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Implementing generative adversarial network (GAN) as a data-driven multi-site stochastic weather generator for flood frequency estimation

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A R T I C L E I N F O

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A B S T R A C T

Precipitation is a key driving factor of hydrologic modeling for impact studies. However, there are challenges due to limited long-term data availability and complex parameterizations of existing stochastic weather generators (SWGs) due to spatiotemporal uncertainty. We introduced state-of-the-art Generative Adversarial Network (GAN) as a data-driven multi-site SWG and synthesized extensive hourly precipitation over 30 years at 14 stations. These samples were then fed into an hourly-calibrated SWAT model for streamflow generation. Results showed that the well-trained GAN improved rainfall data by accurately representing spatiotemporal distribution of raw data rather than simply replicating its statistical characteristics. GAN also helped display authentic spatial correlation patterns of extreme rainfall events well. We concluded that GAN offers a superior spatiotemporal distribution of raw data compared to conventional methods, thus enhancing the reliability of flood frequency evaluations.

Software availability

Name of the software: Soil and Water Assessment Tool (SWAT)/ArcSWAT for ArcGIS 10.5.

Developer: Agricultural Research Service and Texas A&M University.

Cost: Public-domain software.

Software availability: https://swat.tamu.edu/software/arcswat/

Name of the software: pyextremes (pyextremes is a Python library aimed at performing univariate Extreme Value Analysis (EVA))

Developer: George Bocharov.

First year available: 2020.

Program language: Python.

Software availability: https://georgebv.github.io/pyextremes/

License: MIT.

1. Introduction

With the frequency, duration, and intensity of global weather extremes expected to increase, heavy rainfall-induced floods pose a considerable threat to the economy and human lives (Latif and Mustafa, 2021; Mirzaei et al., 2015; Myhre et al., 2019; Seneviratne et al., 2012). This theme has gained significant momentum following the December 2021 floods in Kuala Lumpur, Malaysia and many other devastating global flood events in recent years. Consequently, reliable stormwater modeling and flood estimation are crucial for flood risk management and the design of infrastructure in engineering hydrology.

Flood frequency estimates, or the expected occurrence of flood events in a given area, are a vital component in flood risk assessment and management. However, there is inherent uncertainty associated with these estimates due to a variety of factors (e.g., data quality, assumptions of the chosen statistical models, estimation of the model parameters, and climate change) (Field et al., 2012; Kundzewicz et al., 2014). One major source of uncertainty in flood frequency estimates is the quality of the input data used to calculate them (Galavi et al., 2023; Galavi and Mirzaei, 2020; Goodarzi et al., 2012; Huang et al., 2016; Galavi et al., 2019; Ng et al., 2019; Faghih et al., 2017; Mirzaei et al., 2015). Flood frequency is typically calculated using data from historical flood events, such as peak streamflow or precipitation measurements

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(Mirzaei et al., 2014; Mirzaei et al., 2013). However, the accuracy and completeness of this data can vary greatly depending on factors such as the quality of the measurement equipment, the availability of data to represent spatiotemporal variability, and the record period covered by the data. Additionally, natural variability in weather patterns and climate can impact flood frequency. For example, shifts in precipitation patterns or the occurrence of extreme weather events can alter the likelihood of flooding.

The quality of the weather data used to calculate flood frequency estimates is crucial for ensuring accurate and reliable results. The use of rainfall-runoff models, which input a continuous time series of precipitation data, is a common practice in the scientific literature to calculate the design flood for the desired return period (Pathiraja et al., 2012). Nevertheless, the rainfall datasets required for impact models are often inadequate or not readily available due to difficulties such as data quality, spatial coverage gaps, and the high cost of data gathering, which limits the reliability of implementing such flood risk assessments.

Over the past few decades, numerous weather generators (WGs) have been developed to synthesize realistic time series of various hydrometeorological variables, such as observed rainfall and temperature (e.g., Benoit et al., 2020; Wilks and Wilby, 1999). The mechanisms of different WGs for calculating meteorological variables with different spatiotemporal resolutions can be classified into three types: stochastic-statistical methods; physical-dynamic methods; and hybrid methods (Peleg et al., 2017). The literature is rich with examples of WGs being used, for example, extending unlimited length of meteorological records, supplementing for missing data (Kim and Pachepsky, 2010; Schuol and Abbaspour, 2007), downscaling coarse-resolution of climate variables (Burton et al., 2010; Kilsby et al., 2007; Volosciuk et al., 2017; Wilks, 2010), and impact assessment (Paschalis et al., 2014; Verdin et al., 2018).

However, WGs with physical-dynamical methods are computationally intensive and often fail to generate weather series at finer spatiotemporal scales (Prein et al., 2015). The majority of WGs consequently adopt the stochastic-statistical method, which is based on recreating observable statistical features and relationships among climate variables. Traditional stochastic weather generators (SWGs) first model the occurrence of precipitation to generate time series of wet and dry days, and then parameterize the rainfall intensity on wet days using probability distributions. Other variables, such as temperature, are then generated and cross-correlated with the wet-dry sequence (Peleg et al., 2017). WGEN (Richardson and Wright, 1984) and its future developments such as WXGEN (Sharpley and Williams, 1990) are very popular SWGs in producing daily weather sequences. The various types of SWGs rely either on spatially independent single-site gauges or on multi-site gauges that take spatial correlations into account. In regional hydrological analyses, inter-site correlations of precipitation often need to be properly considered to generate synthetic sequences at multiple sites. Depending on whether a priori distributions are assumed for modelling precipitation occurrence and amounts, multi-site SWGs are further categorized as parametric (Evin et al., 2018; Hundecha et al., 2009; Thompson et al., 2007; Wilks, 1998), non-parametric (Leander et al., 2005; Sharif and Burn, 2007; Verdin et al., 2018), and semi-parametric (Semenov and Barrow, 1997; Steinschneider and Brown, 2013).

Existing SWGs have shown remarkable competence in characterizing spatialtemporal climate variables at multi-site gauges, but many fail to create realistic extreme weather situations, such as heavy precipitation, storms, or droughts (Verdin et al., 2018). Moreover, weather generation for traditional multi-site SWGs often depends on the definition of complex parameterizations, which include the spatial and temporal intermittence that is inherent in weather variables as well as the amount whenever it occurs, and thus may not sample sufficiently to characterize extreme events (e.g., rain storms or droughts) and their spatial correlation. Similarly, resampling-based non-parametric methods, such as the K-nearest neighbor (KNN), have the disadvantage that they do not produce values outside the range of historical data. Therefore, to circumvent the arduous task of defining such parameters and to facilitate interaction as well as spatial consistency among diverse stations, we emphasize the implementation of deep learning generative models such as generative adversarial networks (GANs), as they learn directly from the data and have much greater flexibility in replicating realistic weather sequences than traditional statistical or physics-based models.

To assess the potential impact of input forcing on available water resources, as opposed to event-based models that use design rainfall as the major input for design flood estimation (Mirzaei et al., 2021), the long precipitation sequences generated by WGs were often fed into the continuous rainfall-runoff models (Blazkova and Beven, 2002; Grimaldi et al., 2013; Lamb et al., 2016). In fact, continuous rainfall simulation offers the benefit of providing the complete flood hydrograph characteristics, including the linkages between flood peaks and preceding catchment states, which is necessary for assessing climate sensitivity and evaluating the consequences of alternative adaptation measures (Cameron et al., 1999; Falter et al., 2015; Haberlandt and Radtke, 2014; Pathiraja et al., 2012; Ullrich et al., 2021; Winter et al., 2019). Additionally, as previously unseen meteorological circumstances and catchment states can be incorporated in the generation of sufficiently long time series, sampling uncertainty may also be decreased (Rogger et al., 2012). Typically, these hydrological models were fed with daily rainfall series; However, extreme rainfall events usually occur at finer temporal resolutions (e.g., hourly) and their rainfall intensity often exhibits strong spatial and temporal variability. WGs are required to provide sub-daily meteorological time series to better capture extreme weather events for risk assessment.

In the last decade, the field of water resource engineering and climate data analysis has witnessed a significant surge in the successful application of machine learning and deep learning techniques (Dehghani et al., 2023; Fung et al., 2020; Lian et al., 2019; Mohsenzadeh Karimi et al., 2022; Valizadeh et al., 2017). To date, GANs have been shown prevalent success in many applications, such as image generation. However, only few researchers proposed the use of GANs as a successful application for generating weather sequences (Puchko et al., 2020; Zadrozny et al., 2021). These articles typically explored extreme events on a daily scale or handled only one-dimensional signal data. And there were less applications in the field of hydrology where they were employed as a data-driven multi-site SWG for impact assessment. Whereas in our study, we compared the statistical inferences between synthetic rainfall series with observed data on a multi-site and at hourly scale (i.e., 2-dimension). Ultimately, they were integrated with an hourly calibrated SWAT model to continuously simulate hourly flow sequences, followed by a flood frequency analysis while accounting for inherent uncertainty in precipitation data as input to the model.

Overall, this study aims to demonstrate the potential of using GAN as a tool to better understand and manage the impacts of precipitation uncertainty in hydrologic modeling. The GAN could generate a range of possible precipitation scenarios, allowing for a more comprehensive understanding of the potential flood risk. Additionally, incorporating a multisite approach allows for the examination of spatial variability in precipitation and its impact on flood frequency estimates. The rest of the paper is organized into the following sections. In Section 2.1-2.3, the study area, dataset, implementation of the Soil and Water Assessment Tool (SWAT) and the structure of the Generative Adversarial Network (GAN) are described. Section 2.4 also provides an in-depth exploration of the methodology utilized for assessing the realism of rainfall generated by the GAN within a continuous modeling framework. In Section 3, an evaluation is performed on the capability of GAN to replicate precipitation patterns and integrate them with the SWAT model for the purpose of estimating design floods. The conclusions of this research are presented in Section 4.