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Impact of land use land cover changes on flow uncertainty in Siliana watershed of northwestern Tunisia

Imen El Ghoul [a,b,c,*], Haykel Sellami [b], Slaheddine Khlifi [a], Marnik Vanclooster [c]

[a] UR-Gestion Durable des Ressources en Eau et en Sol, Ecole Supérieure des Ingénieurs de Medjez El Bab, Université de Jendouba, Tunisia
[b] Laboratory of Georesources, Centre for Water Research and Technology, Tunisia
[c] Université catholique de Louvain, Earth and Life Institute (ELI), Louvain-la-Neuve, Belgium

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ABSTRACT

It is widely admitted that changes in land use land cover (LULC) influence the hydrology of the catchment. However, how these changes affect hydrological model prediction uncertainty is still a raising question. In this paper we addressed this question by investigating the impacts of the rapid change in LULC in the Siliana catchment in Tunisia on monthly flow and magnitude of flow extremes using the SWAT hydrological model while quantifying the contribution of LULC to the model parameter and prediction uncertainty. At a first step, the SWAT model parameter and prediction uncertainty were estimated using the GLUE method and acceptable parameter sets were identified. Subsequently, the SWAT model was fed with historical LULC as derived from Landsat 5 and 8 satellite images for the years 1990, 2000, 2013 and 2019, and run with the acceptable parameter sets. The results show that the increase in olive plantations (+380 %), urban area (+200 %), and irrigated lands (+309 %) from 1990 to 2019, has LULC decreased monthly flow, high flows magnitude but did not impact low flows in particular over the previous two decades. The findings also suggest that model prediction uncertainty can mask LULC effects, suggesting that model results can be misleading without explicit consideration of uncertainty when assessing the hydrological impacts of changes in LULC.

1. Introduction

Understanding the effects of changes in land use and land cover (LULC) is of concern for effective water resource management. These changes are important drivers altering the hydrological cycle by influencing infiltration, runoff evapotranspiration and, thus, water availability (Huisman et al., 2009; Kindu et al., 2018; Patil and Nataraja, 2020; Peter et al., 2018). Many authors (Woldesenbet et al., 2017; Yan et al., 2016) reported that changes in LULC incredibly influence the timing and magnitude of extreme events, increasing the risk for droughts and floods (Bradshaw et al., 2007; Lin and Wei, 2008). While there is a consensus about the negative impacts of changes in LULC on the hydrological cycle, literature is still divided on the magnitude of these impacts on hydrologic regime. For instance, Gashaw et al. (2014) showed that the increase in the cultivated and degraded lands in the Geba watershed in Ethiopia at the expense of forest, shrubland and grazing lands, resulted in an increase in surface runoff by 72 % and a decrease in the catchment flow by 32 % during the dry season between 1972 and 2003.Conversely, in northern Ethiopia Bizuneh (2014) reported no significant changes in the hydrologic response of the Suluh river basin were detected as consequence to changes in land use. The recent study by Birhanu et al. (2019) confirms that only a tiny shift (5 %) in water balance of the Gumara catchment in Ethiopia was found despite the significant changes in LULC.

Many studies have proven the impacts of LULC changes on flow extremes such as floods and droughts. For example, Appolonio et al. (2016) found the increase in the peak flows was positively correlated to the decrease in rangelands and forests in the Cervaro basin in Southern Italy. The study conducted by Recanatesi et al. (2020) confirmed an increasing risk of floods in the city of Rome with exacerbated impacts in areas with extensive sealed soils as response to changes in LULC. Shrestha (2019) analyzed flood volume and flood inundation for 50- and 100-year floods in urban land in in the Pampanga River basin of the Philippines and found that flood inundation volume and flood extent areas may increase in the future due to urban extent. These studies clearly show that the hydrologic impacts of changes in LULC could vary in magnitudes and trend from one catchment to another depending on local hydrological processes and catchment characteristics which add

* Corresponding author at: Université catholique de Louvain, Earth and Life Institute (ELI), Louvain-la-Neuve, Belgium.
E-mail address: imen.elghoul@uclouvain.be (I. El Ghoul).

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complexity and uncertainty to the analyses. Indeed, physically based and spatially distributed hydrological models, such as the Soil and Water Assessment Tool SWAT (Fohrer et al., 2001) are extremely useful for assessing the hydrological impacts of LULC changes (Chen et al., 2019; Chim et al., 2021). However, it is well acknowledged that these models are prone to uncertainties arising from model input data, parameters, and structure (Troin et al., 2018; Xu et al., 2007).

While many studies have focused on the hydrological impacts of LULC under various climate and environmental settings, less attention has been paid to the uncertainty associated with these impacts and, in particular to the interaction between LULC and hydrological model uncertainty (Chen et al., 2019). Indeed, LULC has been identified as an additional source of uncertainty besides model structure and parameter, but its contribution to the model prediction uncertainty remains unclear. For instance, Breer et al. (2006) and Eckhardt et al. (2003) used Monte Carlo simulation to investigate the uncertainty of parameters in the hydrological effect of LULC and their findings show significant output uncertainty owing to model parameterization uncertainty. Chen et al. (2019) investigated the influence of parameter uncertainty and the effects of model structure uncertainty in simulation of LULC impacts on catchment runoff at annual, monthly and daily time scales at the Xitiaoxi basin in China. The authors reported that the impacts of LULC change could be potentially hidden by the simulation uncertainty results from model parameters and that model structure represents an additional source of uncertainty in hydrological response to LULC change. According to Niraula et al. (2015), the values of absolute and relative changes in runoff for different calibration methodologies are fundamentally different due to LULC change. Different parameter estimating approaches add uncertainty to LULC effect analyses. Therefore, the need for understanding the interaction between LULC changes and model

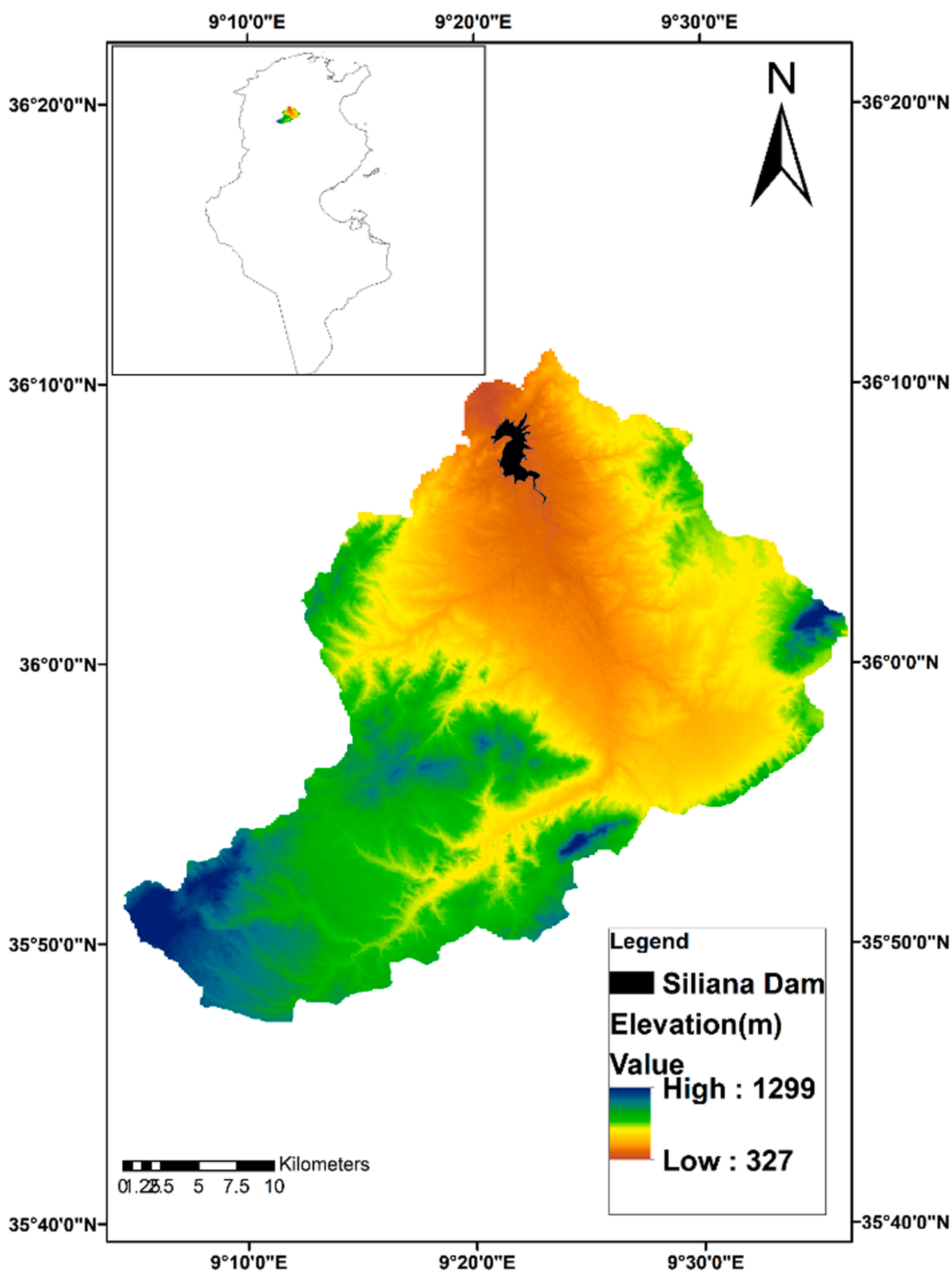

Fig. 1. Location of the study area.

uncertainty is obvious and benefits hydrological models in identifying their limitations and guiding efforts to improve their performances on which are based water management decision processes. Thus, the main objective of this paper is to assess the effect of LULC on hydrological model prediction uncertainty. This is achieved by addressing (1) the hydrological model parameter uncertainty and (2) the trade-off existing between LULC, parameter and model prediction uncertainty in estimating the impacts of land use change on monthly flow and flow extremes magnitudes in the Siliana catchment in Tunisia. The catchment witnessed rapid changes in LULC over the period 1990–2019 towards less water-demand in response to the limited water resources. Thus, addressing the effects of LULC on the flow regime within an uncertainty framework is of a paramount importance to water allocation in the Siliana catchment.

2. Materials and method

2.1. Study area

The Siliana catchment is in the northwestern of Tunisia and covers an area of 1028 km^2 (Fig. 1).

The climate is Mediterranean with an average annual precipitation about 580 mm most of which falls between October and April. The dry season extends from May to September where the temperature can exceed 28 °C. The main economic activity in the catchment is based on agricultural production mainly for cereals and olives (Table 3) with important economic values not only for the local development but also at the national level. During the last three decades the catchment has been facing rapid changes in LULC due to urbanization, industrialization, and agricultural development, increasing the pressure on water resources. Over 80 % of available water is used for irrigation in the catchment with an extensive mobilization and usage of surface water through reservoirs, dams and direct abstraction of water from the river.

2.2. Data acquisition and preprocessing

Historic multispectral satellite images provide valuable spatially distributed information that can be used to produce past land use classifications. In this study-four Landsat images were used. The Landsat5 Thematic Mapper TM 1990, Landsat5 TM 2000, Landsat8 Operational land Imager OLI 2013 and Landsat8 OLI 2019 images with a resolution of 30 m were downloaded from the U.S Geological Survey (USGS) website (https://earthexplorer.usgs.gov/). The satellite images were corrected, and their quality was enhanced. Atmospheric correction was applied to remove the absorption effects from the atmosphere. Then, a new multi band image is produced with the layer stacking procedure and the available LULC classes were identified. Finally, we applied some enhancement algorithms to improve the appearance and the quality of the images. A majority analysis raster based on contiguous neighboring cells was applied to remove misclassified, spatially singular pixels within homogenous areas.

2.3. LULC dynamics and image classification

Supervised classification methods were used to classify the images. Each image was classified using the Maximum Likelihood Classification (MLC) algorithm considered as the most successful classification method (Yuan et al., 2005). Based on visual interpretation, a five-class categorization scheme was constructed utilizing the historical feature of Google Earth with Landsat pictures for the maps 1990 and 2000 with 30 m resolution and Maxar imagery for the maps 2013 and 2019 with 15 cm resolution. Agriculture, pasture, urban, forest and water were the first LULC classifications. A random sampling method was used to acquire 50 points for each land use class's accuracy assessment. The reference data was extracted using Google Earth pictures. The Kappa coefficient, overall accuracy, producer and user accuracy, which were obtained from the error (confusion) matrix as mentioned by Liu et al. (2007), were used to assess accuracy. A minimum of 85 percent overall accuracy is suggested for each LULC map (Anderson et al., 1976). In addition to Google Earth, we used the 1990 forest inventory and agricultural maps from the Tunisian Ministry of Agriculture from 2000 and 2013, to refine the 'Agriculture' class into 'Irrigated land', 'Olive trees', and 'field crop', and the 'Forest' class into 'Dense Forest' and 'Clear Forest'. Finally, the 8 LULC classes were categorized as field crop, olive plantation, pasture, dense forest, clear forest, irrigated land, urban land, and water bodies (Fig. 3).

2.4. Analysis of land use and land cover

The categorized maps 1990, 2000, 2013, 2019 were used to conduct the change analysis. Equations (1) and (2) were used to calculate the magnitude of the differences between the periods, as well as the percent of change (Hassen and Assen, 2018) and rate of change (Gashaw et al., 2014). The percent of change of X results in:

$$PCX = \left(\frac{X - Y}{Y}\right) \times 100 \tag{1}$$

whereas the rate of change (ha/yr) produces:

$$\mathrm{RCX} = \left(\frac{X - Y}{Z}\right) \tag{2}$$

X represents the area of LULC (ha) at the evaluation period, Y represents the area of LULC (ha) at the reference time and Z represents the years between Y and X.

2.5. Modelling approach

The SWAT model is a continuous-time scale, semi distributed model (Arnold et al., 1998). SWAT can be used to model changes in hydrological processes, vegetation growing and water quality at various sizes of watersheds, as well as to assess the effects of water resource management and climate change (Abbaspour et al., 2015; Dile et al., 2016). It splits the watershed into distinct basins, which are further divided into Hydrologic Response Units (HRUs), based on a variety of land use, soil characteristic, topography and management plans. SWAT uses one of two ways to simulate diverse hydrologic processes including surface runoff: the SCS Curve Number (SCS-CN) method or the Green and Ampt infiltration equation. SWAT also employs alternative methodologies to quantify evapotranspiration, such as the Priestley-Taylor, or Penman-Monteith methods. The SCS-CN method is used in this work. It is a practical method for estimating runoff based on the catchment land use, soil qualities, and hydrologic conditions. SWAT uses the water balance equation to model the hydrological cycle:

$$SW_t = SW0 + \sum_{k=1}^{t}\left(R_{day} - \mathrm{Q_{surf}} - \mathrm{E_a} - \mathrm{W_{seep}} - \mathrm{Q_{gw}}\right) \tag{3}$$

where SWt is the final soil water content (mm), SW0 is the initial soil water content (mm), t is the simulation period length (days), R_{day} is the total of precipitation on day k (mm), Q_{surf} is the total of surface runoff on day k (mm), Ea is the total of evapotranspiration (ET) on day k (mm), W_{seep} is the total amount of water that enters the vadose zone from the soil profile on day k (mm), and Q_{gw} is the total return flow that contributes to streamflow on day k (mm).

In addition to the digital elevation model (DEM), land use and soil data, the SWAT model requires daily data for precipitation, maximum and minimum temperature, solar radiation, air relative humidity and wind speed. These data were gathered from various sources and are listed in Table 1.

Table 1
Collected data to be used for SWAT implementation in Siliana catchment.

Available data	Resolution/ scale	Source
Precipitation	Daily (1995–2013)	5 Stations (Lakhmes, Siliana, Makther, Nmaira, Jama). Source: Direction Générale des Ressources en Eau (Tunisia)
Temperature	Daily (1995–2013)	Siliana station. Source: Institut National de la Météorologie (Tunisia)
Wind, Solar radiation, Humidity	Daily (1995–2013)	9 climatic stations (SWAT generated 22 km grid). Source: https://swat.tamu.edu/
Digital Elevation Model	30 m	Shuttle Radar Topography Mission (SRTM) of USGS (https://srtm.csi.cgiar.org/)
Soil map	1.50 000	Agricultural Map; Soil database (Sellami, 2014)
Land use map	1.5 000	Agricultural Map; Landuse database (SWAT model crop database)
Discharge	Monthly (1995–2013)	Direction Générale – Bureau des études hydrologiques BETH (Tunisia)

2.6. SWAT implementation

Monthly simulations were conducted from 1995 to 2013 with a warm-up period of 5 years prior collecting the results. This is to move the initial condition of the model to a hydrologically steady state condition. The modified SCS-CN method was selected for runoff simulation and the storage coefficient approach was used for channel flow routing. We have used observed climate data to compute potential evapotranspiration (PET) using the Penman-Monteith method during model simulation. The entire Siliana catchment was delineated into 21 subcatchments that were subsequently discretized into HRUs according to the soil type, land cover and the slope combinations.

2.7. Sensitivity analysis

The sensitivity analysis is a method for identifying the main parameters for the calibration and validation of the SWAT model (Arnold et al., 2012; Moriasi et al., 2007; Tang et al., 2012). Automatic calibration of model parameters such as SWAT can be time-consuming and computational burden. Thus, a sensitivity analysis was performed to select the set of parameters that have the greatest influence on the model for the calibration purposes. The One-at-a-time (OAT) coupled with the Latin Hypercube Sampling (LH) is a global sensitivity procedure (Chaibou Begou et al., 2016; Khalid et al., 2016) and was used on 16 SWAT related-flow parameters by varying one parameter at a time and calculating indices like *t*-Stat and p-value to provide a measure of sensitivity and its significance, respectively (Narsimlu et al., 2015). A larger *t*-test in absolute values indicates greater sensitivity whereas a p-value of 0 indicates greater significance. Table 2 lists the most sensitive parameters we used in our research.

2.8. SWAT calibration and parameter uncertainty using GLUE

Many studies have used the Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Binley, 1992) method for calibration of the SWAT model parameter and estimation of uncertainty (Sellami et al., 2013; Tegegne et al., 2019; Teweldebrhan et al., 2018; Xue et al., 2018). The GLUE method is based on the idea that there is no optimal collection of parameters for describing the hydrology of a catchment. Instead, parameter sets with different values can be considered as acceptable. This is the basis of the equifinality concept. Within the GLUE, the model is run with a set of parameters sampled randomly from their initial distribution. Then, model performance is evaluated against observation using a likelihood function. Using a threshold value of the likelihood function, acceptable parameter sets are identified, and the model prediction uncertainty is sampled from the cumulative distribution function

Table 2
Selected parameters for SWAT calibration in Siliana catchment.

Parameter name/acronym	Unit	Parameter description	Sensitivity Rank
CN2	–	The SCS runoff curve number parameter for moisture conditions is widely used to estimate the quantity of runoff following a rainfall event in a certain area. The hydrologic soil group, land use and the hydrologic condition of the located area all contribute to the curve number.	1
ESCO	–	The evaporation losses from the watershed are influenced by the soil evaporation compensation factor. The impact of this parameter on ET is determined by the soil depth.	2
ALPHA_BF	Days	The rate at which groundwater is returned to the flow is represented by the baseflow recession constant.	3
EPCO	–	The amount of water required for plant uptake requirement is expressed by the plant evaporation compensation factor.	4
GWQMN	mm	The minimum water depth in the shallow aquifer required for return flow to arise.	5
CH_K2	mm/hr	The effective hydraulic conductivity in the main channel's alluvial deposits.	6
SOL_AWC	mm	The Available Water Capacity is the amount of water that should be available to plants.	7
GW-Revap	–	The passage of water from the shallow aquifer into the capillary fringe is described by the groundwater "revap" coefficient.	8

of the acceptable simulations (Beven and Binley, 1992). The following steps summarize the implementation of the GLUE method with the SWAT model during parameter calibration.

Step 1. Determine a prior range for the sensitive parameters to be calibrated.

Step 2. From prior parameter distributions, sample the selected sensitive parameters 6000 times at random.

Step 3. For each parameter set, run the SWAT model and calculate the likelihood values.

Step 4. To acquire the behavioral parameter sets and the posterior distribution of parameters, define a cut-off threshold.

Step 5. Create the 95 percent uncertainty bound (95PPU) for model prediction uncertainty based on the posterior distribution. To determine the performance of model calibration and uncertainty, the r-factor, p-factor, R^2 and the Nash and Sutcliffe (NS) are used (Abbaspour et al., 2015). The r-factor denotes the width of the uncertainty interval, while the p-factor denotes the percentage of measured data covered by the 95PPU. A higher p-factor and lower r-factor means a less uncertainty (Abbaspour et al., 2009).The NS is a statistic criteria without dimension that represents the relative magnitude of the residual variance in relation to the measured data variance (Nash and Sutcliffe, 1970). The Nash values range from $-\infty$ to 1 with a high value indicating an accurate model. NS was selected as an objective function during the calibration process. The threshold value of NS > 0.5 was adopted similarly to many previous studies (Bouslihim et al., 2016; Sellami et al., 2013; Tuo et al., 2016).

For this analysis, 6000 parameter sets were sampled randomly from a uniform a priori parameter distribution. Simulations with NS > 0.5 were deemed acceptable otherwise they were excluded from the analysis. A modelling platform was developed in Matlab to implement the SWAT model using the harmonized input data with every single LULC scenario and perform simulations using the sampled parameter sets. This is to ensure that any departure in model simulation is only due to change in

Table 3
Accuracy assessment of classified maps.

Land Cover Class	1990		2000		2013		2019	
	Procedure accuracy	**User accuracy**	**Procedure accuracy**	**User accuracy**	**Procedure accuracy**	**User accuracy**	**Procedure accuracy**	**User accuracy**
Agriculture	0.91	0.85	0.9	0.7	0.9	0.84	1	0.88
Pasture	0.74	0.69	0.75	0.713	0.75	0.81	0.79	0.84
Forest	0.8	0.88	0.83	0.96	0.94	0.98	0.91	0.98
Urban	0.89	0.95	0.87	0.925	0.82	0.85	1	0.98
Water	0.91	1	0.93	1	1	1	0.91	1
Overall accuracy	0.85		0.85		0.89		0.92	
Kappa	0.82		0.82		0.87		0.90	

LULC. The modelling framework is described in the flowchart of Fig. 2.

2.9. Hydrological indicators

A wide range of hydrological indicators exist in literature that can be used to examine changes in catchment flow regime due to LULC

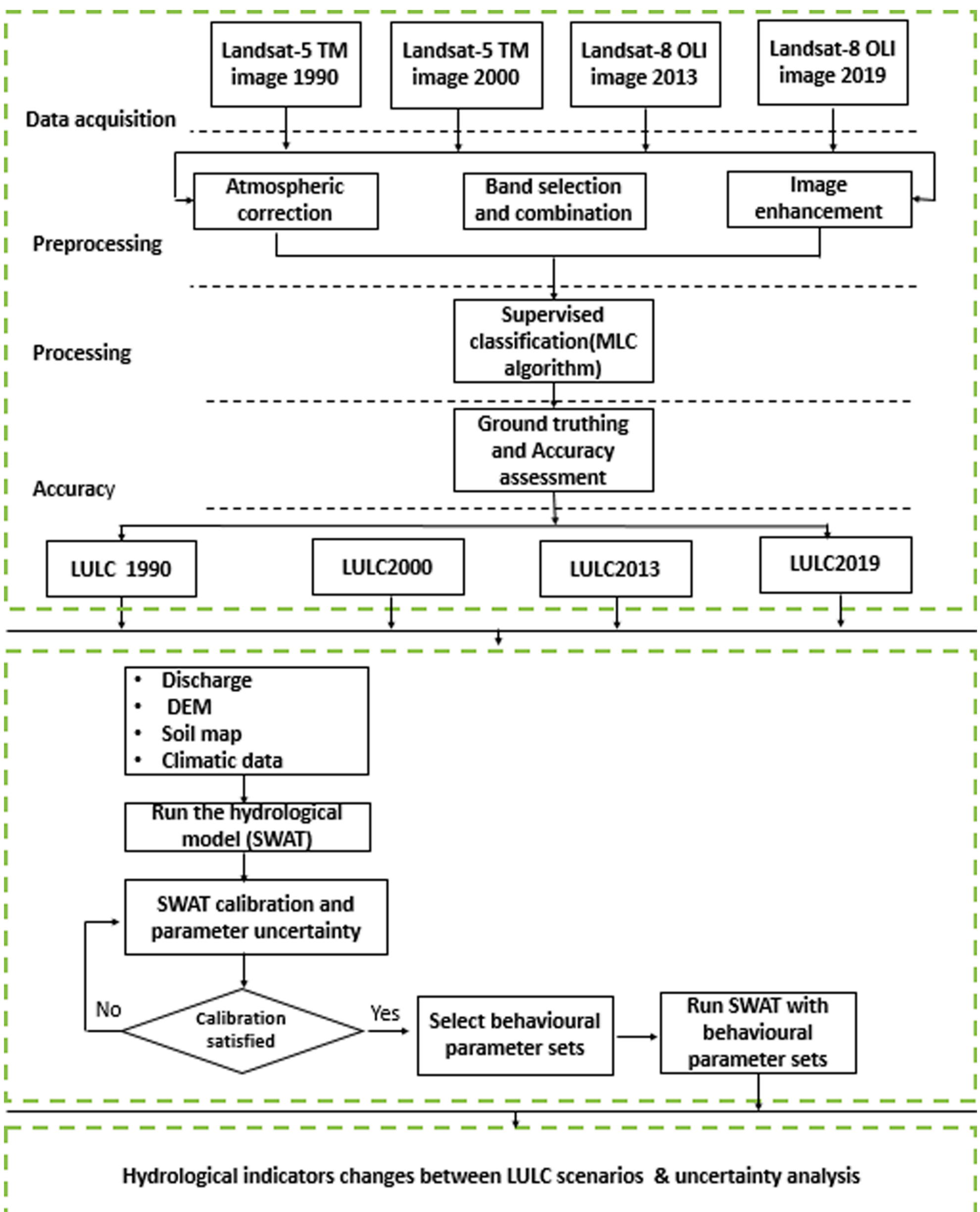

Fig. 2. Flowchart representing the different methodological steps of this study.

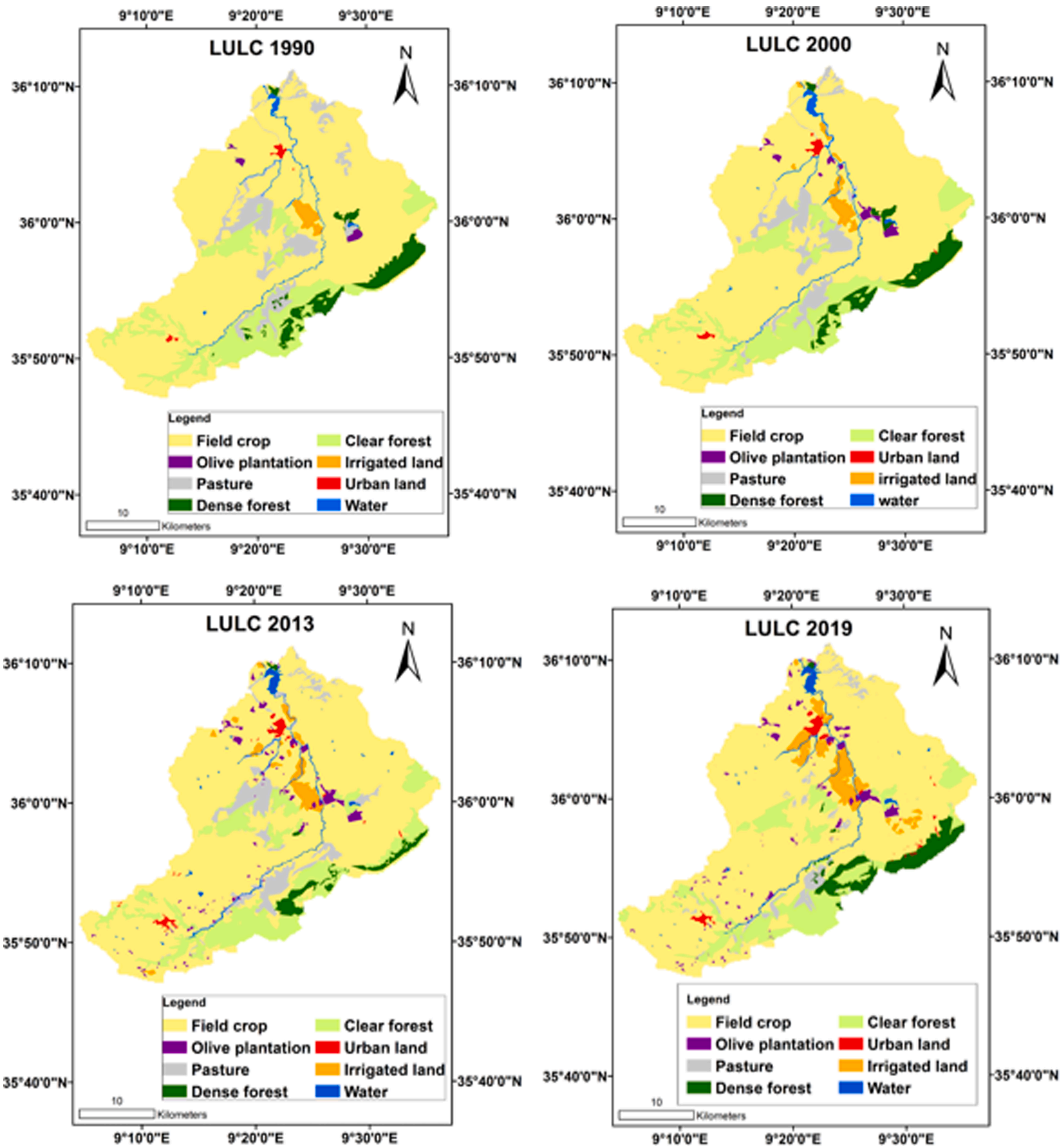

Fig. 3. Evolution of LULC in the Siliana catchment between 1990 and 2019.

changes. The selection of these indicators is based on the goal, the data available and the hydrological characteristics of the site under investigation and to which extent these indicators can be informative not only for the hydrological functioning but also from the management perspective. In this study we investigated the monthly flow as an indicator related to water availability and deemed important for evaluating water supply versus demand in the Siliana catchment. Low flows and high flows were also analyzed. They can be used as surrogates to flood and drought frequency and risk analysis. Many studies demonstrated the sensitivity of low and high flows to changes in LULC (Moghadasi et al., 2018; Shrestha, 2019; Recanatesi et al., 2020). In addition, maintaining minimum low flows in the Siliana river is crucial for meeting the minimum water demand for irrigation and for maintaining ecologically and healthy ecosystem in the catchment. For a given catchment, the Flow Duration Curve (FDC) displays the percentage of time that a daily or monthly streamflow is exceeded during a certain period (Sellami et al., 2014). The FDC can provide useful information about the pattern of river flow variations, making it a useful tool for describing a wide range of river discharges, from low to high flows (Kumar et al., 2022). Extreme events can be immediately derived from different portions of the FDC as high flows (≤Q10) and low flows (>Q70). Extreme occurrences are particularly important for various hydrological services since they serve as a predictor of severe rainfall events or storms, as well as the frequency of flood discharges. Because river low flow regime is influenced by a variety of local elements such as soil attributes, geology, local meteorological conditions and aquifer hydraulic features, low flows must be represented on a local scale.

3. Results and discussion

3.1. LULC maps classification and change analysis

Table 3 reports the accuracy of the LULC classification. The overall accuracy ranges between 0.85 and 0.92 from 1990 to 2019. The Kappa coefficient for the three classified images was above 0.80 which can be considered as very good according to Monserud (1990). These statistics reflect the good accuracy of the classification and validation of the satellite images as compared to the ground truth.

The analysis of LULC from 1990 to 2019 reveals a general trend towards less water-intensive crops demand in the Siliana catchment (Fig. 3). For instance, olives plantation has increased by over 350 % from 1990 to 2019. There are several reasons that could explain this shift. Historically, olives plantations are ancestral practices in the catchment as they do not require intensive irrigation and are highly resilient to low rainfall. Another reason could be attributed to the financial aids provided by the Tunisian government encouraging the farmers to shift to less water-intensive crops. The high economic value of olive oil in both local and international markets could be also a motivation for local farmers to shift from irrigated crops to olive plantations.

Irrigated lands consisting of fruit trees and vegetable crops have increased also by 103.29 ha/yr while pasture and mixed forests were reduced by 159 and 92.96 ha/yr respectively, between 1990 and 2019. Table 4 reports the evolution in the rate of changes in LULC in the Siliana catchment over 1990–2013. It shows that LULC change rates are higher in the 1990–2013 period as compared to 2013–2019. Most of the increase in olive plantation, urban construction and irrigated lands occurred in the period 2000–2013. The decreasing trend in forests and pasture is more important in 2013–2019 than in 1990–2000. These changes could affect the water balance by reducing water infiltration and groundwater recharge and increasing ETP which could lead to a reduction in surface water.

3.2. Sensitivity analysis

From the sensitivity analysis we have selected the most eight sensitive SWAT parameters for calibration (Table 2). The first three ranked parameters have a direct and indirect control on surface water. The remaining sensitive parameters are soil and land use related parameters. The result of sensitivity analysis reflects the large influence of the surface runoff in the water balance of the Siliana catchment. These results in line with these reported by several authors (Abouabdillah et al., 2014; Bouslihim et al., 2016). The choice of these eight parameters was based not only on the results of the sensitivity analysis but also on knowledge of the hydrological processes occurring in the catchment and of previous applications of the SWAT model in similar areas. For instance, Sellami et al. (2016) reported that eight sensitive parameters are enough to reach acceptable calibration performances of the SWAT model without omitting one or more hydrological processes important for the study site.

Table 4
Rate of LULC changes for 1990–2019.

Landuse class	Area 1990 (ha)	Rate of change (ha/yr) as reference to 1990		
		2000	2013	2019
Field crop	73,678	−29.1	+64.45	+67.21
Olive plantation	357	+45	+64.5	+47.97
Pasture	7302	−97.1	−150.2	−159
Clear forest	4481	–23	−64.9	−36.48
Dense forest	14,617	+1.6	−44.65	−56.90
Urban land	271	+17	+20.75	+19.21
Irrigated land	967	+49.5	+94.15	+103.21
Water	1104	+32	+15	+14

3.3. SWAT model calibration and uncertainty

The SWAT prediction uncertainty at the 95 % confidence interval (95PPU) as derived from the GLUE acceptable parameter sets are plotted against the observed discharge for each LULC scenario in Fig. 4. The simulations follow closely the trend and variability of the measured discharge but with a slight overestimation of peak flows. Over 6000 GLUE runs, behavioral simulations with Nash higher than 0.5 were 77,4% and 77 % for the scenarios 1990 and2000; and 84.3 % and 84 % for 2013 and 2019, respectively. The percentage of the observed discharge falling within the 95PPU is 68.7, 67.7, 56.3, and 56.3 % respectively for the 1990, 2000, 2013 and 2019 LULC scenarios. The r-factor, which is a measure of the thickness of the 95PPU, value is 1.3 for 1990 and 2000 and equals to 1 for the 2013 and 2019 scenarios. Ideally, the 95PPU should bracket 100 % of the observed data with an r-factor value as small as possible (Abbaspour et al., 2015). However, this situation is not achievable when dealing with hydrological models due to presence of the uncertainty. Therefore, these statistics reflect the good performances of the SWAT model for simulating the discharge of the Siliana catchment. The GLUE method was also efficient in identifying behavioural parameter sets and uncertainty intervals for each LULC scenario that are able to simulate and capture the observed discharge. These findings are consistent with previous studies (Shen at al., 2012; Chen et al., 2019). Indeed, there are many subjectivities in the selection of the threshold value, the likelihood function and the uncertainty interval in the GLUE method which may affect the interpretation of the results. However, this issue has been widely discussed in the literature and is beyond the scope of this paper. The reader can refer to Stedinger et al. (2008) for such discussion.

The LULC maps of 1990 and 2000 resulted in wider 95 PPU than these for 2013 and 2019. This can be identified by visual inspection of Fig. 4 and was also confirmed by the p- and r- factors values presented in the previous analysis. These results suggest that change in LULC affects model prediction uncertainty. Such findings were also reported by several authors (Breuer et al., 2006; Niraula et al., 2015; Chen et al., 2019). The quality and resolution of the satellite images used to derive the LULC maps influence the model prediction uncertainty. Indeed, the LULC maps of the scenarios 2013 and 2019 were generated with higher classification accuracy and resolution. Thus, they are affected with lower uncertainty than these for 1990 and 2000 LULC maps. As reported by Gebrehiwot et al. (2019) data quality controls can enhance precision of land use change impact. Wagner et al. (2013) demonstrated that difference in LULC classification and image acquisition date represent the phenology of the crop at that date which may results in uncertain crop parameterization in the model.

To better investigate the SWAT model performance, the FDCs of the "behavioral" simulations are constructed and plotted against the observed one in Fig. 5. The FDCs allow to display the full range of discharge value from extreme high flows to extreme low flows (Fig. 5). The slope of the simulated FDCs in the high flows percentiles (probability of exceedance $\leq$ 0.1) indicates that flood discharges are not sustained for an extended period of time and are affected with high inter-annual variability. It is clear from Fig. 5 that the SWAT model over-estimates low flows magnitude and frequency of the observed discharge. Moreover, the model uncertainty interval does not capture the observed low flows observations. This model deficiency is more exacerbated for the LULC of 2013 and 2019. Low flows are more dependent on soil, geological and land use characteristics of the catchment rather on climate condition. Many authors reported the limitation and large uncertainty of the SWAT model in simulating low flows (Coffey et al., 2004; Spruill et al., 2000). For high flows, most of the observation data is captured by the 95 PPU for all LULC scenarios, reflecting the good

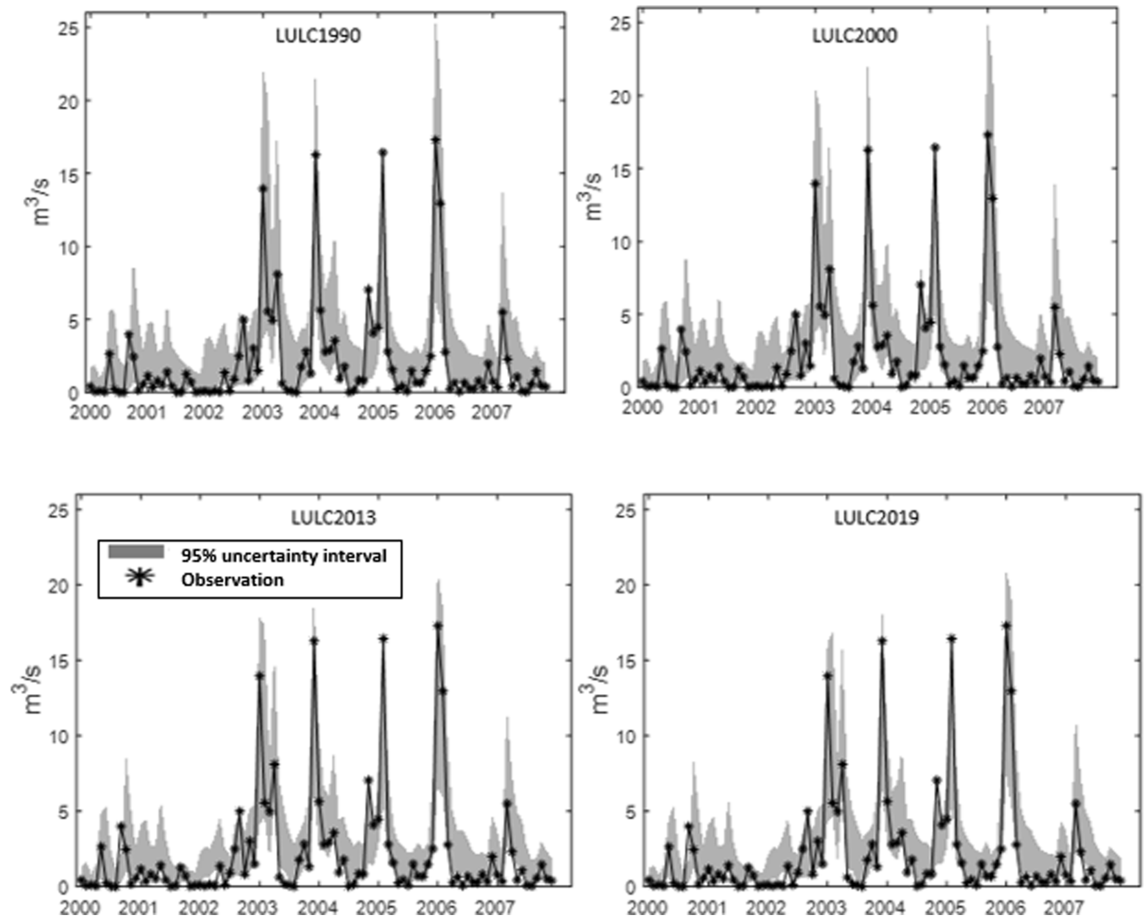

Fig. 4. GLUE prediction uncertainty bands and observed monthly flow for Siliana catchment for different LULC scenarios.The grey area is the 95% prediction uncertainty interval and the dotted black line is the observed monthly averaged discharge.

performances of SWAT in simulating high flows magnitude and frequency of the Siliana catchment (Fig. 5).

There is a consistent trend between simulated and observed monthly flow (Fig. 6). The Siliana catchment has a strong seasonality in flow regime which is also well simulated by the SWAT model. However, the model tends to overestimate the magnitude of the observed monthly flow under all LULC scenarios. This could be related to the sensitivity of the CN2 parameter to land use and its influence on surface runoff simulation in the SWAT model (Chim et al., 2021). The late LULC scenarios generated lower monthly flow magnitudes during the wet months than these simulated using the 1990 and 2000 LULC (Fig. 6). This difference could be attributed solely to the change in LULC as all simulations were performed under the same climate conditions and input data.

The distribution of the high and low flows values for each LULC scenario are plotted as boxplots in Fig. 7. While simulated high flows magnitudes tend to decrease, low flows are not affected by the changes in LULC. These results are in line with these reported in Figs. 5 and 6 suggesting that the effects of LULC on low flows could be hidden by model uncertainty. The decrease in high flows magnitudes is more important during the 2013–2019 than during 1990–2000. Indeed, most of the change in LULC has occurred from 1990 to 2013 and consisted mainly in reduction of pasture, in favor of agricultural crop, olive plantation and irrigated land extension. These crops are parametrized differently in the SWAT model which resulted in less high flows magnitudes. Similar conclusions have been reported by Breuer et al. (2006), who linked the uncertainty in annual and seasonal flows to the crop parametrization in the SWAT-G model. The Effects of land use change on high and low flows magnitude and frequency has been a controversy subject in literature.

For instance Githui et al. (2009) observed an increase in low flows with forest cover loss. As for Eisenbies et al. (2007) and Webb et al. (2007), they found a remarkable rise in dry season flows due to deforestation and assigned this increase to a reduction in ET. In accordance with Liu et al. (2015), variation in low flows include soil changes and vegetation and thus the soil disturbance after deforestation ultimately determines low flows responses. Conversely, Bruijnzeel (2004), noted that deforestation and cropland extension lead to changes in the hydrophysical conditions of the soil in tropical forests, which then leads to reduced low flows due to reduced infiltration and, groundwater recharge. Within the same context, Bewket and Sterk (2005) assigned the downward trend in average low water levels during the dry season to the expansion of eucalyptus plantations, due to the high water consumption of eucalyptus species (up to 7 mm/day), which decreases the water stored in the soil profile and ultimately reduces base flow.

3.4. Interaction between LULC changes and model uncertainty

To investigate the relationship between LULC changes and model parameter uncertainty, the posterior distribution function (pdf) for each parameter as derived from the behavioral parameter sets under each LULC map are superposed in Fig. 8. The shape of the pdf indicates the degree of uncertainty in parameter estimation; sharpened and peaked distribution indicates well-identifiable parameter while flattered and spread distribution indicates uncertain parameter. The results show that the shape of the pdfs depends on the parameter and LULC scenario. For the LULC of 1990 and 2000, the pdfs reflect larger uncertainty parameter than for the 2013 and 2019 LULC. This is particularly true for most of the parameters except for the CH_K2. This parameter is controlling the

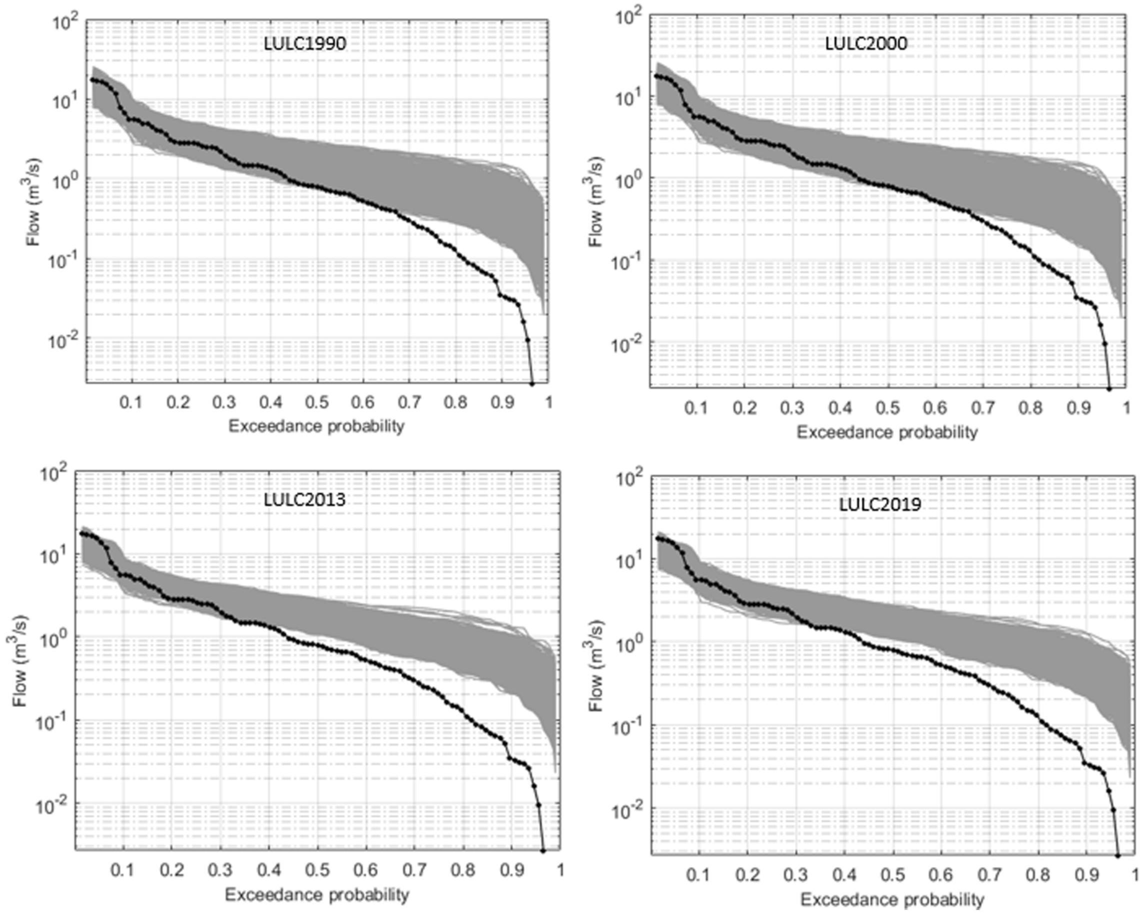

Fig. 5. GLUE predicted monthly averaged Flow Duration Curves (FDCs) for different LULC scenarios in Siliana catchment. The observed monthly averaged FDC is represented by the black dotted line.

hydraulic conductivity of the channel and water infiltration in the riverbed and is less sensitive to the change in LULC. Other parameters are more affected by LULC change. For instance, it is seen from the Fig. 8 that there is more variability in the uncertainty of the CN2 parameter between the LULC scenarios. This could be related to the high sensitivity of this parameter to the LULC. The pdfs of the SWAT parameters deemed sensitive to surface runoff exhibit similar trend across the LULC scenarios with uncertainty being more important in the 1990 and 2000 LULC results as compared to the 2013 and 2019 scenarios. In addition to parameter uncertainty, model structure and data quality can contribute to model prediction uncertainty (Li et al., 2010; Gebrehiwot et al., 2019). In this study, it is very likely that the uncertainty of the initial data mixes up with the parameter uncertainty and propagate to affect the SWAT model prediction uncertainty. Indeed, the 2019 and 2013 maps have been corrected with the Maxar imagery available at the centimeter scale resolution. The quality of LULC of these maps will therefore be intrinsically better than these for 1990 and 2000 derived from Landsat imagery with 30 m resolution (Table 3). These results can explain the wider uncertainty in the SWAT model simulations obtained in the 1990 and 2000 LULC scenarios. However, this variability in parameter uncertainty between LULC scenarios did not affect the general trend of the monthly flow but has an impact on the variability of the flow magnitude as demonstrated with the previous analysis (Figs. 5 and 6). Similar results were also reported by Chen et al. (2019) while investigating the effects of LULC change on the runoff of the Xitiaoxi basin in eastern China. Fig. 8 shows also that the groundwater parameters such as Alpha_BF and GWQMN are affected by the LULC changes. Their corresponding pdfs reflect the uncertainty in these parameters which is also reflected in a wider 95 PPU in simulating low flows (e.g. baseflow) by the SWAT model. In addition, the variability in the uncertainty of these parameter could be explained by the development of water supply capacity for irrigation in the later LULC scenario, that exert a pressure on the groundwater resources and that therefore affects groundwater system parameters in the model (Batelaan et al., 2003; Klöcking and Haberlandt, 2002).

Analysis of the interactions between changes in LULC and model parametric uncertainty is very complex for many reasons. Most importantly, is the possible correlations and interactions between the parameters which add complexity in parameter identifiability. The non-identification of a parameter does not mean that it is not sensitive or important, it may still be important in the context of a set of parameters (Sellami et al., 2013; Shen et al., 2012). This may add uncertainty to the parameter. In addition, it is very common in the hydrological impact of LULC change to restrict the analysis to the calibrated parameters with high sensitivity to the flow simulation and omitting these related to the crops and soils characteristics (Breuer et al. 2006). Thus, wider uncertainty range is obtained for model parameter and prediction which can hide the effects of LULC. Chen et al. (2019) reported that the potential effects of change in land use could be hidden by the simulation uncertainty results from model parameters. Indeed, uncertainties in hydrological models stem not only from model parameters, but also from inputs (ex. precipitation, temperature..) and model structure (Vrugt et al., 2005; Moges et al., 2020; Bermudez et al., 2017).

4. Conclusion

This study investigated hydrological modelling uncertainty while assessing the impacts of changes in LULC as derived from remote sensing

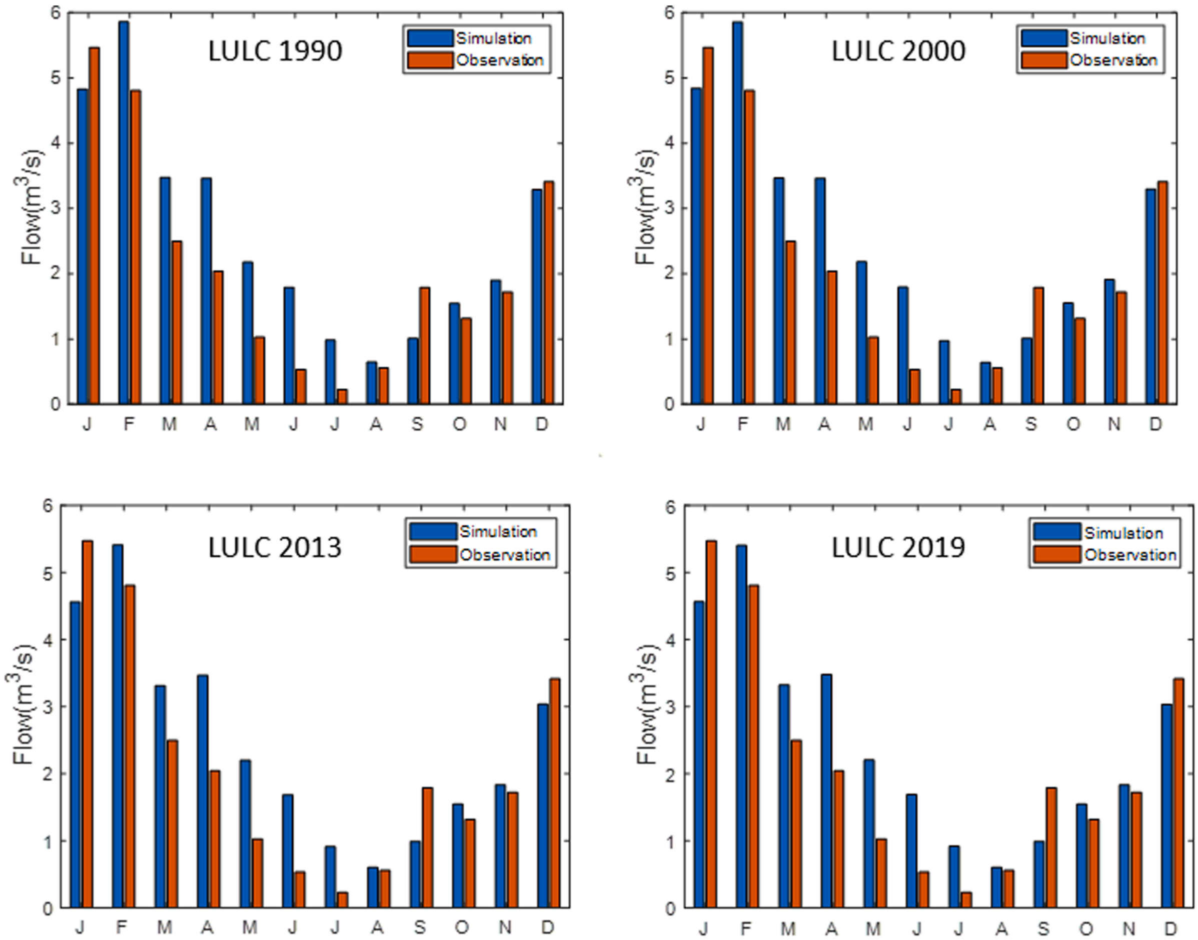

Fig. 6. Monthly averaged simulated and observed streamflow for Siliana catchment (2000–2013). Simulations are shown for different LULC scenarios.

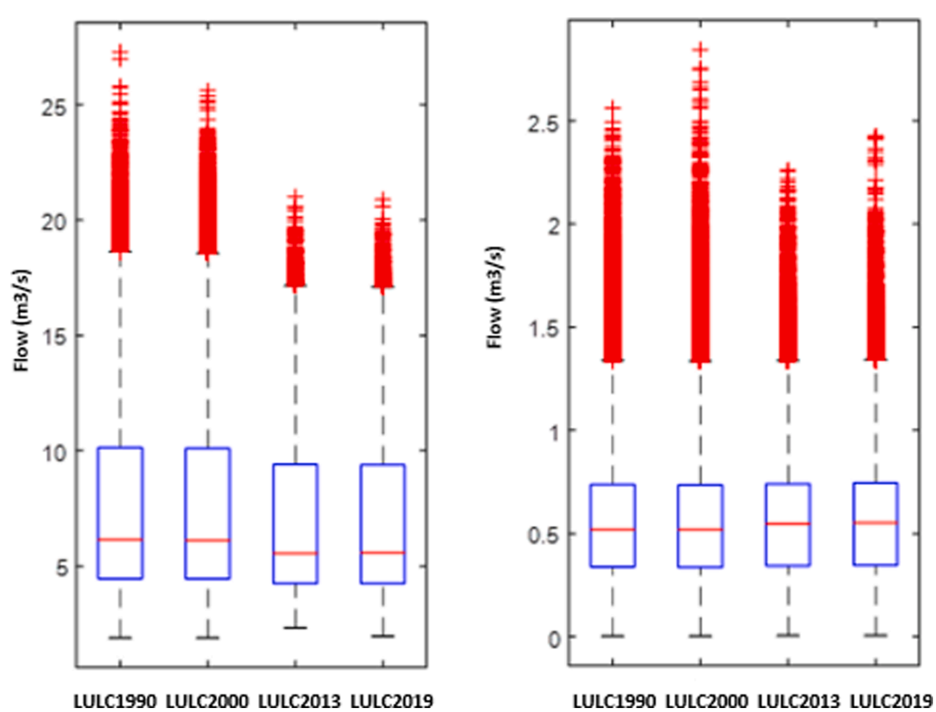

Fig. 7. Boxplot of high and low flows of Siliana catchment under different land use scenarios (High flows are on the left and Low flows are on the right).

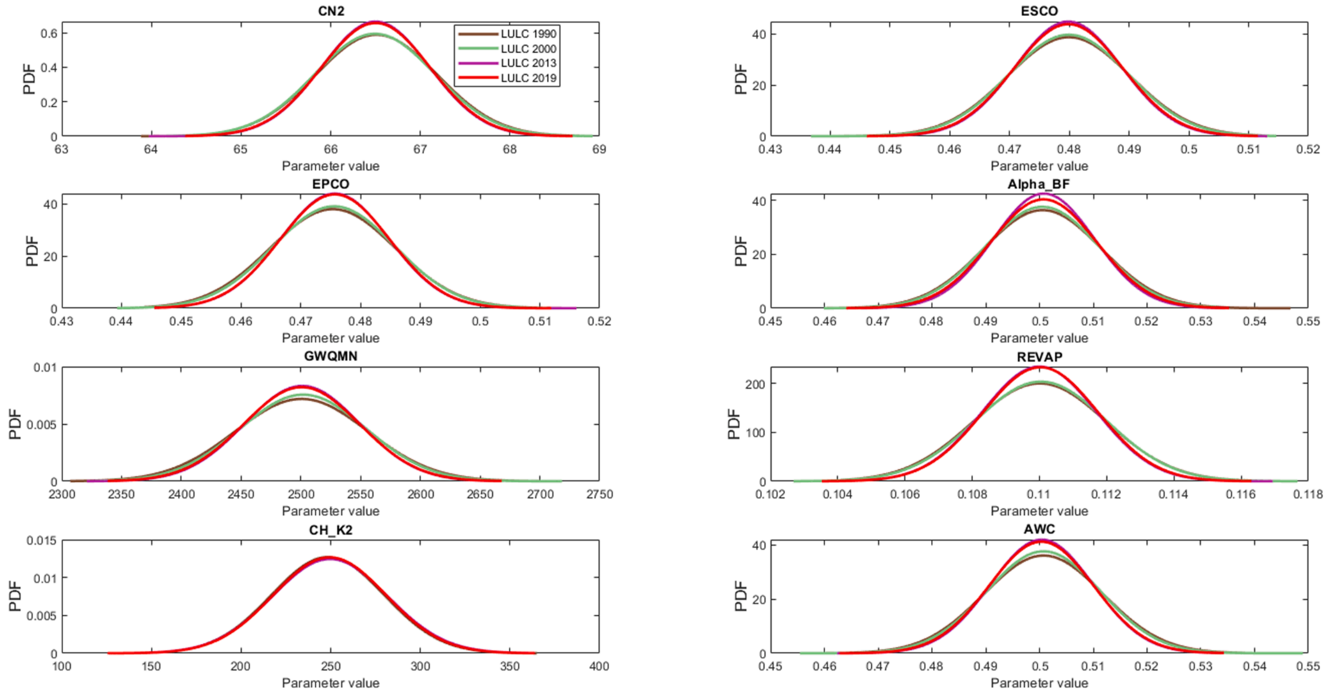

Fig. 8. Posterior parameter distribution for different land use scenarios.

data on the flow regime of the Siliana catchment in Tunisia. We used the SWAT hydrological model with the GLUE method to infer parameter and model prediction uncertainty and perform model simulations for LULC of 1990, 2000, 2013 and 2019. The results showed that the SWAT model has good performances in simulating the monthly flow but showed inadequacy and large uncertainty in low flows simulation. The analysis demonstrated that changes in LULC decreased monthly flow, high flows magnitude but did not impact low flows, in particular during the last two decades leading to a drier hydrological condition in the catchment. By considering hydrological model parameter uncertainty it was able to investigate the relationship between LULC and model parametric uncertainty. It was found that the effects of changes in LULC were hidden by model prediction uncertainty. This highlights the need for adopting uncertainty analysis as a common practice in studying the hydrological impacts of changes in LULC. The findings of this study can be a baseline for assessing the combined effects of climate and land use change on catchment hydrology.

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.

Data availability

The authors do not have permission to share data.

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