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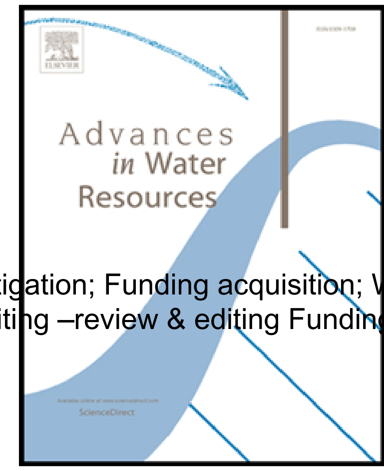

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Highlights

- First SWAT review on hydro-climatic extreme studies.
- Lack of SWAT assessment on extreme flows simulations.
- Comparison of SWAT+ and SWAT should be conducted.
- Incorporation of CMIP6 GCMs in SWAT hydro-climatic studies.
- Integration of artificial intelligence within SWAT modelling

A Review of SWAT Applications, Performance and Future Needs for Simulation of Hydro-Climatic Extremes

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Abstract

Hydro-climatic extremes, such as droughts and floods, have most likely increased due to climatic change and could lead to severe impacts on socio-economic, structural and environmental sectors. With nearly 4,000 publications, the Soil and Water Assessment Tool (SWAT) is clearly one of the most extensively used ecohydrological models worldwide. The model has been widely used for projecting the impacts of future hydro-climatic changes, but application for extreme streamflow conditions is still rarely reported. To date, SWAT application reviews have focused on compilations of SWAT studies for specific or relatively new applications such as eco-hydrological modelling, ecosystem services, sub-daily simulations, and pesticide fate and transport simulations. However, no existing SWAT review studies have focused on simulation of hydro-climatic extremes. Therefore, this research aims to bridge this gap by compiling and reviewing the findings of studies reporting SWAT hydro-climatic extremes including highlighting the performance and future research needs. A total of 111 articles have been identified since 1999; most of these studies were conducted in the United States and China. These articles can be divided into extreme flow assessments, drought studies, flood studies, drought and flood studies, SWAT coupling with other models, and SWAT improvements. Most of the extreme performance assessment studies reported "satisfactory" performance, with a particular emphasis on peak flow comparisons. Future research needs regarding this topic include: (1) a unified SWAT extreme performance assessment framework; (2) SWAT improvements that result in improved replication of peak and low flows; (3) reliability assessment of global and satellite products for SWAT extreme simulations; (4) bias correction of CMIP6 and regional climate projections; (5) comparison of SWAT+ and SWAT for extreme flows simulations in different types of basins; (6) development of an extreme flow module within an overall SWAT modelling system; and (7) integration of artificial intelligence within SWAT modelling.

Keywords: SWAT; Flood; Drought; Extreme; Peak Flow; Climate Change

1.0 Introduction

Hydro-climatic extremes, such as droughts and floods, have most likely increased due to climate change and could lead to severe impacts on socio-economic sectors (Giorgi et al., 2018, Raikes et al., 2019). Concern about hydro-climatic extremes and their consequences has been rising in recent years, as evidenced by the large effort of the Intergovernmental Panel on Climate Change (IPCC) in summarising climate extreme impacts on droughts (sub-chapter 3.1) and floods (sub-chapter 3.2) in the Special Report on Extremes (SREX) (IPCC, 2012). The report stated that some regions have experienced increasing length and intensity of flood and/or drought events. By referring to the definition of "climate extreme" in the SREX, the present study defines hydro-climatic extreme as "the occurrence of a hydro-climatic variable's value higher (or lower) than a defined extremely high (or low) threshold value".

Quantification of hydro-climatic extremes benefits local authorities and researchers in understanding the current status and potential risks of water related disasters. It is advantageous to use long-term observation data to measure the trends of hydro-climatic extremes for a specific region, because it is the most reliable source for understanding the hydro-climatic system (Fu et al., 2010). However, in many regions, the availability of reliable long-term observations remains a strong limitation (Mishra and Singh, 2011, Richts and Vrba, 2016, Ummenhofer and Meehl, 2017). Moreover, reliable long-term hydrological data are normally even less available as compared to climate data. Therefore, provided the models are accurate, ecohydrological modelling could be used to simulate and understand the hydro-climatic extremes and associated environmental impacts in regions without reliable hydrological observations.

Ecohydrological modelling is an indispensable tool in understandig the interaction of hydrological processes and environmental issues. Major advantages of ecohydrological modelling include applicability for a wide range of basin scales and environment conditions and their capability to perform cost effectiveness assessments and simulate "what-if" scenarios for planning purposes. Simulated streamflow could be used to further calculate hydrological and pollutant extremes at locations without a streamflow gauge. Moreover, ecohydrological models can be used to understand the effectiveness of mitigation strategies in hydro-climatic events. An extensive array of hydrological and ecohydrological models have been developed, many of which are described in previous review studies (Shepherd et al., 1999, Singh and Woolhiser, 2002, Borah and Bera, 2004, Daniel, 2011, Fu et al., 2019).

The Soil and Water Assessment Tool (SWAT) ecohydrological model (Arnold et al., 1998, Arnold et al., 2012a, Williams et al., 2008, Bieger et al., 2017) is one of the most widely used models worldwide and has been applied for an extensive suite of water resource issues across a broad range of basin scales and environmental conditions, as evidenced by approximately 4,000 documented publications (CARD, 2019). To date, several SWAT review studies have been reported in the literature which can be divided into four main categories: (1) general review, (2) special issue review, (3) specific region review, and (4) specific application review. General reviews include broad overviews of SWAT applications, performance and future research needs (Gassman et al., 2007) as well as descriptions of specific versions of SWAT (Bieger et al., 2017, Arnold et al., 1998). Special issue reviews provide a summary of the topics and findings of multiple SWAT studies that were published in a special issue of a specific journal; e.g. Krysanova and White (2015), Gassman et al. (2014), Douglas-Mankin et al. (2010), Gassman and Wang (2015), Tuppad et al. (2011). As SWAT is increasingly applied across the globe, compilations of SWAT study findings could be useful for SWAT developers or new users to identify its major applications, capabilities, challenges and limitations in a specific region. To date, regional-based SWAT reviews have been conducted for the Upper Nile River Basin region (van Griensven et al., 2012), Brazil (Bressiani et al., 2015) and Southeast Asia (Tan et al., 2019a). Lastly, a specific application review refers to a compilation of SWAT results and issues for studies focused on specific or relatively new applications such as eco-hydrological modelling (Krysanova and Arnold, 2008), ecosystem services (Francesconi et al., 2016), pesticide fate and transport (Wang et al., 2019) and sub-daily applications (Brighenti et al., 2019).

One of the earliest SWAT hydro-climatic extreme studies was conducted by Van Liew et al. (2003) to understand how flood retention structures would affect streamflow characteristics during dry, average and wet climate conditions. Narasimhan and Srinivasan (2005) and Hwang et al. (2006) used SWAT-simulated soil moisture and evapotranspiration to measure drought indices for studying drought patterns. Similar studies have been increasingly conducted in different regions of the world with more specific focus on extreme hydrological conditions, including coupling models and developing extreme indices as part of the analyses. However, a review of studies that report application of SWAT for the assessment of hydro-climatic extremes has not been previously reported; therefore, this study was conducted to fill this research gap. The overall aim of this study is to summarize the findings of existing studies of SWAT for the assessment of hydro-climatic extremes for answering common questions that might arise before, during and after the SWAT simulation as shown in Figure 1. The scope of this review is limited to hydrologic assessment only, due to the need to provide an in-depth analysis of SWAT's ability to replicate extreme hydrological events. However, the insights gained from this research are foundational for any SWAT application and have important implications regarding use of the model for testing or scenarios that include simulation of pollutant transport.

2.0 SWAT Model Description, Selected Articles and Statistical Evaluation

2.1 SWAT

Current versions of SWAT feature a legacy of nearly continuous model development over multiple decades as described in several previous studies (Arnold et al., 1998, Arnold et al., 2012a, Gassman et al., 2007, Williams et al., 2008, Bieger et al., 2017). SWAT is comprised of several different components including climatic inputs, crop growth and yield, hydrological cycling, representation of management practices, erosion processes and resulting sediment transport, and pollutant (nutrient, pesticide and pathogen) cycling and transport. The model is usually executed using a daily time step although options are also provided to apply it using a sub-daily time step (Arnold et al., 2012b). Partitioning of precipitation at the soil surface between runoff and infiltration, for daily time step simulations, is performed using one of three variants of the U.S. Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) runoff curve number (RCN) method (Arnold et al., 2012b, USDA-NRCS, 2004a, USDA-NRCS, 2004b, Williams et al., 2012). The Green and Ampt Mein Larson (GAML) excess rainfall method (Mein and Larson, 1973), an adaption of the original Green and Ampt infiltration method (Green and Ampt, 1911), is used to partition precipitation between surface runoff and infiltration for sub-daily time step applications (Jeong et al., 2010, Arnold et al., 2012b, Brighenti et al., 2019).

Basins simulated in SWAT are first delineated into sub-basins, which are then sub-divided into hydrologic response units (HRUs) which represent landscapes consisting of homogeneous soil, topographic, land use and management characteristics. These HRUs represent percentage land areas within a sub-basin and are not spatially recognized by SWAT version 2012 (Gassman and Wang, 2015). Enhanced spatial representation of cropland landscapes and other features are possible in newer SWAT+ codes, although HRUs are primarily configured within larger Landscape Units as described by (Bieger et al., 2017), which represent the latest version of SWAT that was released in 2019 (SWAT, 2019c). Landscape-level hydrology flows and pollutant losses are estimated at the HRU level, which are then summed to the corresponding sub-basins outlet and routed via the stream network to the overall basin outlet. Further details regarding the required inputs for SWAT and the range of available outputs are provided in Arnold et al. (2012b).

2.2 Article selection process

The SWAT Literature Database (CARD, 2019) and Web of Science (WoS) database were used to identify SWAT hydro-climatic extremes related research articles. Four main criteria were used for the selection of articles. First, the article title should contain the keywords “extreme”, “flood”, “drought”, “peak flow”, “high flow” and/or “low flow.” This criterion was adopted to ensure that the selected studies specifically focused on the topic. Second, only articles that were published from 1998 on were considered, because that was the year that the first major description of SWAT was published (Arnold et al., 1998) and also marked the beginning of when the extensive SWAT literature began to expand (CARD, 2019). Third, peer-reviewed articles that were included in WoS Core Collection (CC)-indexed journals (Analytics, 2019) were the primary source of information considered in this study. Grey literature such as government reports, technical reports, conference papers and non-English articles were thus excluded from this review. Finally, the selection of articles was also based on the authors’ judgement who have considerable knowledge of the existing SWAT-related literature. For example, some articles were included even though their keywords did not match the searching criteria.

Searching priority was given to the 3,821 articles contained in the SWAT literature database (as of July 15, 2019) because the articles have been filtered and grouped according to specific categories (CARD, 2019). Then, the article selection was based on the four criteria that were mentioned earlier including the WoS CC, which contains additional up-to-date articles that have not been entered in the SWAT Literature Database yet. A total of 147 articles were initially identified in the WoS CC (again on July 15, 2019), based on one or more of the previous keywords within the article title in combination with the additional term "SWAT" as a topic in the WoS. Unrelated studies were then excluded from the review; e.g. flood modelling for the "SWAT" River, Pakistan. In total, 111 articles related to SWAT hydro-climatic extreme simulations were ultimately identified (Table 1) based on the two searches.

The selected articles were further analysed in terms of region, publication year and basin size (Figure 2). Most of the SWAT hydro-climatic studies were conducted in the United States (34.51%) and China (13.27%), as shown in Figure 2c. The reason for the high rate of application in the United States is that the SWAT model was originally developed using United States environmental, land and soil conditions (Arnold et al., 1998). Moreover, a series of SWAT workshops and hands-on training organized by Texas A&M AgriLife has been a further catalyst for increased studies in the United States. Similar studies have also been conducted in transboundary basins (10.62%) such as the Brahmaputra River Basin (Mohammed et al., 2017b) and Mekong River Basin (Arias et al., 2014), showing that understanding of extreme changes is very important for transnational basin management.

Publication of SWAT studies has increased dramatically since 2009 (Tan et al., 2019a, CARD, 2019), but SWAT assessment of hydro-climatic extremes has only started to increase rapidly from 2017. Figure 2a indicates that the number of articles published in 2017 was three times greater than those published in 2016. A possible explanation for this might be the increase of flood and drought disasters around the world in the past few years (Chou et al., 2013, Naveendrakumar et al., 2019). Increasing awareness of climate change and its impact on regional hydrological processes has resulted in the urgent formulation of hydro-climatic related policies based on the possible effects of future extreme events. SWAT has been utilized for future assessment of hydro-climatic extremes in dozens of studies (CARD, 2019) because it can simulate "what-if" scenarios easily. Another reason for the recent increase in SWAT applications for extremes applications could be the availability of hydro-climatic related international grants. For example, an international research grant on "Understanding the Impacts of Hydro-meteorological Hazards in Southeast Asia" was funded by the Newton fund, the UK's Natural Environment Research Council (NERC), the Economic and Social Research Council (ESRC) and local governments. Such funding could result in increased numbers of SWAT hydro-climatic studies in Southeast Asia (Netwon-NERC, 2019).

Figure 2b indicates the studies that report application of SWAT for the assessment of hydro-climatic extremes were mainly conducted in basins of 10,001-100,000 km^2 (34.19%) in size, followed by >100,000 km^2 (17.95%), 101-1,000 km^2 (16.24%) and 1,001-5,000 km^2 (15.38%). By contrast, only 5.13% of the studies were conducted in basins that were smaller than 100 km^2 (Figure 2b). These trends underscore that SWAT hydro-climatic extreme studies were mainly applied in basins of medium to large scales. The biggest study area was the Zambezi River Basin with a drainage area of 1,400,000 km^2, which drains parts of Angola, Botswana, Malawi, Mozambique, Namibia, Tanzania, Zambia and Zimbabwe. The result shows that more studies should be conducted in smaller scale basins in the future.

2.3 Evaluation of the accuracy of SWAT output

Explicit standards have not been established for evaluating the accuracy of hydrological and eco-hydrological models, although various protocols have been proposed for judging simulated hydrological and/or pollutant outputs (Engel et al., 2007, Arnold et al., 2012a, Nair, 2011, Harmel et al., 2018). Typically, both graphical and statistical measures are used to judge model accuracy (Arnold et al., 2012a). Coffey et al. (2004) describe over a dozen different statistical measures that can be used to evaluate hydrological model output including the root mean square error (RMSE), coefficient of determination (R^2) and Nash-Sutcliffe Efficiency (NSE). Krause et al. (2005) provide further insights regarding the strengths and weaknesses of the R^2 and NSE statistics. Other statistical measures have been introduced more recently such as the Kling-Gupta Efficiency (KGE), which is described by Guse et al. (2017). To date, the R^2 and NSE statistics remain the dominant measures that have been used to assess the accuracy of SWAT model output (Gassman et al., 2007, Gassman et al., 2014, Tuppad et al., 2011, Bressiani et al., 2015, Tan et al., 2019a). Criteria suggested by Moriasi et al. (2007), Moriasi et al. (2015) are frequently used to interpret whether calculated NSE and R^2 values reflect satisfactory model results, and are used in this study to discuss the accuracy of reported model outcomes.

The distribution of R^2 and NSE statistics that were reported among the 111 articles reviewed for this study is shown in Figure 4. These statistics are based on comparisons of SWAT simulated streamflow values versus corresponding measured values for monthly (aggregated over daily values), daily and sub-daily time periods. Nearly 90% of the NSE statistics and over 90% of the R^2 statistics exceed 0.5 and 0.6, respectively, which are the thresholds suggested by Moriasi et al. (2007) and/or Moriasi et al. (2015) for satisfactory simulation results. Many of the computed statistics would further satisfy criteria of "good" and "very good" streamflow simulation results as proposed by Moriasi et al. (2007). The relative distribution of the monthly and daily statistics shown in Figure 4 is consistent with previous similar distributions reported by Tuppad et al. (2011), Gassman et al. (2014) and Tan et al. (2019a). The distribution of sub-daily statistics (Figure 4) is similar to the graphical summaries of NSE statistics reported by Brighenti et al. (2019) as part of their review of studies that focused on SWAT sub-daily time step applications.

3.0 Application

The 111 articles were further divided into six major SWAT categories based on their primary focus: (1) SWAT performance regarding replication of extreme flows, (2) SWAT drought-related studies, (3) SWAT flood-related studies, (4) SWAT studies that incorporate both drought and flood analyses, (5) SWAT coupling with other models, and (6) SWAT model applications featuring modifications, enhanced pre- or post-processing capabilities and/or some other improvement (Table 1). The rationale of these categories is to better describe the major findings that are reported in each article. Some articles might fall under two or three categories, but the first priority was given to the "SWAT performance regarding replication of extreme flows" category. This is because the reliability of SWAT to replicate extreme flows is among the major concerns of SWAT users before applying the model for hydro-climatic extremes studies. Also, the majority of existing studies did not evaluate the ability of SWAT to replicate extreme flows.

3.1 SWAT performance regarding simulation of extreme flows

This section addresses questions related to SWAT's reliability regarding replication of extreme events such as: (1) "How to calibrate and validate SWAT for simulating extreme events?", and (2) "How accurately does SWAT replicate extreme events?" (Figure 1). SWAT is a continuous-time model, and thus hydrologic calibration and validation are mainly based on continuous observed streamflow data. Performance of SWAT for continuous simulations has been well-proven in many regions and documented in Figure 4 and in previous SWAT reviews (Tan et al., 2019a, Bressiani et al., 2015, Gassman et al., 2014, Tuppad et al., 2011). Besides that, a comprehensive review covering SWAT sub-daily scale simulations has recently been conducted by Brighenti et al. (2019). Therefore, this review only focuses on SWAT performance assessments that report further validation in terms of specific flood events (event-based), peak flow, low flow, different precipitation intensities and/or flow duration curve simulations, which were analysed beyond typical continuous-time assessment.

Most of the studies only considered one of the criteria (specific flood event, peak flow, low flow, different precipitation intensities or flow duration curve) for their respective SWAT extreme assessment. For example, Bacopoulos et al. (2017) calibrated and validated SWAT using an hourly time step for specific flood events for the St. Johns River in the United States. They concluded that SWAT could reasonably capture flood events, based on NSE values of 0.85 and 0.45 computed for the simulated calibration and validation periods, respectively. Campbell et al. (2018) calibrated and validated SWAT for Pawtuxet River Basin in the United States, using a daily time step for respective one-year periods in 2010 and 2013 that resulted in NSE values ranging from 0.62 to 0.69. They then assessed the effects of urbanization on flood events with SWAT using a sub-daily simulation time step of 5 minutes. Pfannerstill et al. (2014) is among the limited studies that evaluated the ability of SWAT to reproduce both extreme high and low flows. They developed a multi-metric performance framework by dividing a flow duration curve into five different segments: very low, low, medium, high and very high flows. They concluded that the use of this performance framework could result in improved calibration of SWAT, which in turn could lead to better prediction of extreme flows.

Boithias et al. (2017) and Yu et al. (2018a) merged both continuous-time and event-based assessments in their respective studies. The latter authors developed a SWAT-Event model that refined the lumped unit hydrograph from the original SWAT into a set of distributed units to represent spatial variability of a basin. The model was able to accurately reproduce 24 flood events that occurred in the Wangjiaba River, China, as evidenced by NSE values as high as 0.95. Li et al. (2018a) incorporated a flow duration curve assessment as part of their overall evaluation approach that included the continuous-time and event-based approaches mentioned earlier. Meanwhile, Yaduvanshi et al. (2018) introduced precipitation intensity assessment to better understand the performance of SWAT under low, moderate or extreme precipitation events. Both studies reported that SWAT performed well in the context of flood simulations. A combination of continuous-time and peak flows comparison assessment is among the typical approaches used to evaluate peak flows (Dakhlalla and Parajuli, 2016, Javaheri and Babbar-Sebens, 2014, Spellman et al., 2018, Zhang et al., 2015). Javaheri and Babbar-Sebens (2014) estimated simulated sub-daily peak flows for the Eagle Creek basin located in central Indiana in the United States, based on an relationship between the continuous-time daily flows and the sub-daily flows. They found the errors of the predicted SWAT-based peak flows varied only from 1 to 18% relative to the corresponding observed peak flows.

Due to the development of satellite technologies, Kumar and Lakshmi (2018) and Tan et al. (2018) studied the performance of satellite precipitation products in relation to SWAT estimates of extreme events for the Gandak River Basin (India, China and Nepal) and the Kelantan River Basin (Malaysia), respectively. Kumar and Lakshmi (2018) evaluated the performance of the Tropical Rainfall Measuring Mission (TRMM) (Huffman et al., 2007) product using a continuous-time simulation coupled with varying precipitation intensities (light, moderate, heavy and extremely heavy precipitation). They found that the TRMM-based SWAT model performed better for the moderate and heavy precipitation periods versus the light and extremely heavy precipitation periods. In contrast, Tan et al. (2018) used a combined continuous-time and event-based assessment to test the reliability of driving SWAT with three Global Precipitation Mission (GPM) products (Hou et al., 2014). A "satisfactory" performance was reported for SWAT in replicating the "Big Yellow Flood" event using the GPM products.

3.2 SWAT studies on drought

Understanding of historical and future droughts in terms of intensity, duration, severity and spatial extent is very important for freshwater management and planning (Mishra and Singh, 2011). For example, priority irrigation systems could be built for sub-basins with high drought risk to reduce agricultural losses. Drought can be mainly divided into meteorological, hydrological, agricultural and socio-economic droughts (Wilhite and Glantz, 1985, Mishra and Singh, 2011). SWAT is commonly used to evaluate the impacts of meteorological and hydrological droughts. In general, SWAT-based drought studies can be divided into two main groups: (1) index-based, which are based on calculation and analysis of drought indices from SWAT outputs, and (2) non index-based, which involve analysis of SWAT-simulated streamflow in specific low flow periods. In general, future climate projections are incorporated into a calibrated SWAT model to assess the effects of predicted future drought processes. The projected future SWAT outputs are then compared with historical values using various drought indices. The comparison could be done by considering the potential drought risks such as intensity, occurrences, severity and duration in the future.

A drought index is a simplified variable representation of drought severity that uses hydro-climatic inputs such as precipitation, temperature and streamflow. Information about commonly used drought indices, including their strengths and weaknesses is available in a drought indices handbook published by the World Meteorological Organization (WMO) and Global Water Partnership (GWP) (2016). Standardized Precipitation Index (SPI), Standardized Streamflow Index (SSI), Standardized Soil Moisture Index (SSMI) and Palmer Drought Severity Index (PDSI) are popular indices that are frequently used in SWAT drought studies. Tan et al. (2019b), Vu et al. (2015) and Zhao et al. (2019) incorporated climate projections into the SWAT model to calculate future SPI and SSI for river basins in Malaysia, Vietnam and China, respectively. Meanwhile, the SSMI was considered and measured by Narasimhan and Srinivasan (2005), Kamali et al. (2017) and Li et al. (2017) using SWAT-simulated soil moisture data. Kang and Sridhar (2017b) and Zou et al. (2017) modified the PDSI to study drought impact in the United States and China, respectively, using streamflow, soil moisture and evapotranspiration data within SWAT. Most of the studies reported that more severe drought conditions might occur in the future.

Some SWAT drought studies concentrated on analysing potential future low flows. Rahman et al. (2010) evaluated the climate change impact on low flows of the Ruscom River Basin, located in southern Ontario in the eastern part of Canada. They found a potential reduction of up to 50% in the annual minimum monthly flow of a five-year return period. They also reported that the low flows might decrease in the summer and fall, but increase in the spring. The lowest 7-day low flow of each year with a 10-year return period (7Q10) flow was also considered in SWAT analyses conducted in South Korea (Ryu et al., 2011) and the United States (Shrestha et al., 2017, Shrestha et al., 2019). Ryu et al. (2011) found a significant reduction of the 7Q10 flow from 1.54 m^3s^{-1} to 0.03 m^3s^{-1} under the most severe scenario on the Geum River Basin in South Korea. On the other hand, a flow duration curve (FDC) calculated from SWAT outputs has also been applied in drought analysis (Brown et al., 2015, Hoyos et al., 2019, Rahman et al., 2010). The 75 (Q75) and 95 (Q95) percentiles are normally considered as the threshold for extreme low flow and low flow, respectively (Shrestha et al., 2017). Li et al. (2018b) applied the 80 (Q80) percentile to precipitation (station), streamflow (SWAT) and soil moisture (SWAT) for comparison of meteorological, hydrological and agricultural droughts over the Luanhe River Basin, China. The modelling results showed that the number of hydrological and agricultural droughts were less than meteorological droughts, but the durations was longer.

3.3 SWAT flood studies

In recent decades, floods have become more frequent and intense around the world. Quantification of future flood risk is vital to reduce damage to infrastructure and human lives (Cloke and Pappenberger, 2009) Although SWAT is not designed for flood modelling, there still have been reported SWAT flood studies. Overall, SWAT was used to understand the impact of land use and/or climate changes on floods at the basin scale. Besides that, the effectiveness of flood mitigation or retention strategies can also be simulated easily with SWAT. To date, it has been calibrated and validated at the daily scale in most of the SWAT flood-related studies (Maghsood et al., 2019, Cheng et al., 2017, Mohammed et al., 2017a) versus monthly-scale testing that is normally reported in SWAT drought studies (Tan et al., 2019b, Bayissa et al., 2018). Further subdivision of the SWAT-based flood studies (Table 1) results in three main categories, based on the type of analyses: land use change, climate change, and land use and climate change.

Assessment of the impact of land use management on flood risk using the SWAT model has been conducted in China (Zhang et al., 2016), Spain (Jodar-Abellan et al., 2019), South Korea (Lee et al., 2017), and the United States (Mitchell et al., 2018, Schilling et al., 2014, Van Liew et al., 2003). Besides that, Angelidis et al. (2010) compared the flood hydrographs that were simulated by the EvroFloods model they developed versus SWAT for the Evros/Maritza River Basin that drains portions of Bulgaria, Greece and Turkey. They found an approximately 5.8% difference between the historical and future peak flows. Mitchell et al. (2018) proved that water retention sites (WRS) could effectively reduce the high flows of a Minnesota River sub-basin using the SWAT model. Schilling et al. (2014) found a conversion of 50% to 100% of the cropland to perennial vegetation could dramatically reduce the flood risk in the Raccoon River basin in west central Iowa.

SWAT-based climate change impact assessments are conducted by comparing the impacts of historical climate patterns with projected future climate inputs within a calibrated SWAT model. The future “climate input” is usually extracted from the Coupled Model Intercomparison Project (CMIP) 3 (Meehl et al., 2007) and CMIP5 (Taylor et al., 2012) General Circulation Models (GCMs) (Maghsood et al., 2019, Iqbal et al., 2018, Kharel and Kirilenko, 2018) or based on potential “synthetic” precipitation and temperature changes (Gao et al., 2018, Kehew et al., 2010). Kharel and Kirilenko (2018) found the overspill risk ranged from 7.3% to 47.1% for Devils Lake in North Dakota, U.S. in response to CMIP3 and CMIP5 climate projections. Maghsood et al. (2019) evaluated the flood impact using the Flood Frequency Index (FFI) and Sub-basin Flood Source Area Index (SFSAI) as measured from SWAT outputs in the Talar River Basin in northern Iran. Their findings showed that high potential flood risk is found in sub-basins mainly located in the eastern part of the basin. Iqbal et al. (2018) used HEC-SSP, a statistical software packages developed by US Army Corps of Engineers to conduct flood frequency analysis as a function of SWAT-simulated streamflow for the Kabul River Basin that drains parts of Afghanistan and Pakistan,. They found that a 50-year return period flood is likely to occur more frequently in the future.

Assessing combined land use change and climate change impacts could provide a more robust flood risk assessment (Huang et al., 2018). Igarashi et al. (2019) incorporated synthetic climate projections and future projected land use changes from the Conversion of Land Use and its Effects at Small regional extent (CLUE-S) model (Verburg et al., 2002) into SWAT to study high flows in the Song Khwae district, Thailand. The modelling showed that the high flows are projected to decline in the future even with an increase of cropland up to 50% within the basin. Cheng et al. (2017) proposed the need for flood retention sites to reduce potential future flooding based on SWAT simulations driven by low and moderate emission scenarios climate projections in Charles River Basin, which drains portions of the Boston metropolitan area in eastern Massachusetts, U.S.. Similarly, Walters and Babbar-Sebens (2016) applied climate projections from the North American Regional Climate Change Assessment Program (NARCCAP) (Mearns et al., 2009) in SWAT to study the effectiveness of wetlands in mitigating high flows in the Eagle Creek Basin, U.S.. They concluded that the wetlands could reduce the intensity of peak flows by 15% to 20%.

3.4 SWAT studies on drought and flood

Consideration of both low and peak flows could provide an overview of hydro-climatic extreme changes and help to identify which natural hazard will have more impact in the future. Local authorities can thereafter allocate more funding and expertise to mitigate the specific hazard. Interestingly, the Coordinated Regional Climate Downscaling Experiment (CORDEX) (Giorgi et al., 2009) has proven to be one of the most popular climate projections applied for this topic. The CORDEX – South Asia domain database with a spatial resolution of 0.5º (~50 km) was incorporated into SWAT to study low and peak flows for the Brahmaputra River system in south Asia (Mohammed et al., 2017b, Mohammed et al., 2017a). The modelling results showed that floods are projected to become more frequent and intense compared to droughts in the future. Tirupathi et al. (2018) also incorporated the CORDEX South Asia domains within SWAT to investigate the impacts of future climate projections on monsoonal rainfall patterns and excessive precipitation events. Similarly, the CORDEX Africa domain was used by Näschen et al. (2018) to assess the effects of future climate on wetland resources for the Kilombero River Basin in Tanzania.

Several innovative computer tools have been developed to transfer SWAT and other hydrologic output into useful hydrological extremes information. The Water Engineering Time Series PROcessing tool (WETSPRO) was used by Leta and Bauwens (2018) and Leta et al. (2018) to extract daily extreme low and peak flows from the SWAT-simulated daily streamflow in Belgium and Hawaii, respectively. The tool is capable of selecting low and peak flows using the independent peak over threshold (POT) method. By contrast, Chen et al. (2019a) measured hydrological extremes using the Indicators of Hydrologic Alteration (IHA) tool (Richter et al., 1996). The IHA provides 67 statistical parameters related to river ecosystems, including several parameters related to hydrological extremes (i.e. annual 1, 3, 7, 30, 90-day max or min flows, frequency and duration flood or extreme low flows) that can be selected by users. These parameters could be measured using SWAT-simulated historical and future streamflow projections, followed by a comparison between the two periods with statistical analysis.

Stewart et al. (2015) compared historical monthly low and peak flows from 1961 to 1990 with a future period (2071 - 2099) using SWAT to understand their impact on the Sierra Nevada and Upper Colorado River Basin (UCRB) eco-hydrological system in the U.S.. Their findings showed a significant increase in the number of high flows in the winter and spring seasons, particularly in the UCRB. By contrast, the extreme low flows of both basins are projected to increase in spring and summer. This information is important to ecological scientists studying fish habitat and potential fish movement in the future.

3.5 SWAT model coupling with other models

In some cases, a modeller might want to know the impact of hydro-climatic extremes on SWAT outputs that are not based on flow characteristics, e.g. flood extent, aquatic life, agricultural yield, economic losses and hydro-electricity capacity. Coupling of SWAT with other models helps to expand the assessment to other parameters. In general, Hydrologic Engineering Center's River Analysis System

(HEC-RAS) (USACE, 2016), MIKE FLOOD (DHI, 2017) and SOBEK (Deltares, 2019) are some of the most widely used flood models to study potential future flood patterns via couplings with SWAT (Arunyanart et al., 2017, Song et al., 2014, Kuntiyawichai et al., 2011). For example, Robi et al. (2019) coupled SWAT with MIKE FLOOD to identify the flood inundation extent and flooding depth under CMIP5 climate projections for the Ribb River Basin which is located in northwest Ethiopia. They found that the future flood extent area could cover up to 61.01 km^2. Similarly, Chinnasamy et al. (2018) coupled SWAT, MOD-FLOW (Waterloo, 2011) and HEC-RAS to test the potential of the Underground of Taming of Floods for Irrigation (UTFI) system in reducing groundwater depletion and flood extent in the Ramganga River Basin in India. The simulation results showed that the implementation of UTFI can reduce the flood inundation areas by 10% and increase the groundwater level by 7 m.

An insurance fund simulator, called Hydrologic Risk Transfer Model (MTRH-SHS) (Righetto and Mendiondo, 2007) has been developed by coupling SWAT with various vulnerability and financial modules to explore drought and flood risks from an economic perspective (Mohor and Mendiondo, 2017). A case study of the Piracicaba River Basin in southeast Brazil showed that premiums up to 1% of the local Gross Domestic Product (GDP) are required when water demand increases to 20%. Gies et al. (2014) evaluated the impacts of three different drought adaptation policies in for Juba River in East Africa using SWAT and a system dynamics model. They concluded a combination of hydraulic infrastructure and new agricultural practices are the most effective policy to reduce drought impact, based on guidance provided by the coupled modelling system. In Southeast Asia, Arias et al. (2014) coupled SWAT, the Integrated Quantity and Quality Model (IQQM) (Simons et al., 1996), the Hydrologic Engineering Center's Reservoir System Simulation (HEC-ResSIM) (USACE, 2013) and the two-dimensional Environmental Impact Assessment Model (2D-EIA) to quantify how hydropower development could change the hydrological regime in the Sesan, Srepok, and Sekong (3S) river system. They found that full damming will cause significant hydrological alternations, and that the local authorities should practice sustainable hydropower practices in the future.

3.6 SWAT improvement

Efforts to improve SWAT to support more accurate hydro-climatic extreme simulations have focused on development of a new drought or flood index, calibration method improvement, uncertainty analysis and/or SWAT modification. A specific crop-based drought index calculated from precipitation, temperature, soil moisture depletion, transpiration and biomass production, with the latter three variables simulated by SWAT, was developed to quantify agricultural drought in the United States (McDaniel et al., 2017a, McDaniel et al., 2017b, McDaniel et al., 2017c). Esfahanian et al. (2017) developed a new drought index, called Meteorological, Agricultural, Stream Health and Hydrological (MASH) that merges 13 drought indices. These newly developed indices could effectively identify the risk of flood or drought.

Reliable model calibration is essential for providing a strong foundation to support scientific analysis and decision making. Chilkoti et al. (2018) proposed a multi-objective auto-calibration method for improving SWAT low flow simulations. The results showed that the volume efficiency and time series of low flow simulations in the Saugeen River, Canada, were improved by 135% and 65%, respectively. Trudel et al. (2017) evaluated low flow uncertainties based on the SWAT structure and approach that was simulated for the Yamaska River Basin in Canada. They found that the calibration objective function is one of the main uncertainty sources for SWAT low flow simulations. Another SWAT extreme flow uncertainty study was conducted by Zhang et al. (2014) in the Qiantang River Basin, China. The authors considered three major uncertainties that normally arise in SWAT for the assessment of hydro-climatic extremes, namely climate emission scenarios (A1B, A2 and B2), extreme values model (Generalized Pareto distribution, Generalized Extreme Value distribution and Pearson Type 3 distribution) and SWAT parameters (sequential uncertainty method), in their extreme uncertainty analysis. Interestingly, the SWAT model parameters showed a larger uncertainty than the emission scenario and extreme value models for small return periods simulations. Meanwhile, the uncertainties of the three sources for large return period simulations are likely to be similar.

Duan et al. (2018) modified the snow-melting and flood process modules to improve peak flow simulation in SWAT, by incorporating the accumulated temperature and maximum temperature elements in a snow melt processes module within SWAT. They tested the modified SWAT for the Tizinafu River basin in China, and found a 43% improvement in the representation of the observed peak flows. Cohen Liechti et al. (2014) developed a SWAT reservoir model to better model flood plain behaviour in the Zambezi Basin in the southern African continent. For instance, they modified the outflow of the reservoir sub-model of the SWAT2009 model by separating overflow from base flow. The findings indicated that the modified SWAT model resulted in superior replication of low and high flows versus the original SWAT model. Other efforts have focused on modifying the RCN method or other hydrological functions in SWAT, resulting in improved representation of peak flows and overall replication of measured streamflows and other hydrological indicators (Xie et al., 2020, D. White et al., 2009, Kim and Lee, 2008).

4.0 Future Research Directions

4.1 SWAT low and high flows assessment framework

General procedures for building a SWAT model include: (1) creating the model with a GIS interface; e.g. ArcGIS SWAT (ArcSWAT) (Olivera et al., 2006, SWAT, 2019a) or the QSWAT interface (Dile et al., 2016, SWAT, 2019b), (2) parameter sensitivity analysis, (3) calibration and uncertainty analyses, (4) validation of the calibrated model, and (5) performing an impact assessment. Typically, observed streamflow data is divided into two time periods, with one-time period used for sensitivity analysis and calibration while the other one is used for validation. This split-time calibration and validation framework has been applied in the most of the SWAT hydro-climatic extreme studies reviewed here. General guidelines, main issues and solutions for SWAT sensitivity analysis, calibration and validation are available in many previous studies (Arnold et al., 2012a, Abbaspour et al., 2018, Moriasi et al., 2007, Moriasi et al., 2015). Here, we only discuss the main issues and possible solutions for simulating extreme events.

Figure 3 shows the percentage of the finest time-scale streamflow observations that were used in the selected publications. Daily streamflow was used for calibration & validation in nearly half of the studies versus monthly streamflow in the calibration process for about 25% of the studies. Only about 5% of the studies calibrated their model with streamflow data at a sub-daily scale. In general, monthly scale calibration and validation was used to support drought studies. This is because most of the drought index calculations only need monthly data; e.g., Standardized Streamflow Index (SSI). Meanwhile, SWAT-based flood studies were mainly calibrated using daily data (Maghsood et al., 2019, Xu et al., 2017) although some required hourly-scale time steps to capture specific flood events. Widespread availability of hourly streamflow observations and hourly climate data to drive the model are still lacking, particularly in developing and less developed countries. However, daily streamflow data are sufficient for most long-term flood and drought analyses, but a more comprehensive calibration and validation framework is needed for these type of applications.

Generally, studies that relied on a time-continuous framework considered only a single objective function, particularly the NSE or R^2. The squared error statistics used for the NSE have been shown to be biased toward high flows (Chilkoti et al., 2018). In addition, strong R^2 values can still occur even when systematic over- or under-prediction occurs (Krause et al., 2005). Beyond that, validation of SWAT was only performed in a few studies as discussed in Section 3.1. The current testing approaches that have been used for SWAT extreme assessments seem to be inconsistent. For instance, Yaduvanshi et al. (2018) and Bacopoulos et al. (2017) validated SWAT's capability to replicate specific flood events, while Spellman et al. (2018) and Dakhlalla and Parajuli (2016) focused on the comparisons between simulated and measured peak flows. A new unified SWAT-based extreme assessment framework should be developed to produce more reliable outputs that could also facilitate better comparison among studies. Another future need is the incorporation of further calibration and validation for drought or flood index calculations. For example, if the study objectives are related to drought assessment using SSI, then calibration and validation should be done by comparing the SWAT-derived SSI values with corresponding observations. Hence, the framework should consider both the general assessment and extreme flows.

4.2 SWAT low and high flows improvement

Tan et al. (2018) clearly showed that SWAT underestimated the volume of peak flow in the Kelantan River basin during the Big Yellow Flood event by 25.2% to 33.9%. Similarly, Bacopoulos et al. (2017) found that SWAT poorly simulated the timing of peak flows in the lower St. Johns River Basin in northeast Florida. Piniewski et al. (2017) reported SWAT underestimated low flows in small sub-basins of the Vistula and Odra basins in Poland. These inaccurate representations of extreme flows, along with similar results found in other studies (Zhang et al., 2015, Shrestha et al., 2019), indicate that modification of SWAT's internal algorithms are essential to enable the model to more accurately and realistically simulate low and high flows.

The need for improving flood-plain deposition algorithms within SWAT has been noted in previous research (Krysanova and Arnold, 2008, Yu et al., 2018a). As noted in Section 3.1, Yu et al. (2018a) modified SWAT to more accurately simulate flood events using a sub-daily time step. Similar modifications are needed to strengthen SWAT flood event predictions for daily time step simulations. These issues have been considered during the development of SWAT+ (Bieger et al., 2017) However, SWAT+ has not yet been widely applied in different regions across the world. Future research is needed to compare the capability of SWAT+ versus previous SWAT versions, regarding replicating low and peak flows for river basins representing different topographic, geographical and climatic conditions.

Another area of future research need is the development of an extreme flows module that would be directly linked with the SWAT model. Such a module would feature functions capable of providing extreme analyses that would be available in SWAT for users who want to study the impacts of extreme flows. Some common extreme indices such as flow duration curve, 7Q10, SSI, 1-day maximum or minimum flow, and 7-day maximum or minimum flows could be considered as components of an extreme flows module and should also be incorporated as part of the standard SWAT outputs. Hydrological extremes classification can unfortunately be unclear. For example, Stewart et al. (2015) defined extreme flows using a pre-defined threshold method where high flows are the months with streamflow that are 100%, 125% and 150% greater than historical flows, whereas low flows are 25%, 50% and 75% lower than historical flows. By contrast, Tzoraki et al. (2013) applied the POT method to classify floods into “usual”, “ecological” and “hazardous”. Therefore, future research is needed to identify a simple and well-accepted extreme flows classification approach, which can be plugged into a SWAT extreme flows module. A standardized extreme flows classification method would facilitate comparison of flood or drought events in different regions.

4.3 SWAT with gridded precipitation data

Availability of satellite climate data offers another source of input data to SWAT modelling, particularly for regions with limited ground-based climate observations. Modellers should test as many available climate and other input data to choose the best data for a SWAT application (Abbaspour et al., 2018). Reliable precipitation data is especially crucial as one of the main inputs to the SWAT model. Observed precipitation data is almost always regarded as the most reliable precipitation input, but there are many limitations in reality such as missing values, inhomogeneous measurements, uneven station distribution and limited station coverage (Tan and Santo, 2018). For instance, Tan and Yang (2020) reported that missing values of more than 20% in precipitation data would significantly impact on the tropical streamflow simulation, especially in low-flow simulations. All of these issues might affect the simulation of peak and low-flows.

To date, there are more than 30 global precipitation datasets available that can serve as alternative precipitation data sources including gauge-based, reanalysis and satellite data (Sun et al., 2018). These data sets are available for either long-term hydro-climatic extreme analysis (at least 30 years) or short-term events (up to 30-min temporal scale). Although the long-term National Centers for Environmental (NCEP-CFSR) data are available at the SWAT website (SWAT, 2019a), it seems to be less reliable in replicating rainfall for some regions and corresponding streamflow simulation by SWAT. For example, the NCEP-CFSR data did not perform well in SWAT applications for river basins in China (Yang et al., 2014), Brazil (Bressiani et al., 2015, Monteiro et al., 2016), Ethiopia (Roth and Lemann, 2016) and Kenya and Tanzania (Alemayehu et al., 2017). In contrast, Tan et al. (2017) found that the Asian Precipitation—Highly-Resolved Observational Data Integration towards Evaluation of Water (APHRODITE) dataset (Yatagai et al., 2012, NCAR, 2019) performed better than the NCEP-CFSR for two river basins simulated in SWAT in Malaysia. Yang et al. (2014) also report that APHRODITE precipitation data resulted in improved streamflow predictions, relative to CFSR data, for a SWAT application in central China. Therefore, more effort is required to test the reliability of freely available precipitation products for SWAT extreme simulations. Moreover, integration of global, satellite and observed precipitation data might produce better precipitation inputs for SWAT modelling.

4.4 SWAT climate projections

The CMIP3, CMIP5 and CMIP6 GCM climate projections provide a general view on how the earth climate system may change in the future (IPCC, 2013). These projections have been widely applied in SWAT for long-term hydro-climatic extreme assessments. Incorporation of the new CMIP6 GCM projections (LLNL, 2019) into SWAT applications will likely increase significantly in the near future. As climate change analysis is one of the major applications of SWAT modelling (Tan et al., 2019a, Gassman et al., 2014, CARD, 2019), providing the CMIP6 climate projections in a SWAT user friendly format would facilitate increased usage of SWAT. A tool called Climate Model data for hydrologic modelling (CMhyd) is designed to extract and bias correct climate projection data (Rathjens et al., 2016) and is freely available at the SWAT website: https://swat.tamu.edu/software/cmhyd/. The Climate Change Toolkit (CCT) has been developed for similar objectives (Ashraf Vaghefi et al., 2017) and is comprised of five modules: (1) data download, (2) data extraction, (3) global climate data management, (4) bias correction using statistical downscaling, (5) spatial interpolation of climate data, and (6) Critical Consecutive Day Analyser (CCDA). However, these toolkits mainly focused on the manipulation of CMIP5 GCMs. Hence, future research needs to be concentrated on the extraction and bias correction of data from CMIP6 GCMs. Moreover, studies on the regional climate downscaling of CMIP6 GCMs projections within SWAT are necessary to provide more accurate details for representing localised extreme conditions.

Climate projections are commonly known as one of the major uncertainties in any hydro-climatic modelling focused on future conditions (Tan et al., 2014, Kundzewicz et al., 2018). These uncertainties include the selection of future socio-economic scenarios, potential greenhouse gases and aerosol emissions, GCMs climate sensitivity, regional climate models (RCMs), downscaling and bias correction approaches. Climate projection uncertainty reduction or minimization is among the most urgent future research needs (Kundzewicz et al., 2018), but obviously depends on the future decisions on the degree of anthropogenic mitigation and adaptation. Therefore, a range of potential scenarios is required to fully capture the possible future changes. However, the problem of mismatch of scales between global-scale climate models and basin-scale hydrological models needs to studied and solved. With the advent of greater computing power, higher resolution modelling studies are becoming available and will reduce this problem but the computational intensity tends to mean that there are fewer ensemble members of climate scenarios (Haarsma et al., 2016). Additionally, the use of RCMs can overcome mismatch problems, but the usefulness of RCMs is generally limited to large-scale basins. For small basins, only a limited subset of the RCMs grid points will overlay the entire basin, which will not accurately represent the climate system for the entire basin. Thus, basin-scale climate models could be among future climate change modeling development trends. Rapid development of knowledge, computer and internet technologies could result in basin-scale climate models becoming easily available in the future. Also, users are expecting large amounts of data to be freely available, and immediately and easily accessible (Brodaric and Piasecki, 2016). Availability of bias-corrected multiple RCMs or basin-scale climate data in SWAT format, that can be freely downloaded from the SWAT website, would undoubtedly boost SWAT hydro-climatic extremes applications in the near future.

4.5 SWAT comparison with other models

Selection of the most accurate hydrological model could reduce the uncertainty for hydro-climatic extreme simulations. However, the uncertainty of different hydrological models in regards to estimating extreme streamflows is still poorly understood. Singh et al. (2005) compared the performance of SWAT with the Hydrological Simulation Program Fortran (HSPF) model in the Iroquois River Watershed in Illinois and Indiana. They found that SWAT performed slightly better than HSPF, particularly in low flows simulation. On the other hand, Chen et al. (2019b) concluded that both SWAT and HSPF were unable to reproduce the extreme flows (i.e. annual maximum discharge and annual 7-day minimum discharge) accurately in the Xitiaoxi River Basin that is located in eastern China.

Moreover, SWAT and HSPF resulted in different extreme trend directions, showing that a careful consideration is needed when choosing hydrological models. Misuse of hydrological models when simulating extreme streamflows might lead to erroneous decision making. Therefore, comparisons of SWAT with other hydrological models for extreme flow simulations, including between SWAT2012 and SWAT+, should be conducted to identify the best model for further analysis for a respective application.

The application of artificial intelligence (sometime also known as machine learning or deep learning) is increasing in many research fields. To date, a small set of studies have been conducted to compare SWAT versus artificial intelligence (AI) models, which include comparisons for general flow (Singh, 2016) and sediment yield (Singh et al., 2012) outputs. For extreme flow comparisons, Jimeno-Sáez et al. (2018) compared the capability of the Artificial Neural Network (ANN) and SWAT models in Spain. They found that the ANN model performed better for high flow simulations, whereas SWAT was superior at simulating low flows. A similar finding was reported by Kim et al. (2015) for the Taehwa River Watershed in the southern South Korea, where high flows were simulated more accurately by both an ANN AI model and a Self Organizing Map (SOM) AI model, while SWAT was better at capturing low flows. However, such comparisons are still relatively limited in the literature, and therefore require more investigation. Integration of AI within SWAT modelling is a research direction that merits further exploration towards the goals of improving high flow simulations.

5.0 Summary

SWAT is now one of the top hydrological models that has been applied widely in ecological, hydrological and environmental studies. Application of SWAT in hydro-climatic extreme studies has increased rapidly in the past few years, particularly since 2017, as evidenced by the factor of three increases in the number of publications compared to previous years. Nearly half of the reviewed studies were conducted in the United States and China. 52% of the studies were conducted for river basins that drain more than 10,000 km^2, showing the need to understand the effects of potential extreme changes on the hydrology of medium to large scale basins.

Similar to other applications, calibration and validation of SWAT for extreme applications were conducted mainly using the time-continuous approach by daily or monthly streamflow data. Only a few studies further validated the model for specific flood events, peak flow, low flow, flow duration curves and different precipitation intensity comparisons. Hydrological drought indices such as SSI, SSMI, PDSI and 7Q10 are among the popular indices used in SWAT-based drought studies. SWAT was used to study how land use changes such as water retention sites, hydropower development and wetlands could reduce flood risk. Besides that, SWAT was also coupled with flood, economic and habitat suitability models to further study the impacts of extreme events. Improvement of SWAT for hydro-climatic extremes studies will require development of new drought or flood indices, calibration method improvement, uncertainty analysis and SWAT modifications.

The lack of an extreme-based calibration and validation assessment is among the main problems revealed in this study. A new unified SWAT-based extreme assessment framework that combines both "traditional," extreme flows and indices calculation should be developed for more reliable analysis and comparison. As described by Bieger et al. (2017), several of these limitations have been considered in the development of SWAT+, resulting in an improved flood plain module and streamflow-aquifer interaction. However, testing of SWAT+ has so far been limited to basins in the United States (Bieger et al., 2017, Bieger et al., 2019, Wu et al., 2020) Further research is necessary to compare the newly released SWAT+ to previous SWAT versions for extreme flow simulations, in multiple basins in various regions that are characterized by different topographic, geographical and climatic conditions.

Another key problem is that SWAT often does not accurately match peak and low flows, so future research needs to focus on improving the replication of these extreme flows. Besides that, development of an extreme flow module within an overall SWAT modelling system is another area of future need. This would help address the need for reliable impact assessments in relatively short time-frames that are required by policy makers. Also, a SWAT extreme module could help support more consistent and improved comparisons between studies, which is important for understanding current trends as stated in IPCC reports (IPCC, 2013, IPCC, 2012). Some common extreme indices such as SSI and 7Q10, and a standardised extreme classification, should also be incorporated in the SWAT output.

Availability of observations as inputs for SWAT modelling remains a big challenge in many regions (Tan et al., 2019a, Bressiani et al., 2015, van Griensven et al., 2012). Application of global and satellite precipitation data is becoming a new trend in SWAT modelling. Therefore, development of a SWAT-based input data selection framework is essential to choose the most reliable data for extreme simulations. Moreover, integration of global data, satellite products and ground-based observation is an additional future need. Another future research direction is incorporation of CMIP6 GCMs in SWAT hydro-climatic extreme studies. This would involve extraction, downscaling and bias correction improvement, and availability on the SWAT website.

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Declaration of interests

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

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References

Abbaspour, K. C., Vaghefi, S. A. & Srinivasan, R. 2018. A Guideline for Successful Calibration and Uncertainty Analysis for Soil and Water Assessment: A Review of Papers from the 2016 International SWAT Conference. *Water*, 10**,** 18.

Ahn, K.-H. & Merwade, V. 2017. The effect of land cover change on duration and severity of high and low flows. *Hydrological Processes*, 31**,** 133-149.

Ahn, S., Abudu, S., Sheng, Z. & Mirchi, A. 2018. Hydrologic impacts of drought-adaptive agricultural water management in a semi-arid river basin: Case of Rincon Valley, New Mexico. *Agricultural Water Management*, 209**,** 206-218.

Ahn, S. R., Jeong, J. H. & Kim, S. J. 2016. Assessing drought threats to agricultural water supplies under climate change by combining the SWAT and MODSIM models for the Geum River basin, South Korea. *Hydrological Sciences Journal*, 61**,** 2740-2753.

Alemayehu, T., Kilonzo, F., Van Griensven, A. & Bauwens, W. 2017. Evaluation and application of alternative rainfall data sources for forcing hydrologic models in the Mara Basin. *Hydrology Research*, 49**,** 1271-1282.

Alodah, A. & Seidou, O. 2019. Assessment of Climate Change Impacts on Extreme High and Low Flows: An Improved Bottom-Up Approach. *Water*, 11**,** 1236.

Analytics, C. 2019. *Web of Science platform: Web of Science Core Collection. Clarivate Analytics: Philadelphia, PA. Available at: https://clarivate.libguides.com/webofscienceplatform/woscc*. [Online]. [Accessed].

Angelidis, P., Kotsikas, M. & Kotsovinos, N. 2010. Management of Upstream Dams and Flood Protection of the Transboundary River Evros/Maritza. *Water Resources Management,* 24**,** 2467-2484.

Arias, M. E., Piman, T., Lauri, H., Cochrane, T. A. & Kummu, M. 2014. Dams on Mekong tributaries as significant contributors of hydrological alterations to the Tonle Sap Floodplain in Cambodia. *Hydrol. Earth Syst. Sci.,* 18**,** 5303-5315.

Arnold, J., Moriasi, D., Gassman, P., C. Abbaspour, K., White, M., Srinivasan, R., Santhi, C., D. Harmel, R., Van Griensven, A., Van Liew, M., Kannan, N. & Jha, M. 2012a. SWAT: Model use, calibration, and validation. *Transactions of the ASABE,* 55**,** 1491-1508.

Arnold, J. G., Kiniry, J. R., Srinivasan, R., Williams, J. R., Haney, E. B. & Neitsch, S. L. 2012b. *Soil and Water Assessment Tool Input/Output File Documentation: Version 2012 (Texas Water Resources Institute TR-439),* Temple, Texas: USDA-ARS, Grassland, Soil and Water Research Laboratory, and Texas AgriLife Research, Blackland Research and Extension Center.

Arnold, J. G., Srinivasan, R., Muttiah, R. S. & Williams, J. R. 1998. Large area hydrologic modeling and assessment part I: Model development. *JAWRA Journal of the American Water Resources Association,* 34**,** 73-89.

Arunyanart, N., Limsiri, C. & Uchaipichat, A. 2017. Flood Hazards in the Chi River Basin, Thailand: Impact Management of Climate Change. *Applied Ecology and Environmental Research,* 15**,** 841-861.

Ashraf Vaghefi, S., Abbaspour, N., Kamali, B. & Abbaspour, K. C. 2017. A toolkit for climate change analysis and pattern recognition for extreme weather conditions – Case study: California-Baja California Peninsula. *Environmental Modelling & Software,* 96**,** 181-198.

Ashraf Vaghefi, S., Mousavi, S. J., Abbaspour, K. C., Srinivasan, R. & Yang, H. 2014. Analyses of the impact of climate change on water resources components, drought and wheat yield in semiarid regions: Karkheh River Basin in Iran. *Hydrological Processes,* 28**,** 2018-2032.

Bacopoulos, P., Tang, Y., Wang, D. & Hagen, S. C. 2017. Integrated Hydrologic-Hydrodynamic Modeling of Estuarine-Riverine Flooding: 2008 Tropical Storm Fay. *Journal of Hydrologic Engineering,* 22**,** 04017022.

Bayissa, Y., Maskey, S., Tadesse, T., Van Andel, S. J., Moges, S., Van Griensven, A. & Solomatine, D. 2018. Comparison of the Performance of Six Drought Indices in Characterizing Historical Drought for the Upper Blue Nile Basin, Ethiopia. *Geosciences,* 8**,** 81.

Bieger, K., Arnold, J. G., Rathjens, H., White, M. J., Bosch, D. D. & Allen, P. M. 2019. Representing the Connectivity of Upland Areas to Floodplains and Streams in SWAT+. *JAWRA Journal of the American Water Resources Association,* 55**,** 578-590.

Bieger, K., Arnold, J. G., Rathjens, H., White, M. J., Bosch, D. D., Allen, P. M., Volk, M. & Srinivasan, R. 2017. Introduction to SWAT+, A Completely Restructured Version of the Soil and Water Assessment Tool. *JAWRA Journal of the American Water Resources Association,* 53**,** 115-130.

Boithias, L., Sauvage, S., Lenica, A., Roux, H., Abbaspour, K. C., Larnier, K., Dartus, D. & Sanchez-Perez, J. M. 2017. Simulating Flash Floods at Hourly Time-Step Using the SWAT Model. *Water,* 9**,** 25.

Borah, D. & Bera, M. 2004. Watershed-scale hydrologic and nonpoint-source pollution models: Review of applications. *Transactions of the ASAE,* 47**,** 789-803.

Bressiani, D. A., Gassman, P. W., Fernandes, J. G., Garbossa, L. H. P., Srinivasan, R., Bonumá, N. B. & Mendiondo, E. M. 2015. Review of Soil and Water Assessment Tool (SWAT) applications in Brazil: Challenges and prospects. *International Journal of Agricultural and Biological Engineering,* 8**,** 9-35.

Brighenti, T. M., Bonumá, N. B., Srinivasan, R. & Chaffe, P. L. B. 2019. Simulating sub-daily hydrological process with SWAT: a review. *Hydrological Sciences Journal,* 64**,** 1415-1423.

Brodaric, B. & Piasecki, M. 2016. Editorial: Water data networks: Foundations, technologies and systems, implementations, and uses. *Journal of Hydroinformatics,* 18**,** 149-151.

Brown, S. C., Versace, V. L., Lester, R. E. & Todd Walter, M. 2015. Assessing the impact of drought and forestry on streamflows in south-eastern Australia using a physically based hydrological model. *Environmental Earth Sciences,* 74**,** 6047-6063.

Cai, X., Zeng, R., Kang, W. H., Song, J. & Valocchi, A. J. 2015. Strategic Planning for Drought Mitigation under Climate Change. *Journal of Water Resources Planning and Management,* 141**,** 04015004.

Campbell, A., Pradhanang, S. M., Kouhi Anbaran, S., Sargent, J., Palmer, Z. & Audette, M. 2018. Assessing the impact of urbanization on flood risk and severity for the Pawtuxet watershed, Rhode Island. *Lake and Reservoir Management,* 34**,** 74-87.

Card 2019. SWAT Literature Database for Peer-Reviewed Journal Articles; Center for Agricultural and Rural Development: Iowa State University, Ames, IA, USA

Chattopadhyay, S., Edwards, D. R., Yu, Y. & Hamidisepehr, A. 2017. An Assessment of Climate Change Impacts on Future Water Availability and Droughts in the Kentucky River Basin. *Environmental Processes-an International Journal,* 4**,** 477-507.

Chen, F. & Li, J. 2016. Quantifying drought and water scarcity: a case study in the Luanhe river basin. *Natural Hazards,* 81**,** 1913-1927.

Chen, Q., Chen, H., Wang, J., Zhao, Y., Chen, J. & Xu, C. 2019a. Impacts of Climate Change and Land-Use Change on Hydrological Extremes in the Jinsha River Basin. *Water,* 11**,** 1398.

Chen, Y., Xu, C.-Y., Chen, X., Xu, Y., Yin, Y., Gao, L. & Liu, M. 2019b. Uncertainty in simulation of land-use change impacts on catchment runoff with multi-timescales based on the comparison of the HSPF and SWAT models. *Journal of Hydrology,* 573**,** 486-500.

Cheng, C., Yang, Y. C. E., Ryan, R., Yu, Q. & Brabec, E. 2017. Assessing climate change-induced flooding mitigation for adaptation in Boston's Charles River watershed, USA. *Landscape and Urban Planning,* 167**,** 25-36.

Chilkoti, V., Bolisetti, T. & Balachandar, R. 2018. Multi-objective autocalibration of SWAT model for improved low flow performance for a small snowfed catchment. *Hydrological Sciences Journal,* 63**,** 1482-1501.

Chinnasamy, P., Muthuwatta, L., Eriyagama, N., Pavelic, P. & Lagudu, S. 2018. Modeling the potential for floodwater recharge to offset groundwater depletion: a case study from the Ramganga basin, India. *Sustainable Water Resources Management,* 4**,** 331-344.

Chiogna, G., Marcolini, G., Liu, W., Pérez Ciria, T. & Tuo, Y. 2018. Coupling hydrological modeling and support vector regression to model hydropeaking in alpine catchments. *Science of The Total Environment*, 633**,** 220-229.

Chou, C., Chiang, J. C. H., Lan, C. W., Chung, C. H., Liao, Y. C. & Lee, C. J. 2013. Increase in the range between wet and dry season precipitation. *Nature Geoscience*, 6**,** 263-267.

Cloke, H. L. & Pappenberger, F. 2009. Ensemble flood forecasting: A review. *Journal of Hydrology*, 375**,** 613-626.

Coffey, M. E., Workman, S. R., Taraba, J. L. & W. Fogle, A. W. 2004. Statistical Procedures for Evaluating Daily and Monthly Hydrologic Model Predictions. *Transactions of the ASAE*, 47**,** 59-68.

Cohen Liechti, T., Matos, J. P., Ferràs Segura, D., Boillat, J.-L. & Schleiss, A. J. 2014. Hydrological modelling of the Zambezi River Basin taking into account floodplain behaviour by a modified reservoir approach. *International Journal of River Basin Management*, 12**,** 29-41.

D. White, E., W. Feyereisen, G., L. Veith, T. & D. Bosch, D. 2009. Improving Daily Water Yield Estimates in the Little River Watershed: SWAT Adjustments. *Transactions of the ASABE*, 52**,** 69-79.

Dakhlalla, A. O. & Parajuli, P. B. 2016. Evaluation of the Best Management Practices at the Watershed Scale to Attenuate Peak Streamflow Under Climate Change Scenarios. *Water Resources Management*, 30**,** 963-982.

Daniel, E. B. 2011. Watershed Modeling and its Applications: A State-of-the-Art Review. *The Open Hydrology Journal*, 5**,** 26-50.

Dash, S. S., Sahoo, B. & Raghuwanshi, N. S. 2019. A SWAT-Copula based approach for monitoring and assessment of drought propagation in an irrigation command. *Ecological Engineering*, 127**,** 417-430.

Deltares 2019. SOBEK Hydrodynamics, Rainfall Runoff and Real Time Control User Manual. Deltares, Boussinesqweg 1, 2629 HV Delft, P.O. 177, 2600 MH Delft, the Netherlands.

Dhi 2017. MIKE Flood User Manual. Agern Allé 5, DK-2970 Hørsholm, Denmark.

Dile, Y. T., Daggupati, P., George, C., Srinivasan, R. & Arnold, J. 2016. Introducing a new open source GIS user interface for the SWAT model. *Environmental Modelling & Software,* 85**,** 129-138.

Douglas-Mankin, K. R., Srinivasan, R. & Arnold, A. J. 2010. Soil and Water Assessment Tool (SWAT) Model: Current Developments and Applications. *Transactions of the ASABE,* 53**,** 1423-1431.

Duan, Y., Liu, T., Meng, F., Luo, M., Frankl, A., De Maeyer, P., Bao, A., Kurban, A. & Feng, X. 2018. Inclusion of Modified Snow Melting and Flood Processes in the SWAT Model. *Water,* 10**,** 1715.

Engel, B., Storm, D., White, M., Arnold, J. & Arabi, M. 2007. A Hydrologic⁄Water Quality Model Application Protocol. *JAWRA Journal of the American Water Resources Association,* 43**,** 1223-1236.

Esfahanian, E., Nejadhashemi, A. P., Abouali, M., Adhikari, U., Zhang, Z., Daneshvar, F. & Herman, M. R. 2017. Development and evaluation of a comprehensive drought index. *Journal of Environmental Management,* 185**,** 31-43.

Esfahanian, E., Nejadhashemi, A. P., Abouali, M., Daneshvar, F., Alireza, A. R., Herman, M. R. & Tang, Y. 2016. Defining drought in the context of stream health. *Ecological Engineering,* 94**,** 668-681.

Francesconi, W., Srinivasan, R., Perez-Minana, E., Willcock, S. P. & Quintero, M. 2016. Using the Soil and Water Assessment Tool (SWAT) to model ecosystem services: A systematic review. *Journal of Hydrology,* 535**,** 625-636.

Fu, B., Merritt, W. S., Croke, B. F. W., Weber, T. R. & Jakeman, A. J. 2019. A review of catchment-scale water quality and erosion models and a synthesis of future prospects. *Environmental Modelling & Software,* 114**,** 75-97.

Fu, G., Barber, M. E. & Chen, S. 2010. Hydro-climatic variability and trends in Washington State for the last 50 years. *Hydrological Processes,* 24**,** 866-878.

Gao, Y. Q., Guo, Z. C., Wang, D. D., Zhang, Z. X. & Liu, Y. P. 2018. Multivariate Flood Risk Analysis at a Watershed Scale Considering Climatic Factors. *Water,* 10**,** 15.

Gassman, P. W., Reyes, M. R., Green, C. H. & Arnold, J. G. 2007. The Soil and Water Assessment Tool: Historical Development, Applications, and Future Research Directions. *Transactions of the ASABE,* 50**,** 1211-1250.

Gassman, P. W., Sadeghi, A. M. & Srinivasan, R. 2014. Applications of the SWAT Model Special Section: Overview and Insights. *Journal of Environmental Quality,* 43**,** 1-8.

Gassman, P. W. & Wang, Y. 2015. IJABE SWAT Special Issue: Innovative modeling solutions for water resource problems. *International Journal of Agricultural and Biological Engineering,* 8**,** 1-8.

Gharib, A., Davies, E. G. R., Goss, G. G. & Faramarzi, M. 2017. Assessment of the Combined Effects of Threshold Selection and Parameter Estimation of Generalized Pareto Distribution with Applications to Flood Frequency Analysis. *Water,* 9**,** 692.

Gies, L., Agusdinata, D. B. & Merwade, V. 2014. Drought adaptation policy development and assessment in East Africa using hydrologic and system dynamics modeling. *Natural Hazards,* 74**,** 789-813.

Giorgi, F., Coppola, E. & Raffaele, F. 2018. Threatening levels of cumulative stress due to hydroclimatic extremes in the 21st century. *npj Climate and Atmospheric Science,* 1**,** 18.

Giorgi, F., Jones, C. & Asrar, G. 2009. Addressing climate information needs at the regional level: the CORDEX framework. *WMO Bulletin of the American Meteorological Society,* 58**,** 175-183.

Green, N. H. & Ampt, C. A. 1911. Flow of air and water through soils. *Journal of Agricultural Science,* 4**,** 1-24.

Haarsma, R. J., Roberts, M. J., Vidale, P. L., Senior, C. A., Bellucci, A., Bao, Q., Chang, P., Corti, S., Fučkar, N. S., Guemas, V., Von Hardenberg, J., Hazeleger, W., Kodama, C., Koenigk, T., Leung, L. R., Lu, J., Luo, J. J., Mao, J., Mizielinski, M. S., Mizuta, R., Nobre, P., Satoh, M., Scoccimarro, E., Semmler, T., Small, J. & Von Storch, J. S. 2016. High Resolution Model Intercomparison Project (HighResMIP v1.0) for CMIP6. *Geosci. Model Dev.,* 9**,** 4185-4208.

Harmel, R. D., Baffaut, C. & Douglas-Mankin, K. R. 2018. Review and development of ASABE Engineering Practice 621: “Guidelines for calibrating, validating, and evaluating hydrologic and water quality models”. *Transactions of the ASABE,* 61**,** 1393-1401.

Hou, A. Y., Kakar, R. K., Neeck, S., Azarbarzin, A. A., Kummerow, C. D., Kojima, M., Oki, R., Nakamura, K. & Iguchi, T. 2014. The Global Precipitation Measurement Mission. *Bulletin of the American Meteorological Society,* 95**,** 701-722.

Hoyos, N., Correa-Metrio, A., Jepsen, S. M., Wemple, B., Valencia, S., Marsik, M., Doria, R., Escobar, J., Restrepo, J. C. & Velez, M. I. 2019. Modeling Streamflow Response to Persistent Drought in a Coastal Tropical Mountainous Watershed, Sierra Nevada De Santa Marta, Colombia. *Water,* 11**,** 94.

Huang, X. D., Wang, L., Han, P. P. & Wang, W. C. 2018. Spatial and Temporal Patterns in Nonstationary Flood Frequency across a Forest Watershed: Linkage with Rainfall and Land Use Types. *Forests,* 9**,** 20.

Huffman, G. J., Bolvin, D. T., Nelkin, E. J., Wolff, D. B., Adler, R. F., Gu, G., Hong, Y., Bowman, K. P. & Stocker, E. F. 2007. The TRMM Multisatellite Precipitation Analysis (TMPA): Quasi-Global, Multiyear, Combined-Sensor Precipitation Estimates at Fine Scales. *Journal of Hydrometeorology,* 8**,** 38-55.

Hwang, T. H., Kim, B. S., Kim, H. S. & Seoh, B. H. 2006. The estimation of soil moisture index by SWAT model and drought monitoring. *Journal of the Korean Society of Civil Engineers,* 26**,** 345-354.

Igarashi, K., Koichiro, K., Tanaka, N. & Aranyabhaga, N. 2019. Prediction of the Impact of Climate Change and Land Use Change on Flood Discharge in the Song Khwae District, Nan Province, Thailand. *Journal of Climate Change,* 5**,** 1-8.

Ipcc 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change *In:* FIELD, C. B., V. BARROS, T.F. STOCKER, D. QIN, D.J. DOKKEN, K.L. EBI, M.D. MASTRANDREA, K.J. MACH, G.-K. PLATTNER, S.K. ALLEN, M. TIGNOR, AND P.M. MIDGLEY (EDS.) (ed.). Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Ipcc 2013. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, .

Iqbal, M. S., Dahri, Z. H., Querner, E. P., Khan, A. & Hofstra, N. 2018. Impact of Climate Change on Flood Frequency and Intensity in the Kabul River Basin. *Geosciences,* 8**,** 114.

Jain, V. K., Pandey, R. P. & Jain, M. K. 2015. Spatio-temporal assessment of vulnerability to drought. *Natural Hazards,* 76**,** 443-469.

Jamrussri, S. & Toda, Y. 2017. Simulating past severe flood events to evaluate the effectiveness of nonstructural flood countermeasures in the upper Chao Phraya River Basin, Thailand. *Journal of Hydrology: Regional Studies,* 10**,** 82-94.

Javaheri, A. & Babbar-Sebens, M. 2014. On comparison of peak flow reductions, flood inundation maps, and velocity maps in evaluating effects of restored wetlands on channel flooding. *Ecological Engineering,* 73**,** 132-145.

Jeong, J., Kannan, N., Arnold, J., Glick, R., Gosselink, L. & Srinivasan, R. 2010. Development and Integration of Sub-hourly Rainfall–Runoff Modeling Capability Within a Watershed Model. *Water Resources Management,* 24**,** 4505-4527.

Jimeno-Sáez, P., Senent-Aparicio, J., Pérez-Sánchez, J. & Pulido-Velazquez, D. 2018. A Comparison of SWAT and ANN Models for Daily Runoff Simulation in Different Climatic Zones of Peninsular Spain. *Water,* 10**,** 192.

Jodar-Abellan, A., Valdes-Abellan, J., Pla, C. & Gomariz-Castillo, F. 2019. Impact of land use changes on flash flood prediction using a sub-daily SWAT model in five Mediterranean ungauged watersheds (SE Spain). *Science of The Total Environment,* 657**,** 1578-1591.

Kamali, B., Houshmand Kouchi, D., Yang, H. & Abbaspour, K. C. 2017. Multilevel Drought Hazard Assessment under Climate Change Scenarios in Semi-Arid Regions—A Case Study of the Karkheh River Basin in Iran. *Water,* 9**,** 241.

Kang, H. & Sridhar, V. 2017a. Combined statistical and spatially distributed hydrological model for evaluating future drought indices in Virginia. *Journal of Hydrology: Regional Studies,* 12**,** 253-272.

Kang, H. & Sridhar, V. 2017b. Description of future drought indices in Virginia. *Data in Brief,* 14**,** 278-290.

Kang, H. & Sridhar, V. 2018a. Assessment of Future Drought Conditions in the Chesapeake Bay Watershed. *JAWRA Journal of the American Water Resources Association,* 54**,** 160-183.

Kang, H. & Sridhar, V. 2018b. Improved Drought Prediction Using Near Real-Time Climate Forecasts and Simulated Hydrologic Conditions. *Sustainability,* 10**,** 1799.

Kehew, A. E., Milewski, A. & Soliman, F. 2010. Reconstructing an extreme flood from boulder transport and rainfall–runoff modelling: Wadi Isla, South Sinai, Egypt. *Global and Planetary Change*, 70**,** 64-75.

Kharel, G. & Kirilenko, A. 2015. Considering Climate Change in the Estimation of Long-Term Flood Risks of Devils Lake in North Dakota. *JAWRA Journal of the American Water Resources Association,* 51**,** 1221-1234.

Kharel, G. & Kirilenko, A. 2018. Comparing CMIP-3 and CMIP-5 climate projections on flooding estimation of Devils Lake of North Dakota, USA. *PeerJ,* 6**,** e4711.

Kharel, G., Zheng, H. & Kirilenko, A. 2016. Can land-use change mitigate long-term flood risks in the Prairie Pothole Region? The case of Devils Lake, North Dakota, USA. *Regional Environmental Change,* 16**,** 2443-2456.

Kim, M., Baek, S., Ligaray, M., Pyo, J., Park, M. & Cho, K. H. 2015. Comparative Studies of Different Imputation Methods for Recovering Streamflow Observation. *Water,* 7**,** 6847-6860.

Kim, N. W. & Lee, J. 2008. Temporally weighted average curve number method for daily runoff simulation. *Hydrological Processes,* 22**,** 4936-4948.

Kim, S., Parhi, P., Jun, H. & Lee, J. 2018. Evaluation of Drought Severity with a Bayesian Network Analysis of Multiple Drought Indices. *Journal of Water Resources Planning and Management,* 144**,** 05017016.

Krause, P., Boyle, D. P. & Bäse, F. 2005. Comparison of different efficiency criteria for hydrological model assessment. *Adv. Geosci.,* 5**,** 89-97.

Krysanova, V. & Arnold, J. G. 2008. Advances in ecohydrological modelling with SWAT-a review. *Hydrological Sciences Journal-Journal Des Sciences Hydrologiques,* 53**,** 939-947.

Krysanova, V. & White, M. 2015. Advances in water resources assessment with SWAT—an overview. *Hydrological Sciences Journal,* 60**,** 771-783.

Kumar, B. & Lakshmi, V. 2018. Accessing the capability of TRMM 3B42 V7 to simulate streamflow during extreme rain events: Case study for a Himalayan River Basin. *Journal of Earth System Science,* 127**,** 15.

Kundzewicz, Z. W., Krysanova, V., Benestad, R. E., Hov, Ø., Piniewski, M. & Otto, I. M. 2018. Uncertainty in climate change impacts on water resources. *Environmental Science & Policy,* 79**,** 1-8.

Kuntiyawichai, K., Schultz, B., Uhlenbrook, S., Suryadi, F. X. & Van Griensven, A. 2011. Comparison of flood management options for the Yang River Basin, Thailand. *Irrigation and Drainage,* 60**,** 526-543.

Lee, J.-H., Park, S.-Y., Kim, J.-S., Sur, C. & Chen, J. 2018. Extreme drought hotspot analysis for adaptation to a changing climate: Assessment of applicability to the five major river basins of the Korean Peninsula. *International Journal of Climatology,* 38**,** 4025-4032.

Lee, J. E., Heo, J.-H., Lee, J. & Kim, N. W. 2017. Assessment of Flood Frequency Alteration by Dam Construction via SWAT Simulation. *Water,* 9**,** 264.

Leon, A. S., Kanashiro, E. A., Valverde, R. & Sridhar, V. 2014. Dynamic Framework for Intelligent Control of River Flooding: Case Study. *Journal of Water Resources Planning and Management,* 140**,** 258-268.

Leta, O. T. & Bauwens, W. 2018. Assessment of the Impact of Climate Change on Daily Extreme Peak and Low Flows of Zenne Basin in Belgium. *Hydrology,* 5**,** 38.

Leta, O. T., El-Kadi, A. I. & Dulai, H. 2018. Impact of Climate Change on Daily Streamflow and Its Extreme Values in Pacific Island Watersheds. *Sustainability,* 10**,** 2057.

Li, D. C., Qu, S. M., Shi, P., Chen, X. Q., Xue, F., Gou, J. F. & Zhang, W. H. 2018a. Development and Integration of Sub-Daily Flood Modelling Capability within the SWAT Model and a Comparison with XAJ Model. *Water,* 10**,** 17.

Li, J. Z., Guo, Y. G., Wang, Y. X., Lu, S. L. & Chen, X. 2018b. Drought Propagation Patterns under Naturalized Condition Using Daily Hydrometeorological Data. *Advances in Meteorology***,** 14.

Li, P., Omani, N., Chaubey, I. & Wei, X. 2017. Evaluation of Drought Implications on Ecosystem Services: Freshwater Provisioning and Food Provisioning in the Upper Mississippi River Basin. *International Journal of Environmental Research and Public Health,* 14**,** 496.

Llnl 2019. CMIP6 - Coupled Model Intercomparison Project Phase 6. Lawrence Livermore National Laboratory, Livermore, CA. Available: https://pcmdi.llnl.gov/CMIP6/. [Accessed 17 October 2019].

Lopes, C. L., Alves, F. L. & Dias, J. M. 2017. Flood risk assessment in a coastal lagoon under present and future scenarios: Ria de Aveiro case study. *Natural Hazards,* 89**,** 1307-1325.

Lu, J., Cui, X., Chen, X., Sauvage, S. & Sanchez Perez, J.-M. 2017. Evaluation of hydrological response to extreme climate variability using SWAT model: application to the Fuhe basin of Poyang Lake watershed, China. *Hydrology Research,* 48**,** 1730-1744.

Lweendo, M. K., Lu, B., Wang, M., Zhang, H. & Xu, W. 2017. Characterization of Droughts in Humid Subtropical Region, Upper Kafue River Basin (Southern Africa). *Water,* 9**,** 242.

Maghsood, F. F., Moradi, H., Bavani, A. R. M., Panahi, M., Berndtsson, R. & Hashemi, H. 2019. Climate Change Impact on Flood Frequency and Source Area in Northern Iran under CMIP5 Scenarios. *Water,* 11**,** 21.

Mcdaniel, R. L., Munster, C. & Cothren, J. T. 2017a. Crop and Location Specific Agricultural Drought Quantification: Part I. Method Development. *Transactions of the ASABE,* 60**,** 721-728.

Mcdaniel, R. L., Munster, C. & Cothren, J. T. 2017b. Crop and Location Specific Agricultural Drought Quantification: Part II. Case Study. *Transactions of the ASABE,* 60**,** 729-739.

Mcdaniel, R. L., Munster, C. & Nielsen-Gammon, J. 2017c. Crop and Location Specific Agricultural Drought Quantification: Part III. Forecasting Water Stress and Yield Trends. *Transactions of the ASABE,* 60**,** 741-752.

Mearns, L. O., Gutowski, W., Jones, R., Leung, R., Mcginnis, S., Nunes, A. & Qian, Y. 2009. A Regional Climate Change Assessment Program for North America. *Eos, Transactions American Geophysical Union,* 90**,** 311-311.

Meehl, G. A., Covey, C., Delworth, T., Latif, M., Mcavaney, B., Mitchell, J. F. B., Stouffer, R. J. & Taylor, K. E. 2007. THE WCRP CMIP3 Multimodel Dataset: A New Era in Climate Change Research. *Bulletin of the American Meteorological Society,* 88**,** 1383-1394.

Mein, R. G. & Larson, C. L. 1973. Modeling infiltration during a steady rain. *Water Resources Research,* 9**,** 384-394.

Mishra, A. K. & Singh, V. P. 2011. Drought modeling – A review. *Journal of Hydrology,* 403**,** 157-175.

Mitchell, N., Kumarasamy, K., Cho, S. J., Belmont, P., Dalzell, B. & Gran, K. 2018. Reducing High Flows and Sediment Loading through Increased Water Storage in an Agricultural Watershed of the Upper Midwest, USA. *Water,* 10**,** 1053.

Mohammed, K., Islam, A. K. M. S., Islam, G. M. T., Alfieri, L., Bala, S. K. & Khan, M. J. U. 2017a. Impact of High-End Climate Change on Floods and Low Flows of the Brahmaputra River. *Journal of Hydrologic Engineering,* 22**,** 04017041.

Mohammed, K., Islam, A. K. M. S., Islam, G. M. T., Alfieri, L., Khan, M. J. U., Bala, S. K. & Das, M. K. 2018. Future Floods in Bangladesh under 1.5C, 2C, and 4C Global Warming Scenarios. *Journal of Hydrologic Engineering,* 23**,** 04018050.

Mohammed, K., Islam, A. S., Islam, G. T., Alfieri, L., Bala, S. K. & Khan, M. J. U. 2017b. Extreme flows and water availability of the Brahmaputra River under 1.5 and 2 °C global warming scenarios. *Climatic Change*, 145**,** 159-175.

Mohor, G. S. & Mendiondo, E. M. 2017. Economic indicators of hydrologic drought insurance under water demand and climate change scenarios in a Brazilian context. *Ecological Economics,* 140**,** 66-78.

Monteiro, J. a. F., Strauch, M., Srinivasan, R., Abbaspour, K. & Gücker, B. 2016. Accuracy of grid precipitation data for Brazil: application in river discharge modelling of the Tocantins catchment. *Hydrological Processes,* 30**,** 1419-1430.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D. & Veith, T. L. 2007. Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations. *Transactions of the ASABE,* 50**,** 885-900.

Moriasi, D. N., Gitau, M. W., Pai, N. & Daggupati, P. 2015. Hydrologic and water quality models: Performance measures and evaluation criteria. *Trans. ASABE,* 58**,** 1763–1785.

Nair, S. S. 2011. Importance of crop yield in calibrating watershed water quality simulation tools. *Journal of the American Water Resources Association,* v. 47**,** pp. 1285-1297-2011 v.47 no.6.

Narasimhan, B. & Srinivasan, R. 2005. Development and evaluation of Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) for agricultural drought monitoring. *Agricultural and Forest Meteorology,* 133**,** 69-88.

Näschen, K., Diekkrüger, B., Leemhuis, C., Steinbach, S., Seregina, L. S., Thonfeld, F. & Van Der Linden, R. 2018. Hydrological Modeling in Data-Scarce Catchments: The Kilombero Floodplain in Tanzania. *Water,* 10**,** 599.

Naveendrakumar, G., Vithanage, M., Kwon, H. H., Chandrasekara, S. S. K., Iqbal, M. C. M., Pathmarajah, S., Fernando, W. & Obeysekera, J. 2019. South Asian perspective on temperature and rainfall extremes: A review. *Atmospheric Research,* 225**,** 110-120.

Ncar 2019. APHRODITE: Asian Precipitation - Highly-Resolved Observational Data Integration Towards Evaluation) National Center for Atmospheric Research, University Corporation for Atmospheric Research, Boulder, CO. Available: https://climatedataguide.ucar.edu/climate-.

Netwon-Nerc. 2019. *Understanding impacts of flooding and drought in South East Asia* [Online]. Available: https://nerc.ukri.org/press/releases/2019/04-impacts/ [Accessed 30 August 2019].

Nguyen-Tien, V., Elliott, R. J. R. & Strobl, E. A. 2018. Hydropower generation, flood control and dam cascades: A national assessment for Vietnam. *Journal of Hydrology,* 560**,** 109-126.

Olivera, F., Valenzuela, M., Srinivasan, R., Choi, J., Cho, H., Koka, S. & Agrawal, A. 2006. ARCGIS-SWAT: A geodata model and GIS interface for SWAT1. *JAWRA Journal of the American Water Resources Association,* 42**,** 295-309.

Perkins, S. P. & Sophocleous, M. 1999. Development of a Comprehensive Watershed Model Applied to Study Stream Yield under Drought Conditions. *Groundwater,* 37**,** 418-426.

Pfannerstill, M., Guse, B. & Fohrer, N. 2014. Smart low flow signature metrics for an improved overall performance evaluation of hydrological models. *Journal of Hydrology,* 510**,** 447-458.

Piniewski, M., Szcześniak, M., Kundzewicz, Z. W., Mezghani, A. & Hov, Ø. 2017. Changes in low and high flows in the Vistula and the Odra basins: Model projections in the European-scale context. *Hydrological Processes,* 31**,** 2210-2225.

Rahman, M., Bolisetti, T. & Balachandar, R. 2010. Effect of Climate Change on Low-Flow Conditions in the Ruscom River Watershed, Ontario. *Transactions of the Asabe,* 53**,** 1521-1532.

Raikes, J., Smith, T. F., Jacobson, C. & Baldwin, C. 2019. Pre-disaster planning and preparedness for floods and droughts: A systematic review. *International Journal of Disaster Risk Reduction,* 38**,** 101207.

Rathjens, H., Katrin, B., Raghavan, S., Indrajeet, C. & Arnold, J. G. 2016. CMhyd User Manual.

Richter, B. D., Baumgartner, J. V., Powell, J. & Braun, D. P. 1996. A Method for Assessing Hydrologic Alteration within Ecosystems. *Conservation Biology,* 10**,** 1163-1174.

Richts, A. & Vrba, J. 2016. Groundwater resources and hydroclimatic extremes: mapping global groundwater vulnerability to floods and droughts. *Environmental Earth Sciences,* 75**,** 926.

Righetto, J. M. & Mendiondo, E. M. 2007. Modelo de Seguro para Riscos Hidrológicos. Rev. Bras. Recur. Hídricos - RBRH 12, 107–113.

Robi, M. A., Abebe, A. & Pingale, S. M. 2019. Flood hazard mapping under a climate change scenario in a Ribb catchment of Blue Nile River basin, Ethiopia. *Applied Geomatics,* 11**,** 147-160.

Roth, V. & Lemann, T. 2016. Comparing CFSR and conventional weather data for discharge and soil loss modelling with SWAT in small catchments in the Ethiopian Highlands. *Hydrol. Earth Syst. Sci.,* 20, 921-934.

Ryu, J. H., Lee, J. H., Jeong, S., Park, S. K. & Han, K. 2011. The impacts of climate change on local hydrology and low flow frequency in the Geum River Basin, Korea. *Hydrological Processes,* 25**,** 3437-3447.

Schilling, K. E., Gassman, P. W., Kling, C. L., Campbell, T., Jha, M. K., Wolter, C. F. & Arnold, J. G. 2014. The potential for agricultural land use change to reduce flood risk in a large watershed. *Hydrological Processes,* 28**,** 3314-3325.

Sehgal, V. & Sridhar, V. 2018. Effect of hydroclimatological teleconnections on the watershed-scale drought predictability in the southeastern United States. *International Journal of Climatology,* 38**,** e1139-e1157.

Seidou, O., Ramsay, A. & Nistor, I. 2012a. Climate change impacts on extreme floods I: combining imperfect deterministic simulations and non-stationary frequency analysis. *Natural Hazards,* 61**,** 647-659.

Seidou, O., Ramsay, A. & Nistor, I. 2012b. Climate change impacts on extreme floods II: improving flood future peaks simulation using non-stationary frequency analysis. *Natural Hazards,* 60**,** 715-726.

Senent-Aparicio, J., Jimeno-Sáez, P., Bueno-Crespo, A., Pérez-Sánchez, J. & Pulido-Velázquez, D. 2019. Coupling machine-learning techniques with SWAT model for instantaneous peak flow prediction. *Biosystems Engineering,* 177**,** 67-77.

Shepherd, B., Harper, D. & Millington, A. 1999. Modelling catchment-scale nutrient transport to watercourses in the U.K. *Hydrobiologia,* 395-396**,** 227-238.

Shrestha, A., Sharma, S., Mclean, C. E., Kelly, B. A. & Martin, S. C. 2017. Scenario analysis for assessing the impact of hydraulic fracturing on stream low flows using the SWAT model. *Hydrological Sciences Journal,* 62**,** 849-861.

Shrestha, S., Sharma, S., Gupta, R. & Bhattarai, R. 2019. Impact of global climate change on stream low flows: A case study of the great Miami river watershed, Ohio, USA. *International Journal of Agricultural and Biological Engineering,* 12**,** 84-95.

Simons, M., Podger, G. & Cooke, R. 1996. IQQM—A hydrologic modelling tool for water resource and salinity management. *Environmental Software,* 11**,** 185-192.

Singh, A. 2016. Modeling Stream Flow with Prediction Uncertainty by Using SWAT Hydrologic and RBNN Models for an Agricultural Watershed in India. *National Academy Science Letters,* 39**,** 213-216.

Singh, A., Imtiyaz, M., Isaac, R. K. & Denis, D. M. 2012. Comparison of soil and water assessment tool (SWAT) and multilayer perceptron (MLP) artificial neural network for predicting sediment yield in the Nagwa agricultural watershed in Jharkhand, India. *Agricultural Water Management,* 104**,** 113-120.

Singh, J., Knapp, H. V., Arnold, J. G. & Demissie, M. 2005. Hydrological Modeling of the Iroquois River Watershed using HSPF And SWAT. *JAWRA Journal of the American Water Resources Association,* 41**,** 343-360.

Singh, V. & Goyal, M. K. 2017. Unsteady High Velocity Flood Flows and the Development of Rating Curves in a Himalayan Basin under Climate Change Scenarios. *Journal of Hydrologic Engineering,* 22**,** 04017023.

Singh, V., Goyal, M. K. & Chu, X. 2016. Multicriteria Evaluation Approach for Assessing Parametric Uncertainty during Extreme Peak and Low Flow Conditions over Snow Glaciated and Inland Catchments. *Journal of Hydrologic Engineering,* 21**,** 04015044.

Singh, V. & Woolhiser, D. 2002. Mathematical Modeling of Watershed Hydrology. *Journal of Hydrologic Engineering,* 7**,** 270-292.

Song, S., Schmalz, B. & Fohrer, N. 2014. Simulation and comparison of stream power in-channel and on the floodplain in a German lowland area. *Journal of Hydrology and Hydromechanics* 62**,** 133.

Spellman, P., Webster, V. & Watkins, D. 2018. Bias correcting instantaneous peak flows generated using a continuous, semi-distributed hydrologic model. *Journal of Flood Risk Management,* 11**,** e12342.

Stewart, I. T., Ficklin, D. L., Carrillo, C. A. & Mcintosh, R. 2015. 21st century increases in the likelihood of extreme hydrologic conditions for the mountainous basins of the Southwestern United States. *Journal of Hydrology,* 529**,** 340-353.

Sun, Q., Miao, C., Duan, Q., Ashouri, H., Sorooshian, S. & Hsu, K.-L. 2018. A Review of Global Precipitation Data Sets: Data Sources, Estimation, and Intercomparisons. *Reviews of Geophysics,* 56**,** 79-107.

SWAT 2019a. Soil and Water Assessment Tool: Software, ARCSWAT. Texas A&M University, College Station, TX and USDA-ARS Grassland, Soil and Water Research Laboratory, Temple, TX. Available at: https://swat.tamu.edu/software/arcswat/. [Accessed 15 October 2019]. .

SWAT 2019b. Soil and Water Assessment Tool: Software, QSWAT. Texas A&M University, College Station, TX and USDA-ARS Grassland, Soil and Water Research Laboratory, Temple, TX. Available at: https://swat.tamu.edu/software/qswat/. [Accessed 15 October 2019]. .

SWAT 2019c. SWAT+. Texas A&M University, College Station, TX and USDA-ARS Grassland, Soil and Water Research Laboratory, Temple, TX. Available at: https://swat.tamu.edu/software/plus/. [Accessed 15 October 2019]. .

Tan, M. L., Ficklin, D., Ibrahim, A. L. & Yusop, Z. 2014. Impacts and uncertainties of climate change on streamflow of the Johor River Basin, Malaysia using a CMIP5 General Circulation Model ensemble. *Journal of Water and Climate Change*, 5**,** 676–695.

Tan, M. L., Gassman, P. W. & Cracknell, A. P. 2017. Assessment of Three Long-Term Gridded Climate Products for Hydro-Climatic Simulations in Tropical River Basins. *Water*, 9**,** 229.

Tan, M. L., Gassman, P. W., Srinivasan, R., Arnold, J. G. & Yang, X. 2019a. A Review of SWAT Studies in Southeast Asia: Applications, Challenges and Future Directions. *Water*, 11**,** 914.

Tan, M. L., Juneng, L., Tangang, F. T., Chan, N. W. & Ngai, S. T. 2019b. Future hydro-meteorological drought of the Johor River Basin, Malaysia, based on CORDEX-SEA projections. *Hydrological Sciences Journal*, 64**,** 921-933.

Tan, M. L., Samat, N., Chan, N. W. & Roy, R. 2018. Hydro-Meteorological Assessment of Three GPM Satellite Precipitation Products in the Kelantan River Basin, Malaysia. *Remote Sensing*, 10**,** 1011.

Tan, M. L. & Santo, H. 2018. Comparison of GPM IMERG, TMPA 3B42 and PERSIANN-CDR satellite precipitation products over Malaysia. *Atmospheric Research*, 202**,** 63-76.

Tan, M. L. & Yang, X. 2020. Effect of rainfall station density, distribution and missing values on SWAT outputs in tropical region. *Journal of Hydrology*, 584**,** 124660.

Taylor, K. E., Stouffer, R. J. & Meehl, G. A. 2012. An Overview of CMIP5 and the Experiment Design. *Bulletin of the American Meteorological Society*, 93**,** 485-498.

Tirupathi, C., Shashidhar, T. & Srinivasan, R. 2018. Analysis of rainfall extremes and water yield of Krishna river basin under future climate scenarios. *Journal of Hydrology-Regional Studies*, 19**,** 287-306.

Trudel, M., Doucet-Genereux, P. L. & Leconte, R. 2017. Assessing River Low-Flow Uncertainties Related to Hydrological Model Calibration and Structure under Climate Change Conditions. *Climate,* 5**,** 24.

Trung, L. D., Duc, N. A., Nguyen, L. T., Thai, T. H., Khan, A., Rautenstrauch, K. & Schmidt, C. 2018. Assessing cumulative impacts of the proposed Lower Mekong Basin hydropower cascade on the Mekong River floodplains and Delta – Overview of integrated modeling methods and results. *Journal of Hydrology*.

Tuppad, P., Douglas-Mankin, K. R., Lee, T., Srinivasan, R. & Arnold, A. J. 2011. Soil and Water Assessment Tool (SWAT) hydrologic/water quality model: Extended capability and wider adoption. . *Transactions of the ASABE,* 54**,** 1677-1684.

Tzoraki, O., Cooper, D., Kjeldsen, T., Nikolaidis, N. P., Gamvroudis, C., Froebrich, J., Querner, E., Gallart, F. & Karalemas, N. 2013. Flood generation and classification of a semi-arid intermittent flow watershed: Evrotas river. *International Journal of River Basin Management,* 11**,** 77-92.

Ummenhofer, C. C. & Meehl, G. A. 2017. Extreme weather and climate events with ecological relevance: a review. *Philosophical Transactions of the Royal Society B: Biological Sciences,* 372**,** 20160135.

USACE U. a. C. O. E. 2013. HEC-ResSim Reservoir System Simulation User's Manual version 3.1. US Army Corps of Engineers, Institute for Water Resources. Hydrologic Engineering Center, 609 Second Street Davis, CA 95616.

USACE, U. a. C. O. E. 2016. HEC-RAS 5.0, User's Manual. Institute for Water Resources, Hydrologic Engineering Center, 609 Second Street, Davis, CA 95616.

USDA-NRCS 2004a. Chapter 9: Hydrologic soil-cover complexes. National Engineering Handbook Hydrology Part 630. Washington, D.C.: U.S. Department of Agriculture, Natural Resources Conservation Service.

USDA-NRCS 2004b. Chapter 10: Estimation of direct runoff from storm rainfall. National Engineering Handbook Hydrology Part 630. . Washington, D.C.: U.S. Department of Agriculture, Natural Resources Conservation Service.

Van Griensven, A., Ndomba, P., Yalew, S. & Kilonzo, F. 2012. Critical review of SWAT applications in the Upper Nile basin countries. *Hydrological and Earth System Sciences,* 16**,** 3371-3381.

Van Liew, M. W., Garbrecht, J. D. & Arnold, J. G. 2003. Simulation of the impacts of flood retarding structures on streamflow for a watershed in southwestern Oklahoma under dry, average, and wet climatic conditions. *Journal of Soil and Water Conservation,* 58**,** 340-348.

Verburg, P. H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V. & Mastura, S. S. A. 2002. Modeling the Spatial Dynamics of Regional Land Use: The CLUE-S Model. *Environmental Management,* 30**,** 391-405.

Vu, M. T., Raghavan, V. S. & Liong, S.-Y. 2015. Ensemble Climate Projection for Hydro-Meteorological Drought over a river basin in Central Highland, Vietnam. *KSCE Journal of Civil Engineering,* 19**,** 427-433.

Walters, K. M. & Babbar-Sebens, M. 2016. Using climate change scenarios to evaluate future effectiveness of potential wetlands in mitigating high flows in a Midwestern U.S. watershed. *Ecological Engineering,* 89**,** 80-102.

Wang, D., Hejazi, M., Cai, X. & Valocchi, A. J. 2011. Climate change impact on meteorological, agricultural, and hydrological drought in central Illinois. *Water Resources Research,* 47.

Wang, R., Yuan, Y., Yen, H., Grieneisen, M., Arnold, J., Wang, D., Wang, C. & Zhang, M. 2019. A review of pesticide fate and transport simulation at watershed level using SWAT: Current status and research concerns. *Science of The Total Environment,* 669**,** 512-526.

Waterloo, H. 2011. Visual MODFLOW version 2011.1. User manual. Waterloo Hydrogeologic Inc., Waterloo.

Wilhite, D. A. & Glantz, M. H. 1985. Understanding: the Drought Phenomenon: The Role of Definitions. *Water International,* 10**,** 111-120.

Williams, J. R., Arnold, J. G., Kiniry, J. R., Gassman, P. W. & Green, C. H. 2008. History of model development at Temple, Texas. *Hydrological Sciences Journal,* 53**,** 948-960.

Williams, J. R., Kannan, N., Wang, X., Santhi, C. & Arnold, J. G. 2012. Evolution of the SCS Runoff Curve Number Method and Its Application to Continuous Runoff Simulation. *Journal of Hydrologic Engineering,* 17**,** 1221-1229.

World Meteorological Organization (Wmo) & Global Water Partnership (Gwp) 2016. Handbook of Drought Indicators and Indices (M. Svoboda and B.A. Fuchs). Integrated Drought Management Programme (IDMP), Integrated Drought Management Tools and Guidelines Series 2. Geneva.

Wu, J., Yen, H., Arnold, J. G., Yang, Y. C. E., Cai, X., White, M. J., Santhi, C., Miao, C. & Srinivasan, R. 2020. Development of reservoir operation functions in SWAT+ for national environmental assessments. *Journal of Hydrology,* 583**,** 124556.

Xie, K., Liu, P., Zhang, J., Libera, D. A., Wang, G., Li, Z. & Wang, D. 2020. Verification of a New Spatial Distribution Function of Soil Water Storage Capacity Using Conceptual and SWAT Models. *Journal of Hydrologic Engineering,* 25**,** 04020001.

Xu, X., Wang, Y.-C., Kalcic, M., Muenich, R. L., Yang, Y. C. E. & Scavia, D. 2017. Evaluating the impact of climate change on fluvial flood risk in a mixed-used watershed. *Environmental Modelling & Software*.

Yaduvanshi, A., Sharma, R. K., Kar, S. C. & Sinha, A. K. 2018. Rainfall–runoff simulations of extreme monsoon rainfall events in a tropical river basin of India. *Natural Hazards,* 90**,** 843-861.

Yan, D., Shi, X., Yang, Z., Li, Y., Zhao, K. & Yuan, Y. 2013. Modified Palmer Drought Severity Index Based on Distributed Hydrological Simulation. *Mathematical Problems in Engineering,* 2013**,** 8.

Yang, Y., Wang, G., Wang, L., Yu, J. & Xu, Z. 2014. Evaluation of Gridded Precipitation Data for Driving SWAT Model in Area Upstream of Three Gorges Reservoir. *PLOS ONE,* 9**,** e112725.

Yatagai, A., Kamiguchi, K., Arakawa, O., Hamada, A., Yasutomi, N. & Kitoh, A. 2012. APHRODITE: Constructing a Long-Term Daily Gridded Precipitation Dataset for Asia Based on a Dense Network of Rain Gauges. *Bulletin of the American Meteorological Society,* 93**,** 1401-1415.

Yu, D., Xie, P., Dong, X., Hu, X., Liu, J., Li, Y., Peng, T., Ma, H., Wang, K. & Xu, S. 2018a. Improvement of the SWAT model for event-based flood simulation on a sub-daily timescale. *Hydrol. Earth Syst. Sci.,* 22**,** 5001-5019.

Yu, Y., Liu, J., Yang, Z., Cao, Y., Chang, J. & Mei, C. 2018b. Effect of climate change on water resources in the Yuanshui River Basin: a SWAT model assessment. *Arabian Journal of Geosciences,* 11**,** 270.

Zhang, X., Booij, M. J. & Xu, Y.-P. 2015. Improved Simulation of Peak Flows under Climate Change: Postprocessing or Composite Objective Calibration? *Journal of Hydrometeorology,* 16**,** 2187-2208.

Zhang, X., Xu, Y.-P. & Fu, G. 2014. Uncertainties in SWAT extreme flow simulation under climate change. *Journal of Hydrology*, 515**,** 205-222.

Zhang, Y., Zhao, Y., Wang, Q., Wang, J., Li, H., Zhai, J., Zhu, Y. & Li, J. 2016. Impact of Land Use on Frequency of Floods in Yongding River Basin, China. *Water,* 8**,** 401.

Zhao, P. P., Lu, H. S., Yang, H. C., Wang, W. C. & Fu, G. B. 2019. Impacts of climate change on hydrological droughts at basin scale: A case study of the Weihe River Basin, China. *Quaternary International*, 513**,** 37-46.

Zou, L., Xia, J. & She, D. 2017. Drought Characteristic Analysis Based on an Improved PDSI in the Wei River Basin of China. *Water,* 9**,** 178.

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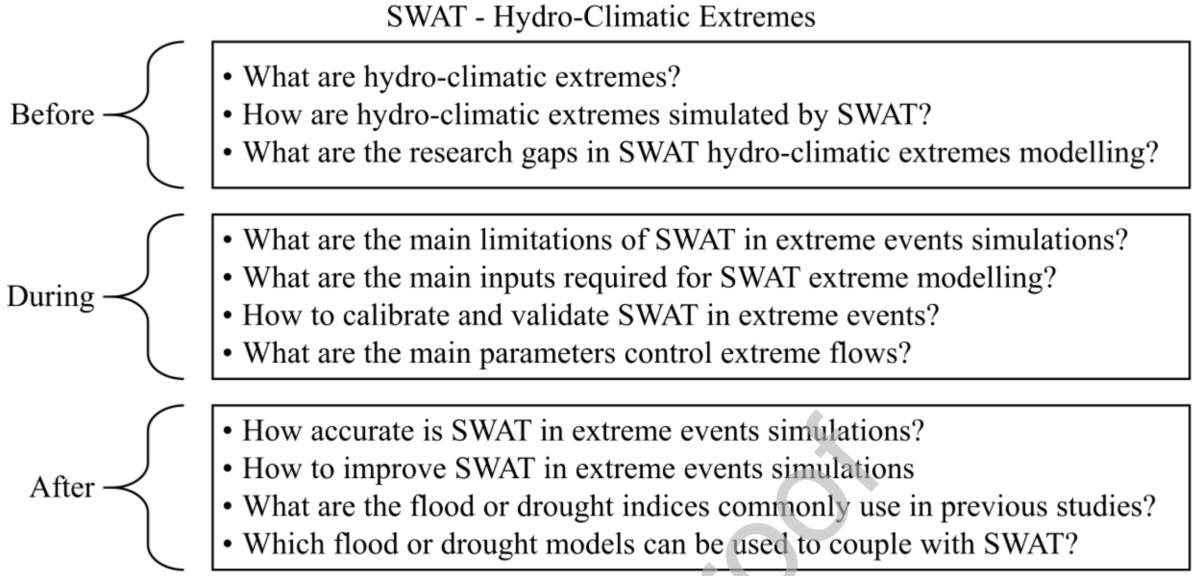

Figure 1: Common questions before, during and after SWAT hydro-climatic extreme studies.

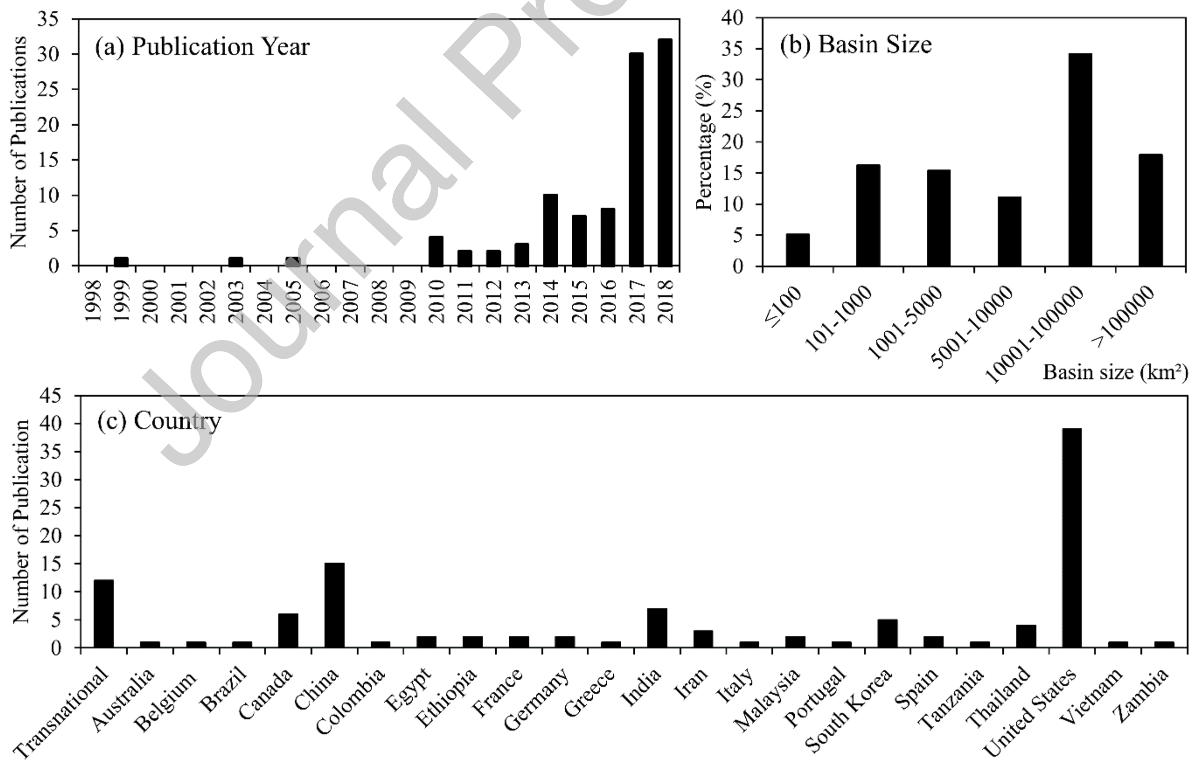

Figure 2: SWAT hydro-climatic extremes publications based on (a) publication years, (b) basin size and (c) countries.

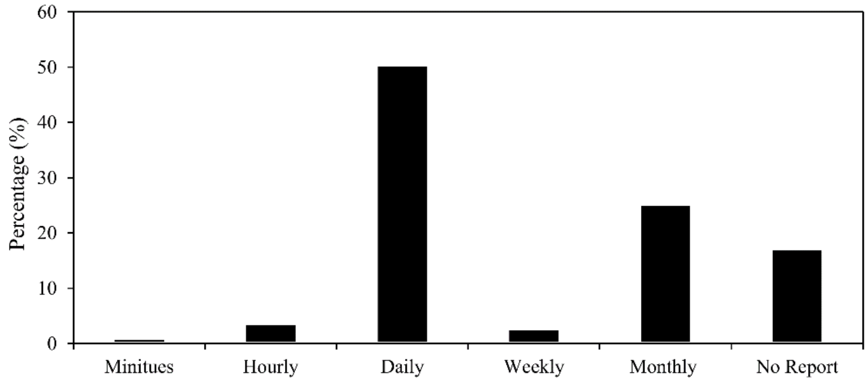

Figure 3: Finest streamflow calibration time-scale reported in the selected publications.

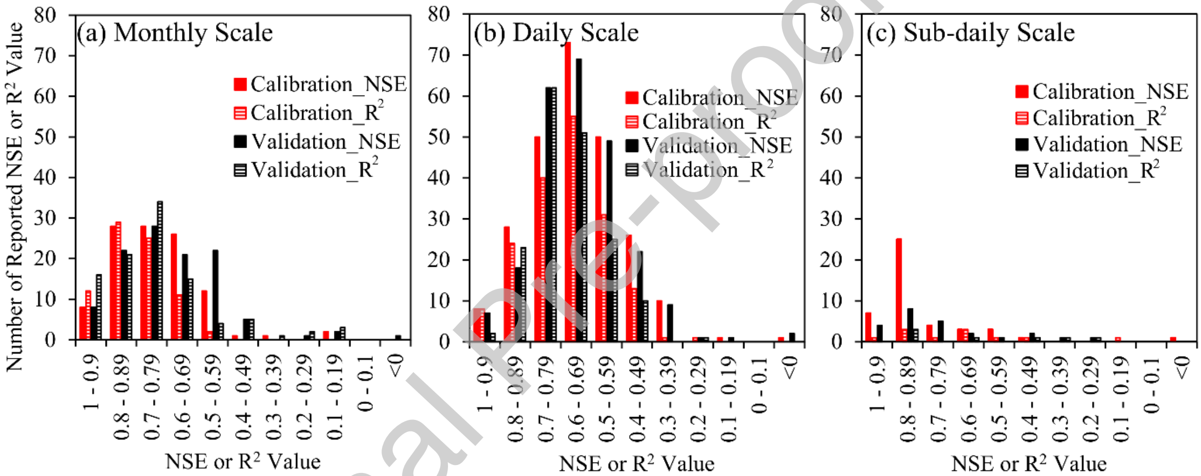

Figure 4: Overall SWAT performance of the selected 111 publications.

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Table 1: Selected publication for the SWAT hydro-climatic review.

Reference	Region	Focus	Climate Projection	Special Notes / Keywords
(Campbell et al., 2018)	USA	Assessment	No	Time-continuous, 5-min
(Kumar and Lakshmi, 2018)	Transnational	Assessment	No	Precipitation Intensities Analysis, TRMM
(Li et al., 2018a)	China	Assessment	No	Event-based + FDC comparison
(Spellman et al., 2018)	USA	Assessment	No	Peak flow comparison
(Tan et al., 2018)	Malaysia	Assessment	No	Event-based, GPM
(Yaduvanshi et al., 2018)	India	Assessment	No	Event-based + Precipitation Intensities Comparison
(Yu et al., 2018b)	China	Assessment	No	Event-based, 2-hour
(Bacopoulos et al., 2017)	USA	Assessment	No	Event-based, hourly
(Boithias et al., 2017)	France	Assessment	No	Event-based, hourly
(Piniewski et al., 2017)	Transnational	Assessment	EURO-CORDEX	Peak & Low flows comparison
(Dakhlalla and Parajuli, 2016)	USA	Assessment	Synthetic	Peak flow comparison
(Singh et al., 2016)	India	Assessment	No	Peak & low flows comparison
(Zhang et al., 2015)	China	Assessment	CMIP3	Peak flow comparison
(Javaheri and Babbar-Sebens, 2014)	USA	Assessment	No	Peak flow comparison
(Pfannerstill et al., 2014)	Germany	Assessment	No	FDC comparison
(Dash et al., 2019)	India	Drought	No	Copula, Drought indices
(Hoyos et al., 2019)	Colombia	Drought	Synthetic	Water yield changes
(Shrestha et al., 2019)	USA	Drought	CMIP5	FDC, 7Q10, 1Q10
(Tan et al., 2019b)	Malaysia	Drought	CORDEX-SEA	Drought Indices
(Zhao et al., 2019)	China	Drought	CMIP5	Drought Indices
(Ahn et al., 2018)	USA	Drought	No	Irrigated agriculture, drought period
(Bayissa et al., 2018)	Ethiopia	Drought	No	Drought Indices
(Lee et al., 2018)	South Korea	Drought	CMIP5	Drought Indices
(Li et al., 2018b)	China	Drought	No	Threshold value method
(Sehgal and Sridhar, 2018)	USA	Drought	No	Correlation Drought Indices
(Chattopadhyay et al., 2017)	USA	Drought	CMIP5	Drought indices
(Kamali et al., 2017)	Iran	Drought	ISI-MIP	Drought Indices
(Kang and Sridhar, 2017b)	USA	Drought	CMIP5	Drought indices
(Kang and Sridhar, 2017a)	USA	Drought	CMIP5	Drought Indices
(Li et al., 2017)	USA	Drought	No	Ecosystem Services
(Lweendo et al., 2017)	Zambia	Drought	No	Drought Indices
(Shrestha et al., 2017)	USA	Drought	SDSM	hydraulic fracturing, 7Q10
(Zou et al., 2017)	China	Drought	No	SWAT_PDSI
(Chen and Li, 2016)	China	Drought	No	Water scarcity
(Brown et al., 2015)	Australia	Drought	No	FDC, drought period assesment
(Cai et al., 2015)	USA	Drought	CMIP5	Drought prepareness
(Jain et al., 2015)	India	Drought	No	Integrated Drought Vulnerability Index
(Vu et al., 2015)	Vietnam	Drought	CMIP3	Drought Indices
(Ashraf Vaghefi et al., 2014)	Iran	Drought	CMIP3	critical continuous day calculator
(Ryu et al., 2011)	South Korea	Drought	CMIP3	7Q10
(Wang et al., 2011)	USA	Drought	CMIP3	Drought Indices
(Rahman et al., 2010)	Canada	Drought	CMIP3	FDC
(Narasimhan and Srinivasan, 2005)	USA	Drought	No	Drought Indices
(Igarashi et al., 2019)	Thailand	Flood	Synthetic	CLUEs, return period
(Jodar-Abellan et al., 2019)	Spain	Flood	Synthetic	Sub-daily SWAT, flash flood
(Maghsood et al., 2019)	Iran	Flood	CIMP5	Flood frequency Index, peak flow
(Gao et al., 2018)	China	Flood	Synthetic	Copula, peak flow
(Huang et al., 2018)	China	Flood	No	Partial Least Square Regression
(Iqbal et al., 2018)	Transnational	Flood	CMIP5	HEC-SSP (flood frequency)
(Kharel and Kirilenko, 2018)	USA	Flood	CMIP3, CMIP5	Overspill risks
(Mitchell et al., 2018)	USA	Flood	No	Water retention site simulation
(Mohammed et al., 2018)	Transnational	Flood	CMIP5	Peak synchronization
(Nguyen-Tien et al., 2018)	Transnational	Flood	No	Hydropower
(Cheng et al., 2017)	USA	Flood	Synthetic	Flood Hazard Index
(Lee et al., 2017)	South Korea	Flood	No	Sangal's method
(Xu et al., 2017)	USA	Flood	Synthetic, CMIP3, CMIP5	Fluvial flood risk
(Walters and Babbar-Sebens, 2016)	USA	Flood	NARCCAP	Wetland-based flood mitigation
(Zhang et al., 2016)	China	Flood	No	Non-point flood alleviation

(Kharel and Kirilenko, 2015)	USA	Flood	CMIP3	Overspill probability
(Schilling et al., 2014)	USA	Flood	No	>24-foot flood stage = flood day
(Angelidis et al., 2010)	Transnational	Flood	No	SWAT, HEC-HMS & EvroFloods comparison
(Kehew et al., 2010)	Egypt	Flood	Synthetic	Palaeoflood
(Van Liew et al., 2003)	USA	Flood	No	Flood retarting structure
(Alodah and Seidou, 2019)	Canada	Flood & Drought	CMIP5	Kernel Density Estimations
(Chen et al., 2019a)	China	Flood & Drought	CMIP5	Indicators of Hydrologic Alterations (IHA)
(Leta and Bauwens, 2018)	Belgium	Flood & Drought	CMIP3	WETSPRO
(Leta et al., 2018)	USA	Flood & Drought	CMIP5	WETSPRO
(Näschen et al., 2018)	Tanzania	Flood & Drought	CORDEX Africa	FDC
(Tirupathi et al., 2018)	India	Flood & Drought	CORDEX	Water yield
(Ahn and Merwade, 2017)	USA	Flood & Drought	No	Copula
(Lu et al., 2017)	China	Flood & Drought	No	Wet and dry years
(Mohammed et al., 2017b)	Transnational	Flood & Drought	CORDEX	Probability Density Function
(Mohammed et al., 2017a)	Transnational	Flood & Drought	CORDEX	Annual max / min flow
(Stewart et al., 2015)	USA	Flood & Drought	CMIP3	Stream temperature
(Robi et al., 2019)	Ethiphio	Coupling	CMIP5	SWAT + MIKEFlood
(Chinnasamy et al., 2018)	India	Coupling	No	SWAT + MODFLOW + HEC-RAS
(Chiogna et al., 2018)	Italy	Coupling	No	SWAT + SVM
(Kang and Sridhar, 2018b)	USA	Coupling	No	SWAT & VIC
(Kang and Sridhar, 2018a)	USA	Coupling	CMIP5	SWAT & VIC
(Trung et al., 2018)	Transnational	Coupling	No	SWAT + MIKEBasin
(Arunyanart et al., 2017)	Thailand	Coupling	CMIP3	SWAT + HECRAS
(Jamrussri and Toda, 2017)	Thailand	Coupling	No	SWAT + iRIC
(Lopes et al., 2017)	Portugal	Coupling	No	SWAT + ELCIRC
(Mohor and Mendiondo, 2017)	Brazil	Coupling	No	SWAT + Vulnerability + Financial
(Singh and Goyal, 2017)	India	Coupling	No	SWAT + Mike11
(Ahn et al., 2016)	South Korea	Coupling	CMIP5	SWAT + MODSIM
(Esfahanian et al., 2016)	USA	Coupling	No	SWAT + Regional-scale Habitat Suitability
(Kharel et al., 2016)	USA	Coupling	No	SWAT + Economic model
(Arias et al., 2014)	Transnational	Coupling	No	SWAT + IQQM + HecResSim + 2DEIA
(Gies et al., 2014)	Transnational	Coupling	No	SWAT + System dynamics
(Song et al., 2014)	Germany	Coupling	No	SWAT + HECRAS
(Kuntiyawichai et al., 2011)	Thailand	Coupling	No	SWAT + SOBEK
(Perkins and Sophocleous, 1999)	USA	Coupling	No	SWAT + MODFLOW
(Senent-Aparicio et al., 2019)	Spain	Improvement	No	Machine Learning
(Chilkoti et al., 2018)	Canada	Improvement	No	Multi-objective autocalibration
(Duan et al., 2018)	China	Improvement	No	Modify Snow & Flood
(Kim et al., 2018)	South Korea	Improvement	No	Bayesion Network
(Ashraf Vaghefi et al., 2017)	United States	Improvement	CMIP5	Climate Change Toolkit
(Esfahanian et al., 2017)	USA	Improvement	No	MASH Drought Index
(Gharib et al., 2017)	Canada	Improvement	No	Extreme Value Analysis
(McDaniel et al., 2017a)	USA	Improvement	No	SWAT + EPIC
(McDaniel et al., 2017b)	USA	Improvement	No	Crop-specific Drought Index
(McDaniel et al., 2017c)	USA	Improvement	No	Crop-specific Drought Index
(Trudel et al., 2017)	Canada	Improvement	No	Low flow uncertainty
(Cohen Liechti et al., 2014)	Transnational	Improvement	No	Modify SWAT reservoir
(Leon et al., 2014)	USA	Improvement	No	Flood operation Model
(Zhang et al., 2014)	China	Improvement	PRECIS	Uncertainty Analysis
(Tzoraki et al., 2013)	Greece	Improvement	No	Flood Classification
(Yan et al., 2013)	China	Improvement	No	Modified PDSI
(Seidou et al., 2012a)	Canada	Improvement	No	Improve peak flow
(Seidou et al., 2012b)	Canada	Improvement	CMIP3	Statistical downscaling

Graphical Abstract