 can be referred to Abbaspour et al. (2004). In this study, the SUFI-2 was implemented using a SWAT-CUP software (Abbaspour, 2007) for SWAT. A HSPF-PY package that was developed in Python by the authors was used for auto-calibration of SUFI-2 for HSPF.

Ideally, when a hydrological model is used to evaluate the impact of land use change, it should be validated by comparing with the scenario after the land use change (Huisman et al., 2009). Considering the land use change because of the urbanization in the study area (Fig. 2), we select the periods close to the year of land use maps available for calibration or validation. Therefore, calibrations for SWAT and HSPF in the period of 1981 to 1989 were performed using the land use data in 1985, while validations in the period of 1998 to 2006 were performed using the land use in 2002. The years of 1981 and 1998 were regarded as warm-up periods for model simulation. The Nash–Sutcliffe efficiency coefficient (NSE) (Nash and Sutcliffe, 1970), which is the most widely used criterion for assessing the performance of hydrologic models, was chosen as the objective function in this study. Besides the NSE, other conventional model performance statistics including percent bias (PBIAS), the coefficient of determination ($R^2$), the root mean square error (RMSE), the mean absolute error (MAE) and the error variance (VE) were also calculated to evaluate the performances of the hydrological models. These statistics are defined as:

\[
\text{NSE} = 1 - \frac{\sum_{i=1}^{n} (S_i - O_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2} \tag{1}
\]

\[
\text{PBIAS} = \frac{\sum_{i=1}^{n} (S_i - O_i) \times 100}{\sum_{i=1}^{n} (O_i)} \tag{2}
\]

\[
R^2 = \left[ \frac{\sum_{i=1}^{n} (O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n} (O_i - \bar{O})^2 \sum_{i=1}^{n} (S_i - \bar{S})^2}} \right] \tag{3}
\]

\[
\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |S_i - O_i| \tag{4}
\]

\[
\text{VE} = 1 - \frac{1}{n} \sum_{i=1}^{n} |S_i - O_i| / \sum_{i=1}^{n} O_i \tag{5}
\]

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{n} (S_i - O_i)^2} \tag{6}
\]

where $O_i$ and $S_i$ are observed and simulated flows at the $i$th time step, and $\bar{O}$ and $\bar{S}$ are the average values of the observed and simulated flows, respectively.

### 3.4. Quantification of flow changes in multi-timescales due to land use change with uncertainty

For a better assessment of the runoff at different time scales due to land use change, the analyses have been conducted at the whole basin and sub-basin scales. In particular, the effects of land use change on streamflow have a greater magnitude (in relative terms) in the selected sub-basin than that in the whole basin. The most significant increases in urban area occurred in sub-basin 4, the urban area has increased significantly from 1985 to 2014 by 1257.65%. Correspondingly, the percentage of urban area has increased from 5.8% in 1985 to 13.1% in 2002 and to 78.0% in 2014 (Fig. 2(b)). Therefore, the uncertainties in land-use change impacts were analyzed at the whole basin and the sub-basin 4.

### 3.4.1. Temporal change analysis

Hydrological response due to land use change was simulated by fixing the climate data from 1978 to 2014, and altering the LUS, referred from the data of years 1985, 2002 and 2014. Different flow characteristics at different time scales were analyzed, including the average annual runoff, average monthly runoff, annual 1-day maximum flow ($R_{1,\text{dMAX}}$), and the mean annual 7-day minimum flow ($R_{7,\text{dMIN}}$). The $R_{1,\text{dMAX}}$ and $R_{7,\text{dMIN}}$ were used to assess the effect of land use change on extremely high and low flows respectively. The relative change (RC) was adopted to investigate the impact of LUSs on flow indicators. It assesses the sign of the change and quantifies its magnitude relative to a base reference. The LUS of 1985 was used as the baseline/control scenario against all changes. It is expressed as:

\[
\text{RC} (\%) = (R(Y) - R(X)) / R(X) \times 100 \tag{7}
\]

where $R(Y)$ and $R(X)$ are the values of the flow characteristics for the LUS Y (2002 or 2014) and the baseline LUS X (1985).

### 3.4.2. Uncertainty analysis

The uncertainty in the hydrological response to land use change can be introduced from different sources, but with the main source of parameter uncertainty (Zhang et al., 2014b). Several methods for investigating the parameter uncertainty, such as GLUE (Generalized Likelihood Uncertainty Estimation), MCMC (Markov chain Monte Carlo), and SUFI-2 methods have been developed. Yang et al. (2008) compared the results of five techniques for parameter uncertainty analysis in a SWAT application. The SUFI-2 algorithm is found to be most efficient in terms of computational effort to reach a satisfactory simulation. SUFI-2 is used for the parameter uncertainty analysis in the study. The uncertainty in parameterization is quantified for behavioral parameters identified during the model calibration by SUFI-2 for the two models (HSPF and SWAT). The uncertainty of model simulation results is analyzed using 95PPU that is calculated as the difference of 2.5% and 97.5% levels of cumulative distribution of an output variable obtained through LHS. Here, the uncertainty is quantified by a P-factor and a R-factor. The P-factor represents the percentage of observed data within the 95PPU band, and the R-factor is the average width of the 95PPU band divided by the standard deviation of the observed data. An ideal case would result in a P-factor of about 1 and a R-factor near 0. However, an ideal situation cannot be achieved for real cases due to the multiple sources of uncertainties. The R-factor and P-factor are defined as follows:

\[
\bar{r} = \frac{1}{n} \sum_{i=1}^{n} \left( y_{i,0.975\%} - y_{i,0.025\%} \right) \tag{8}
\]

\[
R = \bar{r} / \sigma_{\text{obs}} \tag{9}
\]

\[
P = nq_{\text{obs}} / n \times 100\% \tag{10}
\]

where $y_{i,0.975\%}$ and $y_{i,0.025\%}$ represent the upper and lower levels of the 95PPU, $n$ is the number of data records, $\sigma_{\text{obs}}$ is the standard deviation of the observed data, and $nq_{\text{obs}}$ is the measured value number bracketed by the 95PPU. More details can be found in Abbaspour et al. (2004).

As demonstrated by Bastola et al. (2011), the uncertainty stemming from the model parameters in model prediction is expressed in terms of the average width of prediction interval PI (% of average relative change). The PI is quantified as:

\[
P_{\text{fl}} = \frac{S^u - S^l}{S^l} \times 100\% \tag{11}
\]

where $S^u$ and $S^l$ represent the upper and lower 95% confidence limits of the simulated RC for the behavioral parameter sets, and $S$ represents the average value for the behavioral parameter sets, respectively. In order to reduce the impact of different signs of $S$, the values of RC for each parameter set between 1978 and 2014 must be standardized with the formula: $X_{\text{std}} = (X_i - X_{\text{min}}) / (X_{\text{max}} - X_{\text{min}})$. 
Another uncertainty source considered in this study is the model structure. The average change value in the flow characteristics of the behavioral parameters for each model is regarded as a true value for the model parameter. Subsequently, the results from the HSPF and the SWAT models are compared to estimate the uncertainty due to the model structure.

4. Results

4.1. Evaluation of models performance

Sensitivity analysis is used to estimate the influence of uncertainty factors on the output of a function. The Morris method is used to identify the sensitive parameters affecting the simulations of output variables (Touhami et al., 2013). Based on the Morris results (Fig. 3), there were six sensitive parameters, namely INFILT, AGWRC, IRC, DEEPFR, BASETP and UZSN for HSPF, while nine sensitive parameters including CN2, CHN2, ALPHA_BF, SOL_K, ESCO, SOL_AWC, RCHRG_DP, GW_REVAP and SURLAG, for SWAT (Table 3).

Table 3 shows the sensitive parameters and their initial ranges. The initial ranges were determined primarily according to HSFP and SWAT manuals and authors’ knowledge of the Xitiaoxi basin. The SUFI-2 method was employed for calibration at a daily time step, and three iterations with 1000 runs were executed for both models. The optimum model structure and validation periods are presented in Table 4. Moriasi et al. (2007) proposed that stream flow simulations are considered satisfactory for SWAT when NSE ≥ 0.5 and PBIAS ≤ ± 25%. The models were considered “very good” for simulating daily flows at the Hengtangcun Station for the calibration and validation periods, with a NSE ≥ 0.85 and a PBIAS ≤ ± 10%. When the wet and dry seasons were considered separately, each model performed well at simulating the observed daily flows, with a NSE ≥ 0.70 and a PBAIS ≤ ± 15%. Based on the PBIAS, a majority of the discharge values were underestimated (except during the wet season for the SWAT model) in the calibration period, and overestimated for both models in the validation period.

Based on the entire performance statistics, it is difficult to judge on the outperformance of one model over the other. For example, HSPF had consistently better NSE, R² and VE values, not only for the daily flows during the calibration and validation periods, but also in the wet season, compared to those of SWAT. However, except for the daily flow during the dry season, the SWAT model showed lower (i.e., better) PBIAS values than HSPF at daily and seasonal time steps during both periods (Table 4).

According to Wu et al. (2015), when NSE ≥ 0.7 and R² ≥ 0.7, P-factor ≥ 0.5, and R-factor ≤ 1, the model simulation results are acceptable and the parameter uncertainty ranges are considered as appropriate. The results from the third iteration for HSPF and SWAT were considered as appropriate based on the above criteria. The two measures, the P-factor and R-factor, are summarized in Table 4. The P-factor values for both models were much lower than 1, which indicate that the model simulation results are satisfactory. The P-factor values of SWAT were higher than those of the HSPF for both calibration and validation periods.

Table 3

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Initial range</th>
<th>Final Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>HSPF</strong></td>
<td>INFILT</td>
<td>Index to infiltration capacity of soil</td>
<td>0.025–0.07</td>
</tr>
<tr>
<td></td>
<td>AGWRC</td>
<td>Basic groundwater recession rate</td>
<td>0.6</td>
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<tr>
<td></td>
<td>IRC</td>
<td>Interflow recession parameter</td>
<td>0.18–0.20</td>
</tr>
<tr>
<td></td>
<td>DEEPFR</td>
<td>Fraction of groundwater inflow entering inactive groundwater</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>BASETP</td>
<td>Fraction of potential ET satisfied from base flow</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>UZSN</td>
<td>Nominal upper zone storage</td>
<td>0.05–0.10</td>
</tr>
<tr>
<td><strong>SWAT</strong></td>
<td>CN2</td>
<td>Runoff curve number</td>
<td>54–83</td>
</tr>
<tr>
<td></td>
<td>CHN2</td>
<td>Manning’s n for the main channels</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>ALPHA_BF</td>
<td>Base flow alpha factor</td>
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</tr>
<tr>
<td></td>
<td>SOL_K</td>
<td>Soil hydraulic conductivity</td>
<td>4–10.0</td>
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<tr>
<td></td>
<td>ESCO</td>
<td>Soil evaporation compensation factor</td>
<td>0.001–0.15</td>
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<tr>
<td></td>
<td>SOL_AWC</td>
<td>Available water capacity of the soil layer</td>
<td>0</td>
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<td></td>
<td>RCHRGDP</td>
<td>Deep aquifer percolation fraction</td>
<td>0</td>
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<tr>
<td></td>
<td>GW_REVAP</td>
<td>Groundwater “revap” coefficient</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>SURLAG</td>
<td>Surface runoff lag time</td>
<td>0</td>
</tr>
</tbody>
</table>

* These parameters are allowed to vary across land use or soil.
validation periods, which imply that SWAT has a larger contribution of parameter uncertainty to the simulation uncertainty than HSPF. This could be explained as a larger number of high NSE values were attained for the HSPF model than for the SWAT model. The median NSE values for HSPF and SWAT were 0.89 and 0.85 in the calibration period, while 0.92 and 0.86 in the validation period, respectively. This leads to a smaller band of 95PPI for HSPF, which comprised fewer observed values. It can also be seen from the R-factor values of HSPF which were 0.92 and 0.86 in the validation period, respectively. This leads to a smaller R-factor value of HSPF which were much lower than those of SWAT. Moreover, both models had lower R-factors for the dry season, which suggest that the models may not completely capture the baseflow component of the hydrological process.

4.2. Effects of parameter uncertainty on the impact assessment of land use change

The average values of relative changes with behavioral parameter sets in the annual and monthly runoffs due to land use change from 1985 to 2014 are shown in Fig. 4, along with the related uncertainty in model prediction arising from model parameters of HSPF and SWAT. In the LUSs 2002 and 2014, both models simulate increases (at the 95% confidence level) in the annual and monthly discharges for land use change from cropland and forest to urban areas at the whole basin scale. Although HSPF and SWAT simulated the same direction of change in the annual and monthly discharges, the impacts of uncertainty derived from model parameters on the relative changes cannot be neglected. As illustrated in Table 5, in the LUSs 2002 and 2014, at an annual scale, the average widths of PI arising from uncertainties associated with the parameterization were 157.3% and 173.9% of the average values of relative change for SWAT respectively, and were 151.7% and 152.0% for HSPF respectively. For the monthly scale, HSPF and SWAT showed the same pattern of variation. It was found that the parameter uncertainties in the relative changes of annual and monthly runoffs of HSPF were lower than those of SWAT. Similar to the whole basin, sub-basin 4 presented the same change characteristics for the annual and monthly discharges (Fig. 5).

It is seen from Fig. 4 that for high and low flows, both models showed large variations in magnitude. The two models had inconsistent trends (e.g. negative and positive relative changes co-exist) of relative changes (at the 95% confidence level) under the LUSs 2002 and 2014 for the whole basin. For high flows, the simulated relative changes in R_1dMAX showed an inconsistent trend between 1978 and 2014 at the 95% confidence level. However, the relative changes for most years exhibited a consistent increase. In the LUSs 2002 and 2014, the average widths of PI arising from uncertainties associated with the parameterization were 162.9% and 165.2% of the average values of relative change for SWAT respectively, and were 213.4% and 206.3% for HSPF, respectively. It indicates that the parameter uncertainties in the relative changes of R_1dMAX of HSPF were higher than those of SWAT. Unlike the changes for the whole basin, both models simulated increases in the R_1dMAX in sub-basin 4 in the LUS 2014 (Fig. 5).

For R_7dMIN, both models simulated inconsistent trends of relative changes from 1978 to 2014 (at the 95% confidence level), under the LUSs 2002 and 2014 for the whole basin. Moreover, compared to the R_1dMAX, the inter-annual variations of the average relative changes in the R_7dMIN were larger for both models. In the LUSs 2002 and 2014, the average widths of PI arising from uncertainties associated with the parameterization were 117.3% and 100.1% of the average values of relative change for SWAT respectively, and were 158.0% and 150.4% for HSPF respectively (Table 5). It indicates that the parameter uncertainties in the relative changes of R_7dMIN of HSPF were higher than those of SWAT. At the sub-basin 4, we found that both models simulated inconsistent trends of relative changes in R_7dMIN from 1978 to 2014 (at a 95% confidence level), even under the LUS 2014. However, unlike the changes in the whole basin, the relative changes for most years exhibited a consistent decrease, and the parameter uncertainties in the relative changes of R_7dMIN of SWAT were higher than those of HSPF.

4.3. Effects of models’ structure on the impact assessment of land use change

In order to evaluate the effects of model structural uncertainty on the land-use change impacts, the values of the average relative change in flow index based on the behavioral parameter sets for SWAT and HSPF were compared. As presented in Figs. 4, 5 and Table 5, the magnitude of the relative change in annual and monthly discharges varied between the two models. The HSPF showed more sensitivity to land use change than SWAT at the whole basin and the subbasin-4. The differences of the magnitude of relative change in annual and monthly discharges were larger when a significant land use change occurred in 2014. Figs. 6 and 7 present the cumulative distribution functions (CDFs) of the average relative changes in R_1dMAX and R_7dMIN for the LUSs 2002 and 2014 for the whole basin and the subbasin-4, respectively. The CDFs are plotted to reflect the uncertainty in land use impacts arising from model structure. At the whole basin, for the LUSs 2002 and 2014, the R_1dMAX increases for all years using SWAT, while the changes in R_1dMAX were bidirectional (e.g. negative and positive relative change in R_7dMIN).
changes co-exist) using HSPF. The changes in $R_{7dMIN}$ are also bidirectional for HSPF and SWAT. For the LUS 2014, the larger differences in the likelihood of decreased $R_{7dMIN}$ between SWAT and HSPF were found. It indicates that the model choice could affect the direction change (e.g. to negative or positive direction) in $R_{1dMAX}$ and $R_{7dMIN}$. In terms of sub-basin 4, for the LUS 2014, both models simulated increases in $R_{1dMAX}$ and decreases in $R_{7dMIN}$. However, there are larger differences in CDFs between HSPF and SWAT than that.

Fig. 4. Simulated relative changes in yearly runoff (a, b), monthly runoff (c, d), $R_{1dMAX}$ (e, f) and $R_{7dMIN}$ (g, h) for HSPF (left panels) and SWAT (right panels) between the control scenario (LUS 1985) and the other scenarios (LUS 2002 and LUS 2014) for the whole basin.

Table 5

<table>
<thead>
<tr>
<th>Model</th>
<th>Flow characteristics</th>
<th>PI (%)</th>
<th>$\overline{S}$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SWAT</td>
<td>Annual flow</td>
<td>157.3</td>
<td>150.4</td>
</tr>
<tr>
<td></td>
<td>Monthly flow</td>
<td>152.7</td>
<td>150.2</td>
</tr>
<tr>
<td></td>
<td>R_1dMAX</td>
<td>162.9</td>
<td>165.2</td>
</tr>
<tr>
<td></td>
<td>R_7dMIN</td>
<td>117.3</td>
<td>100.1</td>
</tr>
<tr>
<td>HSPF</td>
<td>Annual flow</td>
<td>151.7</td>
<td>152.0</td>
</tr>
<tr>
<td></td>
<td>Monthly flow</td>
<td>145.6</td>
<td>145.3</td>
</tr>
<tr>
<td></td>
<td>R_1dMAX</td>
<td>213.4</td>
<td>206.3</td>
</tr>
<tr>
<td></td>
<td>R_7dMIN</td>
<td>158.0</td>
<td>150.4</td>
</tr>
</tbody>
</table>

for the whole basin. In Table 5, for the LUS 2014, the average values of relative changes of HSPF and SWAT were −34.74% and −50.86% for R_7dMIN, and 109.31% and 20.92% for R_1dMAX for sub-basin 4, respectively. SWAT produced larger hydrological changes in R_7dMIN due to land use change while HSPF showed more sensitivity to change in R_1dMAX. The results suggest that when the land use change rate is beyond a certain level, both models simulate the same trend in R_1dMAX and R_7dMIN for the sub-basin 4. However, the difference of the simulated relative change between the two models could be significant.

5. Discussion

5.1. Effects of parameter uncertainty on the land use change impact assessment

Both models indicated increases in annual and monthly discharges due to urbanization with the trends consistent with previous studies (e.g., Choi et al., 2003; Tang et al., 2005; Hurkmans et al., 2009; Kim et al., 2011; Zhou et al., 2013; Niraula et al., 2015; Li et al., 2018a). The uncertainty due to model parameters did not alter the trend of annual and monthly discharge changes due to land use change. However, a considerable variation in the magnitude of hydrological response for the different LUSs was observed. Similar conclusions have been reported by Breuer et al. (2006), who found a significant output uncertainty in the absolute change of annual and seasonal discharge between LUSs due to the uncertainty in plant parameterization. Although not entirely related to model parameter uncertainty, Niraula et al. (2015) found that the relative changes in annual streamflow produced with single outlet calibrated and spatially-distributed calibrated models were significantly different, and the differences in the calibration approach for model simulation were reflected in the different parameter sets. In addition, we found that the uncertainty derived from the behavioral model parameters for each model for the LUSs 2002 and 2014 exceeds 100% of estimated average relative change of annual/monthly flow. This indicates that the impact of land use change could be potentially hidden by the simulation uncertainty derived from model parameters at the 95% confidence level.

The parameter uncertainty in extreme runoff is different compared to that in monthly and annual runoffs. The parameter uncertainty not only results in considerable magnitude variations of relative change, but also alters the trend of the hydrological response. This indicates a considerable insufficiency in the use of hydrological models calibrated against daily streamflow in the evaluation of changes in extreme runoffs due to land use change. Larger uncertainty bounds and inconsistent trends in relative change of extreme flows may be due to the inability of models to accurately predict flows. Table 6 and Fig. 8 show that both models yield systematic underestimation of extreme flows and highly biased predictions for R_7dMIN, although both models have been calibrated to match the daily average streamflow well. The weakness in predicting extreme flows has been reported for SWAT (Borah et al., 2007; Gebremariam et al., 2014; Lian et al., 2007; Pfannerstill et al., 2014; Srinivasan et al., 2005; Zhang et al., 2014b) and HSPF (Ackerman et al., 2005; Lian et al., 2007; Gebremariam et al., 2014). The highly biased prediction of the models in R_7dMIN is caused partly by the calibration method. The objective function, NSE, adopted in this study tends to emphasize flood features (Zhang et al., 2015; Lin et al. (2017) found that the NSE value was not sensitive to the simulation results of R_7dMIN. Furthermore, the possible reason for such a large bias in R_7dMIN is the deficiency of the model structure. For example, both models simulate one active groundwater storage, and they adopt linear storage approach to calculate baseflow which cannot fully reproduce nonlinearities of groundwater processes (Guse et al., 2014; Pfannerstill et al., 2014). An improved SWAT performance during the dry season was reported when a multi-storage groundwater module was incorporated into the SWAT model (Pfannerstill et al., 2014).

5.2. Effects of models’ structure on the assessment of land use change impact

Although many hydrological models have been applied in land use change impacts studies, the uncertainty stemming from model structure is always ignored. The evident differences in hydrological response predictions to land use change between HSPF and SWAT were observed. This indicates that the selection of a hydrological model plays a significant role in land use change impact analysis. This is similar to the studies by Morán-Tejeda et al. (2015) and Sharifi et al. (2017).

In this study, HSPF produced larger changes in monthly or annual runoffs compared to SWAT. The differences in hydrological responses may be due to the different equations for hydrological processes (i.e., direct runoff, ET) in SWAT and HSPF. For SWAT, a modified soil conservation service curve number (SCS-CN) method is used to calculate the direct runoff generation. Once the land use altered, the CN changes accordingly, which leads to a variation for runoff. In HSPF, an infiltration-excess model is employed, which divides precipitation inputs into infiltrating and non-infiltrating fractions according to three conceptual parameters: a surface storage capacity value (UZSN), an interflow-inflow index (INTFW), and an infiltration-capacity index (INFILT). Once the land use altered, the UZSN, INFILT and INTFW change accordingly, which result in differences for runoff.

The actual ET, which is a key factor influencing the water yield, also varies with land use change. The two models estimate the actual ET by different methods. SWAT estimates the actual ET as sum of the actual ET from soil and plant water evaporation. These ET components are represented mainly by two parameters: the maximum canopy storage (CANMX) and the soil evaporation compensation coefficient (ESCO) (Guse et al., 2014). However, these two parameters do not change with
Fig. 5. Simulated relative changes in yearly runoff (a, b), monthly runoff (c, d), $R_{1dMAX}$ (e, f) and $R_{7dMIN}$ (g, h) for HSPF (left panels) and SWAT (right panels) between the control scenario (LUS 1985) and the other scenarios (LUS 2002 and LUS 2014) for the sub-basin 4.
different LUSs. Du et al. (2013) summarized that no study has adopted varied parameter values, except the CN, for the new LUS when applying the SWAT model to simulate the hydrological response to land use change. The parameters associated with the ET process are assumed to be identical. HSPF simulates the actual ET based on the potential ET demand and amount of water available in the soil and on the land surface for ET. Since there is no plant-growth component in HSPF, the effect of vegetation type, density, root growth, and stage of

Fig. 6. Cumulative distribution functions of $R_{1dMAX}$ change (a, b) and $R_{7dMIN}$ change (c, d) between the control scenario (LUS 1985) and the other scenarios (LUS 2002 and LUS 2014) for the whole basin.

Fig. 7. Cumulative distribution functions of $R_{1dMAX}$ change (a, b) and $R_{7dMIN}$ change (c, d) between the control scenario (LUS 1985) and the other scenarios (LUS 2002 and LUS 2014) for the sub-basin 4.
development along with the moisture characteristics of the soil layer are lumped into the lower zone ET parameter (LZETP), which controls actual ET from the lower zone storage (Singh et al., 2005). Moreover, the LZETP values varied with the land use types in this paper and were the case in other studies (e.g., Im et al., 2003; Xu et al., 2007; Ribarova et al., 2008; Ames et al., 2014; Baloch et al., 2015). Taking the best parameter set based on the maximum NSE value under the LUS 2014 as an example, the actual ET estimated by HSPF decreased by 5.15%, and by 1.12% for SWAT. HSPF showed a larger relative change than SWAT for the actual ET.

In terms of the changes for R_1dMAX and R_7dMIN, we found that the model choice could impact the direction change. However, when land use changes are significant to a certain degree (e.g., the LUS 2014 in sub-basin 4), both models simulated increased R_1dMAX and decreased R_7dMIN, but with different significances. For R_1dMAX, HSPF simulated more significant change than SWAT, while SWAT simulated more significant change than HSPF for R_7dMIN. There appear to be two possible reasons for the magnitude of R_1dMAX is smaller in SWAT than that in HSPF. One is the use of CN2 in SWAT versus infiltration in HSPF, and the other is hourly time step of precipitation data in HSPF versus daily time step of precipitation data in SWAT. The CN2 methods and daily time step cannot allow SWAT to consider the rainfall intensity and duration well, but only total rainfall volume (Butcher et al., 2014).

Comparison of watershed response to land use change using HSPF and SWAT suggests that one should be caution when attempts to estimate the relative change using models with different underlying concept and formulations. It is difficult to identify which model provides a more accurate estimate of hydrological change. Although, SWAT is said to be a physically-based model while HSPF is a conceptual model, when look at the main processes involved in water yield, it is revealed that most of hydrological processes of SWAT are computed through empirical equations. SWAT is less than ideal for assessing runoff response to land use change for a variety of reasons, including simplified simulation of direct runoff using CN2, and simplified simulation of groundwater. In addition, a fixed parameterization strategy is adopted in this study and most cases when applying SWAT to simulate the hydrological response to land use change (Du et al., 2013; Wang et al., 2017; Yin et al, 2017). It cannot simulate the influence of land use changes on ET, and channel flow and so on. On the other hand, HSPF uses an infiltration-excess mechanism to simulate overland flow, which may be not suitable for a certain environment. For example, in the study area, the runoff tends to be generated by a mixture of infiltration-excess flow and saturation excess process depending on the season and places in the catchment. Additionally, the semi-distributed conceptual nature of HSPF limits its use for predicting spatial distribution of soil moisture content, as well as other physically measurable parameters at specific location within the watershed (Johnson et al., 2003). HSPF aggregates soil moisture content, which is generally related to a specific pervious land unit across the entire watershed, whereas the predictions of moisture content distribution are geographically specific by SWAT. Therefore, it is hard to evaluate which model provides more accurate estimation of land use change impacts. Further analysis of model simulation against more observations (e.g., soil moisture content) is needed to determine an optimum model. It should be evaluated in land use change impacts analysis, and the estimation of structural uncertainty could be explored by combining their predictions in a systematic manner.

<table>
<thead>
<tr>
<th></th>
<th>SWAT</th>
<th>HSPF</th>
</tr>
</thead>
<tbody>
<tr>
<td>R_1dMAX</td>
<td>PBIAS (%)</td>
<td>11.49</td>
</tr>
<tr>
<td></td>
<td>RMSE (m³/s)</td>
<td>129.34</td>
</tr>
<tr>
<td>R_7dMIN</td>
<td>PBIAS (%)</td>
<td>42.95</td>
</tr>
<tr>
<td></td>
<td>RMSE (m³/s)</td>
<td>14.20</td>
</tr>
</tbody>
</table>
5.3. Effects of other uncertainty sources on the assessment of land use change impact

Apart from model parameters and structure, the input data (for example, land use data, precipitation) also cause uncertainties in land use change impact assessments. In this study, different sources of land use data with almost equally the same resolution were used to investigate the land use change impacts. Numerous publications acknowledged the uncertainty contribution in hydrological models due to land use data (Endreny et al., 2003; Alfieri et al., 2007; Miller et al., 2010; Sharifi and Kalin, 2010; Pai and Saraswat, 2013; Yen et al., 2015; Bahareh et al., 2017). Some of these have analyzed the effect of land use categorical errors in hydrological model output (Finke et al., 1999; Miller et al., 2010; Pai and Saraswat, 2013); some of these evaluated the model prediction error due to different sources of land use data (Endreny et al., 2003; Sharifi and Kalin, 2010; Yen et al., 2015). Endreny et al. (2003) found that peak flows were sensitive to the source of land use data, which could cause a range of uncertainty from 35% underestimation to 20% overestimation for HSPF. However, the spatial resolutions of three alternative land cover maps adopted in Endreny et al. (2003) were different. Sharifi and Kalin (2010) reported that the results of using different land use data sets coming from different sources based on no-calibrated SWAT model have a close R² in flow, but biased in the volume of flow. They emphasize that land use maps determine uncertainty in model predictions, which could be reduced by calibration. Yen et al. (2015) found that flow prediction was fairly unaffected by the source of land use data, and model parameters may be transferable by using different sources of land use data on the same watershed in SWAT. Similar to the result of Yen et al. (2015), Bahareh et al. (2017) found that runoff seems to be less sensitive to different land use sources in SWAT, but land use data have impacts on different components of water balance, such as soil water and ET. Therefore, based on the previous and our studies, we conclude that the discharge prediction seems to be less sensitive to different land use sources, but the components of water balance may be sensitive to land use sources.

On the other hand, it is widely acknowledged that the uncertainty in precipitation data has a critical effect on the accuracy of hydrological model predictions (Li and Xu, 2014; Cristiano et al., 2018). SWAT adopted daily inputs, while HSPF requires hourly weather inputs, and hourly HSPF results were aggregated to a daily time step prior to the comparison. The difference of input meteorological data at multiple time steps represents the discrepancy of model structures. Therefore, the uncertainty of model structure contains the uncertainty related with different temporal resolution of weather inputs in HSPF and SWAT. Furthermore, for usage of HSPF, daily precipitation data were disaggregated into hourly data on the reference station that has hourly precipitation data using the Data Disaggregation Tool in WDMUtils of HSPF. The errors in hourly weather data due to disaggregation in HSPF could cause uncertainty. The impact of rainfall errors on predicted flow has been highlighted by many studies, e.g. Xu et al. (2006), Moulin et al. (2009), McMillan et al. (2011), Engeland et al. (2016), and Zeng et al. (2018). Cocca and Doherty (2003) found that a 5% random error in precipitation generated a large range in predictions, and thus significant predictive uncertainty in HSPF. Strauch et al. (2012) indicate that parameter uncertainty varied significantly depending upon the method used for precipitation data-set generation in SWAT. It was not our intention in this work to evaluate the influence of precipitation errors, but this will be carried out in future research to better understand the uncertainties in land use change impacts related to models.

6. Conclusions

This study investigated the uncertainties in hydrological modeling associated with parameters and structure in assessing the hydrologic response to land use change. The study was conducted over different time scales using the HSPF and SWAT models at the whole basin and the sub-basin scales in the Xitiaoxi basin of eastern China. HSPF and SWAT performed well to simulate daily and seasonal streamflows. However, both models showed inadequacies for the extreme flows. It is difficult to arbitrarily judge a model that provides a consistently better result than the other simply based on performance metrics. The parameter uncertainty in simulated streamflow changes that are induced by land use change varies over time scales. The simulated R_1dMAX and R_7dMIN changes often show different directions. This result suggests a considerable limitation on the usage of hydrological models for the variations of extreme runoffs due to land use change, even if with a high NSE at daily time step. The impacts of land use change could be potentially hidden by the simulation uncertainty results from model parameters. Apart from the model parameters, the model structure represents an additional source of uncertainty in hydrological response to land use change. The model selection could impact the change direction of extreme runoff when minor or moderate changes of hydrological responses were observed.

This study demonstrates that the uncertainty in hydrological modeling that stems from model parameters and structure, has a significant influence and should be considered in land use change impact assessment, especially for decision maker. For future land use impact analysis, a multi-model ensemble approach (Bastola et al., 2011) could be adopted to improve the reliability of model predictions and the decision making process by better assessing the hydrological modeling uncertainty.

Declaration of interest
None.

Acknowledgments

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