Tikrit Journal of Engineering Sciences (2025); 32(4): 2136
DOI: http://doi.org/10.25130/tjes.32.4.14

IRAQI Academic Scientific Journals

ISSN: 1813-162X (Print); 2312-7589 (Online)

Tikrit Journal of Engineering Sciences

available online at: http://www.tj-es.com

TJES Tikrit Journal of Engineering Sciences

Implementing Weather Generators for Prediction of Future Climate Changes: A Review Paper

Mohammed A. Dheyaa [a*], **Mustafa M. Al-Mukhtar** [a], **Khalid Shemal** [b]

a Water and Hydraulic Structures Division, Civil Engineering Department, University of Technology, Baghdad, Iraq.
b The General Commission for Irrigation and Reclamation Projects, Ministry of Water Resources, Baghdad, Iraq.

Keywords:
Weather generators; Climate changes; Meteorological parameters; GCM; Scenarios.

Highlights:

- This study analyzes various weather generator models used in climate change research and their connection to meteorological parameters.
- It classifies these models to assist researchers in selecting the most suitable generator for their hypotheses.
- Highlighting their advantages, the study emphasizes the significant role of weather generators in fields like energy, meteorology, and urban planning. As such, this study is important in providing a detailed survey of the uses of weather generators.

ARTICLE INFO

Article history:

Received	14 Apr. 2024
Received in revised form	12 Jul. 2024
Accepted	31 Oct. 2024
Final Proofreading	25 Aug. 2025
Available online	30 Aug. 2025

Citation: Dheyaa MA, Al-Mukhtar MM, Shemal K. **Implementing Weather Generators for Prediction of Future Climate Changes: A Review Paper**. *Tikrit Journal of Engineering Sciences* 2025; **32**(4): 2136.
http://doi.org/10.25130/tjes.32.4.14

Corresponding author:
Mohammed A. Dheyaa
Water and Hydraulic Structures Division, Civil Engineering Department, University of Technology, Baghdad, Iraq.

Abstract: The changes in weather and climate patterns have prompted the world to conduct comprehensive and in-depth studies and research due to their direct impact on all aspects of life. Therefore, predicting climate using historical data for a specific area is vital to studying and knowing the level of impact of the resulting change in terms of hydrological, meteorological, and agricultural aspects. In this study, a comprehensive review of the latest and most popular weather generators used in the world was surveyed. A thorough evaluation of 92 papers published between 2000 and 2023 was analyzed and discussed in terms of the geographical locations and climatological conditions, time scale, predictors, and capabilities of weather generators models. Starting in early September 2023, the study made use of the search boxes on Scopus, IEEE Xplore, ScienceDirect, Web of Science, Semantic Scholar, PubMed, and Connected Papers databases. The terms "Weather Generators", "Climate Changes", and "Meteorological Parameters" were mixed with auxiliary words like "Applications", "Program," "Code", and "Software", as well as different variations of the terms "forecasting", "projection", and "prediction", in addition to the main terms. Hence, the reviewed papers provide an insightful tool for researchers to use the weather generator models in similar studies. Ultimately, the study presents a comprehensive and cutting-edge overview of weather generator applications, highlighting the most promising approach for future studies, which helps researchers and those interested in understanding the causes of climate change.

تنفيذ مولدات الطقس للتنبؤ بتغيرات المناخ المستقبلية، ورقة مراجعة

محمد علاء ضياء[1]، مصطفى مجيد المختار[1]، خالد شمال[2]

[1] فرع هندسة المياه والمنشات الهيدروليكية / قسم الهندسة المدنية / الجامعة التكنولوجية / بغداد – العراق.

[2] الهيئة العامة لمشاريع الري والاستصلاح / وزارة الموارد المائية / بغداد – العراق.

الخلاصة

إن التغيرات التي تحدث في أنماط الطقس والمناخ جعلت العالم يتجه نحو إجراء دراسات وأبحاث شاملة ومتعمقة، لما لها من تأثير مباشر على كافة جوانب الحياة. ولذلك فإن التنبؤات بشأن المناخ المستقبلي باستخدام البيانات التاريخية لمنطقة معينة أمر حيوي يجب دراسته ومعرفة مستوى تأثير التغير الناتج من النواحي الهيدرولوجية والجوية والزراعية. تم في هذه الدراسة استعراض شامل لأحدث وأشهر مولدات الطقس المستخدمة في العالم. وقد تم تحليل ومناقشة تقييم شامل لـ ٩٢ ورقة بحثية منشورة بين عامي ٢٠٠٠ و٢٠٢٣ من حيث المواقع الجغرافية والظروف المناخية، والمقياس الزمني، والتنبؤات، وقدرات نماذج مولدات الطقس. بدءًا من أوائل سبتمبر ٢٠٢٣، استخدمت الدراسة صناديق البحث في قواعد بيانات Scopusو IEEE Xplore و ScienceDirect و Web of Science و Semantic Scholar و PubMed و Connected Papers, وتم خلط مصطلحات "مولدات الطقس" و"التغيرات المناخية" و"معلمات الأرصاد الجوية" مع كلمات مساعدة مثل "التطبيقات" و"البرنامج" و"الكود" و"البرمجيات"، فضلاً عن صيغ مختلفة لمصطلح "التوقع". و"التنبؤ" و"التكهن" بالإضافة إلى المصطلحات الرئيسية. ومن ثم، توفر الأوراق التي تمت مراجعتها أداة ثاقبة للباحثين لاستخدام نماذج مولدات الطقس في دراسات مماثلة. وفي نهاية المطاف، تقدم الدراسة نظرة شاملة ومتطورة عن تطبيقات مولدات الطقس وتسليط الضوء على النهج الواعد للدراسات المستقبلية، والذي يساعد الباحثين والمهتمين على فهم أسباب حدوث التغيرات المناخية.

الكلمات الدالة: مولدات الطقس، التغيرات المناخية، معلمات الأرصاد الجوية، نموذج المناخ العالمي، السيناريوهات.

1.INTRODUCTION

Climate change is a complicated and diverse process with far-reaching ramifications for our planet's ecosystems, human communities, and global economy. Human actions, including the use of fossil fuels, deforestation, and industrial operations that emit greenhouse gases into the atmosphere, are mostly to blame. These gases trap heat from the sun, causing global temperatures to rise and weather patterns to shift throughout the planet [1]. Climate change has a wide range of consequences, including rising sea levels, increasing the frequency and intensity of extreme weather events, changes in temperature and precipitation patterns, and hydrological and ecological disturbances. These shifts pose significant challenges to long-term development, food security, water resources, and public health [2,3]. Understanding and mitigating the consequences of climate change requires modern tools and approaches. One such approach is the usage of weather generators, which are computer models or software programs that mimic weather conditions based on historical climate data. Weather generators are critical in studying the effects of climate change on diverse sectors, such as hydrology, agriculture, energy, and urban planning. Climatic-hydrological-crop models are essential for comprehending and forecasting the intricate relationships between climatic variables, hydrological processes, and crop development. The scarcity of trustworthy and comprehensive long-term meteorological and stream flow data hinders capturing local-scale processes and crucial conditions for robust modeling. More efforts are required to address these difficulties and increase the dependability of climate-hydrological-crop models by improving data availability, collecting methods, and data quality [4]. Weather generators use statistical algorithms to produce synthetic weather data, including precipitation, temperature, solar radiation, and wind speed, allowing researchers to study probable future weather situations. These models can recreate realistic weather patterns for many places and periods by using historical climate data and statistical approaches, allowing decision-makers to analyze the possible effects of climate change on specific places, assess the susceptibility of infrastructure and ecosystems, and devise adaptation and mitigation plans [5,6]. Ansari et al [4] found that by incorporating the outputs of weather generators into climate and hydrological crop models, researchers can gain comprehensive insights into the potential consequences of climate change on crop production. Duan and Song [7] proposed that combining weather generators and remote sensing provides a practical estimation method in areas that lack detailed historical measurement data. Hong et al. [8] recommended that weather generators should consider drought characteristics measured using standardized precipitation indices to reduce uncertainty in climate change and water shortage assessments. Stochastic precipitation modeling for estimating hydrological extremes is an important component of flood risk assessment and management. The calculation of spatially consistent rainfall fields and their temporal variability is a challenge that has been addressed by various stochastic weather generators [9]. Collados-Lara et al. [10] analyzed the influence of climate change and uncertainty on snow and found acceptable adaption mechanisms in water-dependent ecosystems. As a result, they proposed a new technique for assessing the impact of climate change on snow-cover regions. They developed a Monte Carlo analysis approach that employed various methods to generate multiple input series. Possible future local scenarios were developed using regional climate models and a random weather generator. Li and Sun [11] presented a novel multisite rainfall generator that influences both occurrence and intensity. The suggested ensemble of random weather generators was shown to be beneficial in simulating skewed and heavy data with simple physical and statistical interpretations. The use of a stochastic weather generator supported by large-scale reanalysis data is used to simulate hydrometeorological variables at near-daily resolution in semi-arid climates, as well as regression models driven by a large set of covariates, including other hydrometeorological variables, large-scale variables, and cycles. Seasonal and diurnal, geographic information, and memory effects were used to simulate hydrometeorological variables, which helped to correct bias in recreating the statistical features of hydrometeorological observations and predicting evaporation and water stress [12]. By combining the yearly and daily weather generators, Ahn [13] developed a novel two-stage, multivariate, and multisite weather generator. They discovered that the suggested weather generator reproduced marginal distributional patterns, multisite interdependence, and climatic variability on a daily and yearly basis. In addition, Ahn [13] used a quantitative mapping approach to include long-term distributional changes in generated climatic sequences for use in climate change assessments. Thus, the weather generator methodology is hierarchical, so the weather generator can generate synthetic weather sequences with a more realistic range of uncertainty and demonstrate the effectiveness of the weather generator in capturing the prevailing instabilities in inter-seasonal precipitation and temperature data. In addition, it can serve as a spatiotemporal scale reducer for seasonal forecasts and multi-decadal projections [14]. Figure 1 represents the LARS-WG model's flow chart, which shows a weather generator's representative steps. As such, the fundamental purpose of this research is to give significant insights into approaches utilized in future climate change forecasts, as well as to highlight their environmental, hydrological, and meteorological consequences. Especially those that fall within the programming specialization of those weather generators, whether it is a programming language, program, application, or programming code, and all of that software has its characteristics, advantages, disadvantages, and loopholes, depending on its input of data to obtain more accurate and realistic outputs. Furthermore, the study intends to identify the most widely used approaches and decide the optimal one. It assists researchers in identifying the alternatives and gaps that might be gained in this form of research. It also attempts to highlight the efforts of researchers in this subject and create a map of the research reality into a logical classification. Previous evaluations, on the other hand, rarely addressed this issue. Contributions to this article may be submitted in advance on behalf of the following list:

1) The study will be presented in the form of a cohesive taxonomy of weather generators.
2) The importance of these weather generators will be highlighted, and prediction accuracy will be improved.
3) The findings of prior studies using these weather generators will be reviewed and presented, including the most popular and effective varieties, as well as some recommendations for future study.
4) The study's proposed classification of relevant literature has significant ramifications.
5) This analysis highlights possible research pathways, has the ability to reveal research gaps, and gives a map of the academic literature on weather generators.

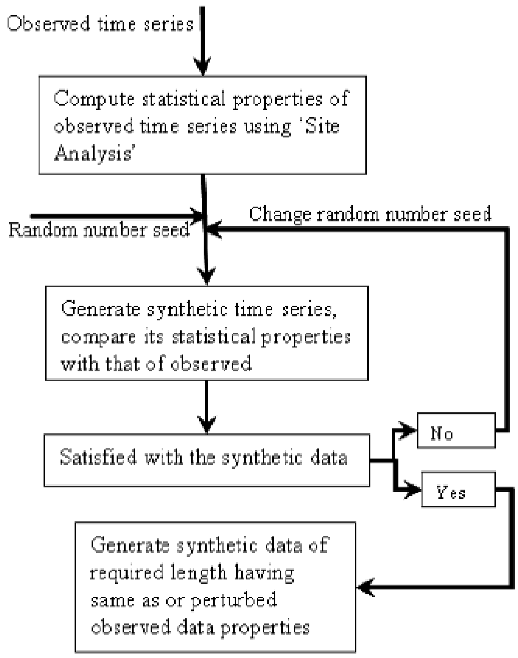

Fig. 1 The LARS-WG Model Flow Diagram [15].

2. WEATHER GENERATORS MATHEMATICAL FORMULAS

The basic concept of the weather generator algorithm mainly relies on the use of probability distributions. Therefore, the future predictions of climate variables produced by the weather generators are divided into two main groups: the Markov chain and probability distribution [16]. The Markov chain method is a useful tool for simulating future precipitation periods, especially in scenarios where there are disruptions in precipitation gauge readings over short periods. This ability is essential to maintain continuous precipitation data records [17]. The first-order Markov chain method achieved better performance, especially in modeling wet chains [17–19] second-and third-order Markov chains were also suitable for simulating monthly and annual precipitation events, respectively [18], as for applying a high-order Markov chain. The results indicated an exaggeration in the wet series, while it was appropriate in the dry series (semi-arid and arid regions) and even with long periods of drought [18], as shown in the following equations:

$$P_r(X_{t+1} = s|X_0 = q_0, X_1 = q_1, \ldots, X_t = q_t) = P_r(X_{t+1} = s|X_t = q_t) \quad (1)$$

$$P_r(X_{t+1} = s|X_0 = q_0, X_1 = q_1, \ldots, X_t = q_t) = P_r(X_{t+1} = s|X_t = q_t, X_{t-1} = q_{t-1}) \quad (2)$$

$$P_r(X_{t+1} = s|X_0 = q_0, X_1 = q_1, \ldots, X_t = q_t) = P_r(X_{t+1} = s|X_t = q_t, X_{t-1} = q_{t-1}, X_{t-2} = q_{t-2}) \quad (3)$$

$$P_r(X_{t+1} = s|X_0 = q_0, X_1 = q_1, \ldots, X_t = q_t) = P_r(X_{t+1} = s|X_t = q_t, X_{t-1} = q_{t-1}, X_{t-2} = q_{t-2}, X_{t-3} = q_{t-3}) \quad (4)$$

$$P_r(X_{t+1} = s|X_0 = q_0, X_1 = q_1, \ldots, X_t = q_t) = P_r(X_{t+1} = s|X_t = q_t, X_{t-1} = q_{t-1}, X_{t-2} = q_{t-2}, X_{t-3} = qt-3, X_{t-4} = q_{t-4}) \quad (5)$$

Probability distributions are essential for understanding and modeling climate variables, a fundamental aspect of weather and climate forecasting [20–22]. Different types of probability distributions, including normal, lognormal, gamma, Weibull, and exponential, are used to analyze phenomena and their prediction, which shows the flexibility of these methods and their ability to adapt to different data types and prediction needs [21], as expressed in the following equations:

Normal distribution:

$$\mathbf{f}(\mathbf{x}) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{\left(\frac{-(x-\mu)^2}{2\sigma}\right)} \quad (6)$$

Lognormal distribution:

$$\mathbf{f}(\mathbf{x}) = \frac{1}{\sqrt{2\pi x^2\sigma^2}} \cdot e^{\left(\frac{-(Ln(x)-\mu)^2}{2\sigma^2}\right)} \quad (7)$$

Gamma distribution:

$$\mathbf{f}(\mathbf{x}) = \frac{x^{(\alpha-1)}}{\beta^\alpha\,\Gamma(\alpha)} \cdot e^{\frac{x}{\beta}} \quad (8)$$

Weibull distribution:

$$\mathbf{f}(\mathbf{x}) = \frac{\alpha}{\beta}\left(\frac{x}{\beta}\right)^{\alpha-1} \cdot e^{-\left(\frac{x}{\beta}\right)^{\alpha}} \quad (9)$$

Exponential distribution:

$$\mathbf{f}(\mathbf{x}) = \lambda\, e^{-\lambda x} \quad (10)$$

The choice of the most appropriate probability distribution often depends on the statistical goodness-of-fit tests, which compare observed data with values estimated from different distributions. This method ensures that the chosen model accurately represents the data, enhancing the predictions' reliability [20,21]. However, the effectiveness of the probability distribution method can vary depending on the geographical location and the nature of the data being analyzed [18,21].

3.METHODOLOGY

The methodology of this study mainly used the keyword "Weather generators" to review the recent literature relevant to the topic from different repositories. The aim was to highlight the latest developments in the field and provide a better understanding of the possible future trends of this subject research. Figure 2 shows the arithmetical estimate of the papers published between 2000 and 2023 in the Scopus database using the relevant keywords. Figures 3 and 4 depict the document published in the Scopus database according to the subject area and country, respectively.

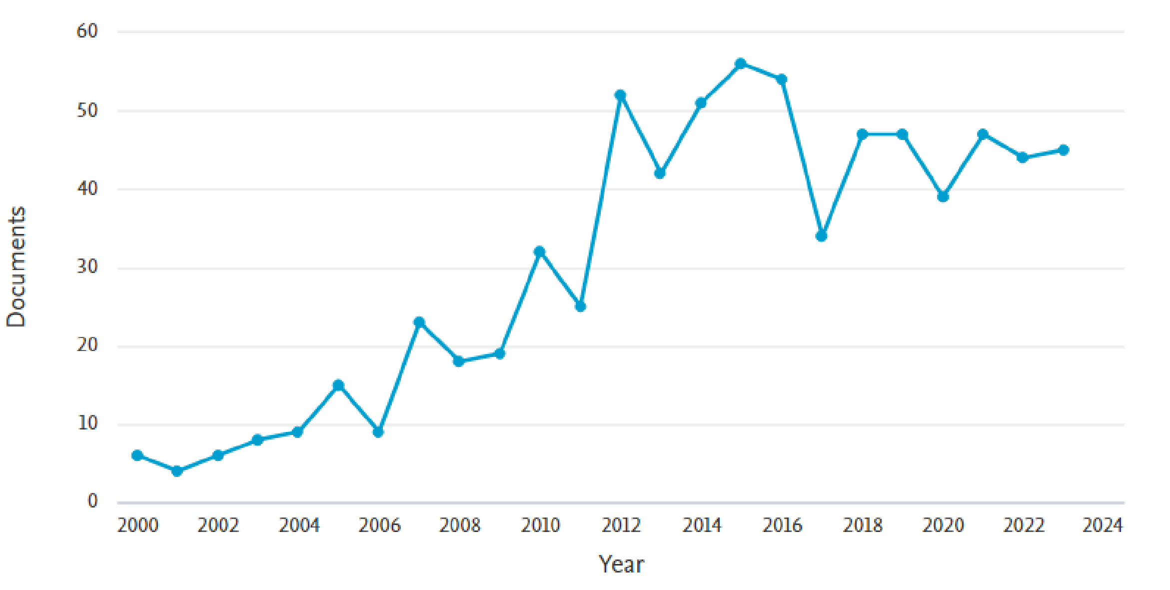

Fig. 2 The Arithmetical Estimate of the Papers Published Between 2000 and 2023 in the Scopus Database.

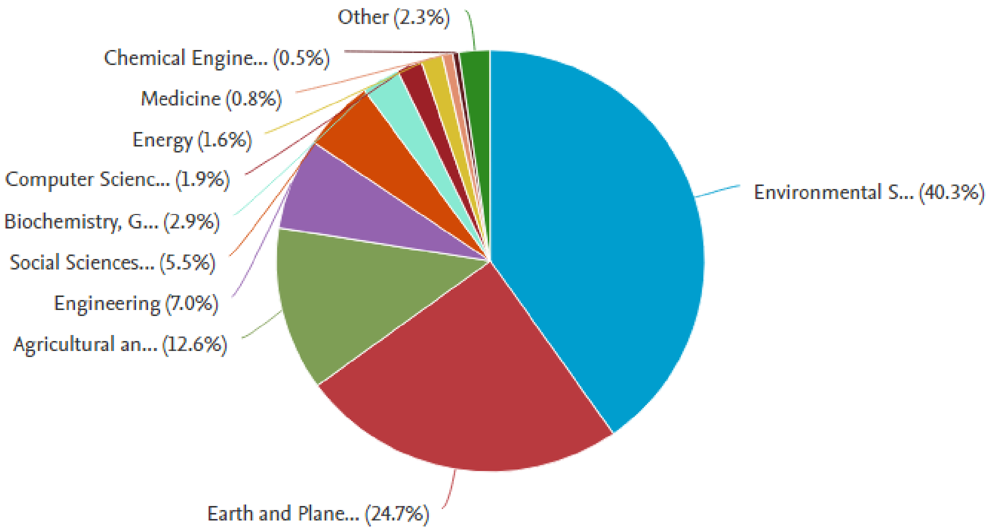

Fig. 3 Documents Published in the Scopus Database According to Subject Area.

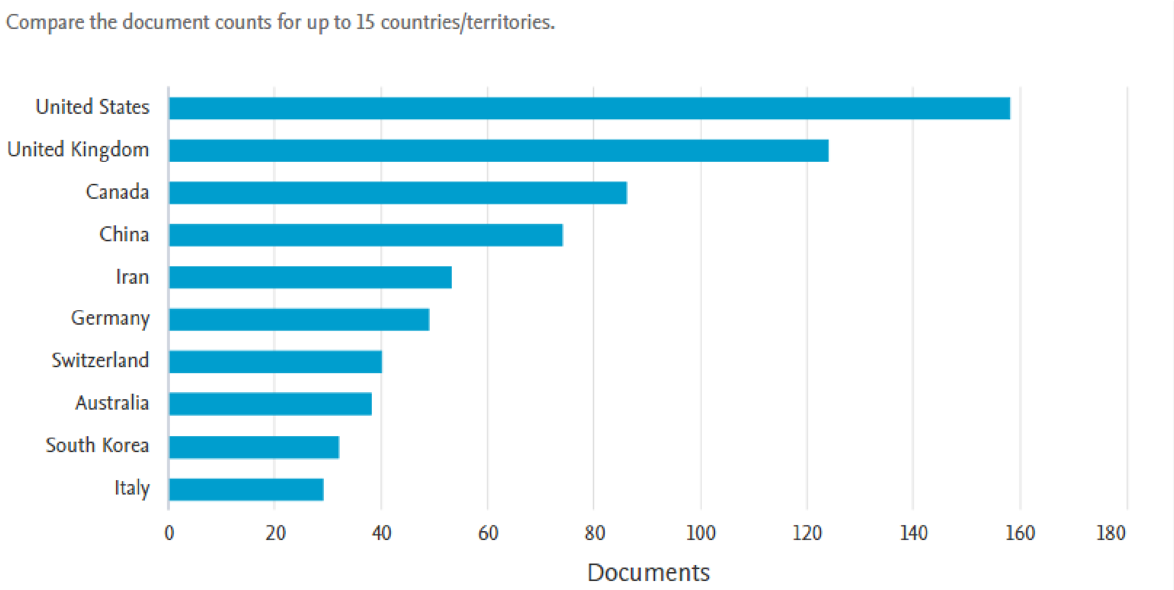

Fig. 4 Documents Published in the Scopus Database Based on the Country or Territory.

3.1.Source of Information

To search for relevant articles, six online resources were used: (1) Scopus, which through indications were obtained, showing the volume of scientific work in previous studies, (2) IEEE Xplore, which contains scientific and technical publications, (3) The Web of Science, which indexes research from a wide range of scientific disciplines, (4) ScienceDirect, it gives access to the technical and scientific literature, (5) Semantic Scholar, (6) PubMed, and (7) Connected Papers. in addition, the websites of international organizations and institutions specialized in climate change, including IPCC, NASA, NOAA, FAO, and WCRP, were searched through their research and data. The purpose of this selection is to offer a complete overview of the status of research in this field by relying on a wide variety of relevant publications.

3.2.Study Selection

A lot of research has contributed to preparing studies on climate change using weather generators. A search of relevant literature sources was followed by two rounds of screening and filtering to find the relevant research. After eliminating any duplicates and irrelevant papers from the findings by screening their titles and abstracts, the remaining articles were submitted to a more thorough screening procedure that included evaluating the articles' full contents.

3.3.Search

The research began at the beginning of September 2023 using Scopus, IEEE Xplore, ScienceDirect, Web of Science, Semantic Scholar, PubMed, and Connected Papers databases via their search boxes. A mix of keywords was used, i.e., “Weather Generators”, “Climate Changes”, and “Meteorological Parameters”, besides auxiliary words, such as, "Applications", "Program", "Code " and "Software", and also "forecasting", "projection" and "prediction" in different variations, combined with main words. Furthermore, the tools supplied by each search engine were used to filter out book chapters and other report types in favor of journal and conference articles, which were judged to be the most likely to include recent and relevant scientific publications.

3.4.Eligibility Criteria

All articles that matched the requirements were incorporated utilizing comprehensive textual material. Once duplicate articles were removed, any articles that did not match the qualifying conditions were excluded. The following exclusion criteria were used:

1) The articles were not written in the English language.
2) The use of weather generators in conjunction with climate changes is not discussed in the articles.

3.5.Process of Data Collection

The included articles were collected from a variety of sources. They were compiled into a set of folders and organized into a single Excel file, with initial classifications by date of release, article type, and degree of importance, from oldest to newest. All of the papers were reviewed, and comprehensive notes on what was most intriguing and how to organize the articles into a more precise taxonomy were taken. All highlighting and annotations were done directly on the text. The findings were tallied, summarized, and extensively debated. The survey articles, summary and description tables, source indices, objectives, review sources, validation procedures, used datasets, and various associated figures were stored in separate Word and Excel spreadsheets. For ease of reference, all of the relevant information was supplied with the results.

3.6.Co-Occurrence

Co-occurrence networks are constructed from existing literature using common terms. Academics, researchers, and practitioners in a particular field may benefit from it, mostly due to its network structure for analyzing co-occurring events, which can highlight the underlying theoretical frameworks of the discipline to understand commonly better used terminology. Figure 5 shows its co-occurrence networks, which reflect a network of previous literature topics. It consists of interconnected lines and nodes. In the literature, a stronger node indicates more prevalent topics. Weather generators are among the terms most used by academics in forecasting models of meteorological parameters under the influence of climate change because researchers may use data networks to help them reorganize prevailing information and results.

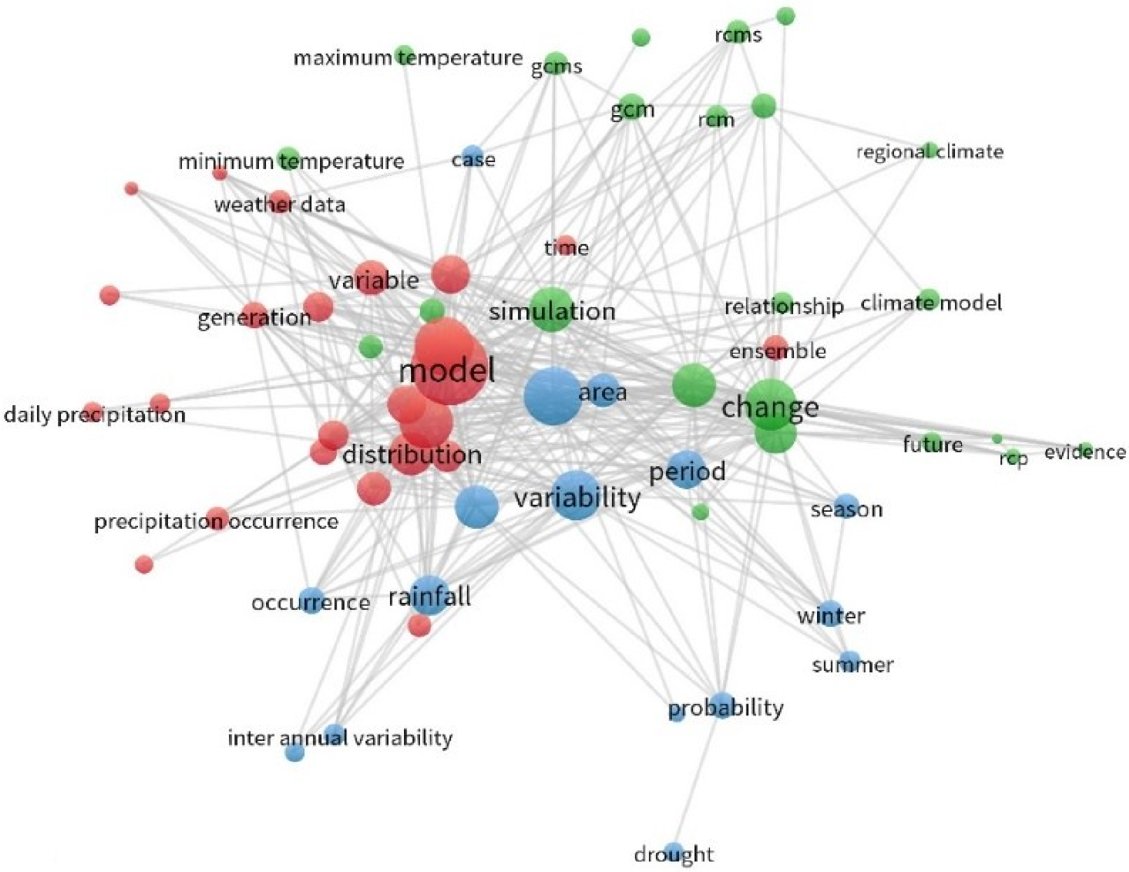

Fig. 5 A Network Structure for Co-Occurrences.

4. RESULTS

4.1. Weather Generators Applications

Weather generators are computer programs that simulate and produce realistic weather conditions for various uses. These technologies are used in various disciplines, such as climate research, agriculture, urban planning, and renewable energy. Weather generators may produce synthetic weather data that mimics real-world conditions by using historical climate data and statistical algorithms, enabling academics and practitioners to investigate the possible implications of climate change, improve agricultural practices, build robust infrastructure, and evaluate the performance of renewable energy systems. Weather generators are critical in understanding and adjusting to changing weather patterns and their repercussions across several industries.

4.2. Weather Generators Classifications

Weather generators can be classified into two ways: Richardson-type or serial approach. In the first type, a Markov procedure is used to model the occurrence of wet and dry days. A functional estimate of the precipitation frequency distribution is then used to model the amount of precipitation that falls on wet days [23]. The remaining climatological variables are then calculated using the correlations between them and the daily wet/dry status. There are numerous successful applications of the Richardson-type generator in agriculture, environmental management, and hydrology. The Richardson-type WG has been criticized for its inability to sufficiently characterize the duration of both wet and dry series, i.e., persistent events like drought and prolonged rainfall. In some applications, these can be crucial, e.g., agricultural impacts. In the serial approach, which was developed by Racsko [24], the sequence of dry and wet series is first modeled and then models other weather variables like precipitation amount and temperature as dependent on the wet or dry series.

4.3. Results of Previous Studies

Many studies and articles have focused on weather generators and their use in climate change, which has gained the attention of the whole world. The present research summarizes the most important results of previous studies and research on the most prominent weather generators used either for reproducing the climate data or for future climate changes, as shown in Table 1.

4.3.1. Weather Generator for Reproducing Data

Yiou [25] presented a weather generator called AnaWEGE (Analogues of circulation WEather Generator) that uses daily temperature patterns to predict weather changes. The study area was throughout Europe within the historical period of 1948-2012. The weather generator's ability to simulate European temperatures during winter and summer and create long sequences of weather data that can help study climate variability and extreme conditions was tested. Ullrich et al. [10] used AWG (Multisite auto regressive Weather Generator) in a study area of the Rhine catchment in two countries, i.e., Germany and Switzerland, which is among the ten largest Eurasian River basins. They used data from 1951 to 2003 to simulate future years' length for the occurrence and amounts of daily precipitation at different locations. They concluded that AWG modeled the spatial correlation structure between stations to generate realistic rainfall fields. Al-Mukhtar et al. [16] utilized CLIGEN (CLImate GENerator) to generate daily, monthly, and yearly precipitation data for the Bautzen catchment area in Germany, based on historical data (1991-2010), aiming to reproduce precipitation data over 20 years. They evaluated CLIGEN's reproducing capability spatially and temporally and found it to be adequate for simulating rainfall characteristics. Mairech et al. [26] used ClimaSG (Climate Stochastic weather Generator) to estimate extreme daily and monthly values of maximum and minimum temperature, solar radiation, rainfall, vapor pressure, and wind speed from 1988 to 2017 for several locations in Spain. They concluded that ClimaSG performed well in predicting monthly rainfall in moderate weather; however, it performed poorly in very hot or cold temperatures. Saha and Ravela [27] assessed a stochastic weather generator known as GAN (Generative Adversarial Networks) in Cook County, which includes Chicago, Illinois, USA, to estimate rainfall in the historical period of 1981-2019 using coarse-resolution climate model outputs (0.25° × 0.25°). They reported that the GAN successfully downscaled coarse-resolution climate data to high-resolution rainfall fields, which are more detailed and useful for risk assessment. Gilewski [28] presented the technique known as GEM (Generation of weather Elements for Multiple applications) for forecasting the hourly and daily precipitation in the upper part of the Skawa catchment, Poland, for historical periods of 2010, 2014, and 2019. It was concluded that GEM can predict rainfall for hydrological modeling in mountain areas, and it is used for event-based flow modeling in small mountain catchments. Sommer and Kaplan [29] presented GWGEN (Global Weather Generator) in their study, which was conducted in several locations in the world to estimate daily and monthly precipitation, besides minimum and maximum temperature. GWGEN was used to create daily weather data from monthly statistics. The researchers concluded that GWGEN performs improperly in terms of spatial and autocorrelated multipoint daily downscaling. However, they recommended that this additional functionality might be implemented in future versions. Vallam and Qin [30] utilized KNN-WG (K-Nearest Neighbor Weather Generator) to simulate 30 years of monthly rainfall data in Singapore, based on the historical period of 1980–2009, to reproduce data for 30 years during rainy seasons. The improved KNN model performed satisfactorily and was able to nearly simulate extreme precipitation levels. Hartkamp et al. [31] utilized MarkSim in northwest Mexico to generate daily and monthly values of precipitation, besides the maximum and minimum temperatures, aiming to reproduce 20 years of data using the historical period from 1965 to 1990. The authors concluded that the weather generator MarkSim created a high inter-annual variability and long chains of wet days that are not found in observed data. Hernández-Bedolla et al. [32] used MASCV (Multivariate Auto-regreSsive model of Climate Variables) in the Jucar River Basin, located in the eastern part of the Iberian Peninsula, Spain, to evaluate precipitation and maximum and minimum temperatures in daily and monthly modes using the historical period of (1950-2015). The MASCV was simulated in MATLAB, and the model properly captures the temporal tendency of yearly temperatures as well as the fluctuation of maximum and minimum values. It was capable of simulating low-frequency occurrences and reproducing the interannual variability of actual data. Farhani et al. [33] used a stochastic weather generator known as MetGen (Multivariable stochastic weather Generator) to estimate sub-daily values of air temperature, relative air humidity, global radiation, and wind speed of the historical period (2011-2016) in the downstream plain of the Merguellil catchment called the Merguellil plain, lying in a semi-arid region located in central Tunisia. The MetGen model generated sub-daily meteorological data and rectified biases in large-scale meteorological data, which is critical for accurate weather simulations. Mehrotra et al. [34] utilized the MRS (Multisite Rainfall Simulator) in Sydney, Australia, to evaluate rainfall based on a daily mode for the historical period of (1979-2008). The researchers showed that the model preserves observed year-to-year variability, interannual persistence, and various daily distributional and spacetime dependence attributes. Hermann et al. [35] presented MulGETS (Matlab-based weather GEneraTor) in the Lobo watershed, located in central-western Côte d'Ivoire, to generate daily and monthly values of precipitation and maximum and minimum temperatures, according to the historical data of (1997-2013). They showed that the model adequately reproduced the meteorological data, where the observed and simulated values showed a significant correlation. Fodor et al. [36] utilized MVWG (Multivariable Weather Generator) in the Midwest and Southern regions of the United States to assess daily and monthly values of precipitation during 1961–1990. They concluded that MVWG was able to generate accurate weather data for locations with no observations located in climatically and geographically homogenous areas. Vu et al. [37] utilized RainSim (Rainfall Simulation) to evaluate stochastic rainfall generators in three diverse climatic regions: a Mediterranean climate in the western USA, a temperate climate of eastern Australia, and a tropical monsoon region in northern Vietnam for daily and monthly values of precipitation using data from the historical period of (1961–1990). The authors concluded that RainSim was effective in creating patterns of wet and dry spells, especially in areas with a lot of rain, like Australia and Vietnam. However, RainSim performed poorly in drier areas, like the western USA, compared to other weather generators. The study suggested that RainSim is satisfactory for understanding rainfall patterns; however, it may not be the best choice for every climate. Fu et al. [38] utilized R-GENERAT-PREC (R-multisite PRECipitation GENERATor) in the Gloucester catchment in Australia to estimate daily and monthly values of rainfall based on the historical period (1923-2012). The R-GENERAT-PREC weather generator was good for creating daily rainfall patterns that look like real data, including how often it rains and how much rain falls. Wang et al. [39] utilized R-GLIM-CLIM (R-Generalised LInear Model for daily CLIMate time series) in the eastern USA to evaluate temperature, precipitation, and wind speed in daily and monthly modes by using two historical periods, i.e., 1958–2015 and 1959–2016. R-GLIM-CLIM passed the stationarity test at more stations than quantile mapping. It was less affected by an increase in the resolution of input data. However, the method could not reliably downscale the entire marginal distribution or time series of precipitation. Cordano and Eccel [40] assessed R-MAW-GEN (R-Multisite Autoregressive Weather GENerator) in the Trentino region in the North-Eastern Italian Alps to generate daily precipitation using the historical period of (1961-1990). They proved that R-MAW-GEN can generate daily maximum and minimum temperatures and precipitation series that match real observations. It also preserves the temporal and spatial correlations among weather variables. Ullrich et al. [9] utilized RWG (Raster-based resampling Weather Generator) in the Rhine catchment, spanning two countries—Germany and Switzerland, among the ten largest

Eurasian River basins, using data from 1951 to 2003 to estimate daily precipitation values. They showed that RWG tends to slightly underestimate observed extreme weather; however, it still provides satisfactory results for understanding climate changes. Soltani and Hoogenboom [41] utilized SIMMETEO in five contrasting climate locations in Iran to estimate precipitation, solar radiation, maximum and minimum temperatures in daily and monthly modes using data from 1966–1995 to reproduce 30 years. As a result, SIMMETEO was discovered to be less sensitive to the volume of input data. Ng et al. [42] assessed TCRG (Tropical Climate Rainfall Generator) in the Kelantan River Basin in Malaysia to evaluate daily rainfall using data from 1953 to 2012. They demonstrated that TCRG is superior for simulating rainfall occurrence and retaining low-frequency variability of wet spells, according to its spectrum correction technique, which successfully preserves seasonal and inter-annual rainfall variability. Flecher et al. [43] used WACS-Gen (Weather state Approach with a multivariate Closed Skew-normal GENerator) in Colmar, France, to simulate minimum and maximum temperatures, global radiation, wind speed, and precipitation based on a daily mode using data from 1973 to 1992. The study concluded that the weather generator WACS-Gen simulated radiation and wind dispersion more accurately than other parameters. Chen et al. [44] used WeaGETS in two Canadian meteorological stations to estimate precipitation, maximum and minimum temperatures in daily, monthly, and yearly modes using data from 1891-2008 in Ottawa and 1947-2006 in Churchill. They revealed that the tool is especially good at keeping track of how often weather patterns change over months and years, which is important for understanding long-term trends. Additionally, they argued that WeaGETS is generally reliable; however, it sometimes does not accurately capture the all-time lowest temperatures, especially for the Churchill station. It also tends to underestimate the longest dry spells, which is a slight downside for the dry Churchill station. WeaGETS is seen as a useful tool for making weather data, but like all tools, it is not perfect and could be better in some areas. Vu et al. [37] utilized WeatherMan (Weather and Manage) to assess daily and monthly values of precipitation in three diverse climatic regions: a Mediterranean climate in the western USA, a temperate climate of eastern Australia, and a tropical monsoon region in northern Vietnam for predicting daily and monthly values of precipitation based on the historical period of (1961–1990). They suggested WeatherMan as a good tool for generating precipitation occurrence statistics across different climatic regions. Muza [45] used WGEN (Weather GENerator) in São Paulo, Southeastern Brazil, to estimate daily and monthly values of precipitation and maximum and minimum temperatures using historical data from 1961 to 2011. The study concluded that WGEN was good for reproducing daily weather details from monthly data for São Paulo and matching real weather patterns well. Also, it worked well for showing rain and temperature day by day, which is hard for some climate models. On the other side, WGEN's performance was satisfactory in showing how often and how severe weather events occur, such as heavy rain or extremely hot days. Although it did not perfectly show changes in weather from season to season or very rapid changes, it was still useful.

4.3.2.Weather Generators for Future Climate Changes

Qian et al. [46] used a stochastic weather generator known as AAFC-WG (Agriculture and Agri-Food Canada) to estimate extreme daily values of maximum and minimum temperatures and precipitation using data from the historical period of (1961-1990) to generate future data for the time period of (2040–2069) for the agricultural regions of Canada using four global climate models: CGCM3, HadCM3, ECHAM5/MPI-OM, and CSIRO-Mk3.5. Their results revealed that the AAFC-WG provided more detail at the finer spatial scale. Yang et al. [47] utilized AWE-GEN (Advanced WEather GENerator) to simulate hourly rainfall patterns for climate change impact studies in the Ru River Basin, China. They utilized the historical period data of (1970-1999) to generate rainfall projections for the future period of 2040-2099, assessing the impact of climate change on water movement and nutrient flow in a heavily polluted river basin. They revealed an improvement in the performance of rainfall simulation by determining optimal aggregation intervals for the hourly rainfall series. Vesely et al. [48] used Climak to assess the impacts of climate changes up to 2040 on precipitation and air temperature at 15 sites worldwide, utilizing data from the historical period of (1986–2005). They found that the use of Climak as a weather generator can significantly enhance the results of future climate changes. Osborn et al. [49] utilized ClimGen (Climate Generator) in India to estimate monthly values of precipitation and temperature in two historical periods (1961-1990 and 1950-1999) to generate future data for 2051-2100 using 39 GCMs. They concluded that ClimGen facilitated the comparison of climate projections from different climate models. Forsythe et al. [50] utilized the CRU-WG (Climatic Research Unit daily Weather Generator) in a semi-arid climate area of the Upper Indus Basin in Pakistan to evaluate daily and monthly precipitation and temperature using two historical periods of (1961-1990) and (1979-2007) for forecasting the future period of (2071-2100). They reported the importance of using multiple climate model ensembles to capture uncertainty in future projections. Xu et al. [51] evaluated the performance of the GiST model (GeoSpatial–Temporal weather generator) for simulating precipitation in the Qiantang River Basin, East China, based on daily and monthly modes using data from 1961 to 1990 to generate future climate data of (2071-2100). The researchers aimed to use the GiST model to generate synthetic weather data that considers the spatial structure of weather data and also to investigate future changes in precipitation under climate change. Doaa and Ruqayah [52] utilized LARS-WG (Long Ashton Research Station Weather Generator) in the Upper Zab basin, a tributary of the Tigris River, to forecast daily values of rainfall and maximum/minimum temperatures for the future period of (2021-2040) using historical data, i.e., 1990-2021. Five GCMs were selected for climate projection analysis under two typical concentration path scenarios: viz. RCP4.5 and RCP8.5. The authors revealed a superior performance of LARS-WG simulations in terms of prediction accuracy, where the results were in parallel with previous research [53–56]. Liu et al. [57] used MODAWEC (MOnthly to DAily WEather Convertor) in the Arlington Agricultural Research Station–USA to project daily and monthly values of precipitation, maximum and minimum temperature for the period of 2001-2100 using historical data of (1958-1991). The researchers concluded from monthly statistics that the MODAWEC model effectively generated daily weather data. However, the study indicated that the MODAWEC model may incorrectly reproduce extreme weather events. Al-Mukhtar and Qasim [58] presented SDSM (Statistical DownScaling Model) to project temperature and precipitation, during three future periods: 2011-2040, 2041-2070, and 2071-2099 based on a daily mode using the historical period (1961-1990) in twelve locations distributed throughout Iraq by using the Canadian GCM model (CanESM2) under various scenarios, i.e., RCP2.5, RCP4.5, and RCP6.5. The authors concluded that the downscaled models SDSM can reduce the uncertainties in projections to obtain more reliable future predictions. Smith et al. [59] used SHArP (Stochastic Harmonic Auto-regressive Parametric) in northern Utah, USA, to evaluate daily values for precipitation and temperature for a future period (up to 2100) using the historical data of (1950–2005). The SHArP weather generator can properly simulate weather at numerous sites simultaneously, preserving individual site statistics and spatial correlation. Despite detecting major spatial and temporal disparities in observed temperature covariance, SHArP delivers realistic hydrologic models and handles complex terrain. Dubrovsky et al. [60] used SPAGETTA (SPAtial GEneraTor, Trend Analysis and Tyrolian Alps) in eight European regions to estimate daily values of precipitation and temperature from 2071 to 2100 using the historical period (1961–1990). The weather generator produced an excellent match for the frequency of regionally hot days and the length of spatially hot periods. Demonstrating that SPAGETTA accurately captures spatial temperature characteristics when compared to observed data. Glenis et al. [61] used UKCP09 (UK-Climate Projections) in the United Kingdom to estimate daily values of rainfall and potential evapotranspiration during (2010-2099) using the historical data of (1961-2000). The study concluded that the weather generator UKCP09 is satisfactory as it allows for a detailed examination of the potential impacts of climate model uncertainties on water resources. Yaqubi et al. [62] applied UWG (Urban Weather Generator) in the city of Nantes, France, to estimate temperature, relative humidity, and wind speed in hourly and monthly modes during 2040-2070, using three dynamically downscaled models generated from RCMs: IPSL-SMHI, CNRM-ALADIN, and MPI-REMO. The UWG forecasted the urban heat island influence on future weather data. The study showed the need to employ two weather files and at least two overheating indices for accurate results. Aliabadi et al. [63] used VCWG (Vertical City Weather Generator) in Toronto, a cold Canadian city, to assess the temperature of hourly, daily, and monthly modes from 2020 to 2100 using data from 2020, 2021, and 2022. They used two Representative Concentration Pathways: RCP4.5 and RCP8.5. The authors concluded that the weather generator VCWG successfully predicted the impact of different building retrofits. The model is considered computationally fast, which is beneficial for practical applications.

Table 1 Summary of Previous Studies.

No.	WG-Model	Authors	Study Year	Study Area	Data Period	Scale	Predictors	Accuracy Measures	Projection Period
1	AAFC-WG	[46]	2010	Canada	1961-1990	Daily	P, T_{max}, T_{min}	L-moments, GEV, Monte Carlo	2040–2069
2	AnaWEGE	[25]	2014	Europe	1948-2012	Daily	T	——	——
3	AWE-GEN	[47]	2020	China	1970-1999	Hourly	P	Mean, maximum, standard deviation, skewness, (K-S) test	2040-2099
4	AWG	[9]	2021	Germany and Switzerland	1951-2003	Daily	P	Mean, average	undefined, but use 53 years
5	CLIGEN	[16]	2014	Germany	1991-2010, 2004-2010, 2005-2010	Daily, monthly, annual	P	Mean, average, maximum, minimum, standard deviation, MAREs, (K–S) test, Mann–Whitney test, Levene's test	undefined, but use 20 years
6	CLIMAK	[48]	2019	multiple sites worldwide	1986-2005	Daily	P, T_{air}	(ANOVA) test	At 2040 only
7	ClimaSG	[26]	2022	Spain	1988-2017	Daily, monthly	T_{max}, T_{min}, S.RAD, P, P_{vapor}, W.S	Mean, average, variation, maximum, minimum, standard deviation, CV, (KS) test, r^2, MAE, MBE, RMSE	——
8	ClimGen	[49]	2016	India	1961-1990 1950-1999	Monthly	P, T	Mean, average, variation, standard deviation	2051–2100
9	CRU-WG	[50]	2014	Pakistan	1961-1990 1979-2007	Daily, monthly	P, T	Mean, average, maximum, minimum, skewness, Pearson's correlation, T-test, Von Neumann ratio test, RMSE,	2071-2100
10	GAN	[27]	2022	USA	1981-2019	——	P	mean, average, bias, standard error, CGP	——
11	GEM	[28]	2022	Poland	2010, 2014, 2019	Hourly, daily	P	Mean, average, standard deviation, NSE, RMSE, P.bias, Pearson's correlation coefficient (r)	——
12	GiST	[51]	2014	China	1961–1990	Daily, monthly	P	Mean, average, standard deviation	2071-2100
13	GWGEN	[29]	2017	worldwide	undefined, but use 120 last years	Daily, monthly	p, T_{max}, T_{min}	Mean, standard deviation, SE, Q–Q plots, (K-S) test	——
14	KNN-WG	[30]	2016	Singapore	1980–2010	Monthly	P	Mean, average, variation, maximum, minimum, standard deviation, RMSE, R^2	undefined, but use 30 years
15	LARS-WG	[52]	2024	Iraq	1990-2021	Daily	P, T_{max}, T_{min}	Mean, average, maximum, minimum, (K-S) test	2021-2040
16	MarkSim	[31]	2003	Mexico	1965-1990	Daily, monthly	p, T_{max}, T_{min}	Mean, average, maximum, minimum, standard deviation, T-test, signed rank test, Wilcoxon test,	undefined, but use 20 years
17	MASCV	[32]	2022	Spain	1950-2015	Daily, monthly	p, T_{max}, T_{min}	Mean, average, maximum, minimum, standard deviation, MAE, RMSE, PE, chi-squared test, (K-S) test, T-test, F-test, Wilcoxon test, skewness coefficient	undefined, but use 66 years
18	MetGen	[33]	2022	Tunisia	2011-2016	Sub-daily	T_{air}, R.H., G.RAD, W.S	Mean, average, maximum, minimum, standard deviation, RMSEs, Q–Q plots,	——
19	MODAWEC	[57]	2009	USA	1958-1991	Daily, monthly	p, T_{max}, T_{min}	Mean, average, maximum, minimum, standard deviation, NMSE, r^2, F-test	2001-2100
20	MRS	[34]	2015	Australia	1979-2008	Daily	P	Mean, average, variation, maximum, minimum, standard deviation	——
21	MulGETS	[35]	2020	Côte d'Ivoire	1997-2013	Daily, monthly	p, T_{max}, T_{min}	Mean, average, maximum, minimum, standard deviation, R^2	——
22	MVWG	[36]	2013	USA	1961–1990	Daily, monthly	P	Mean, average, maximum, minimum, standard deviation, U-test, t-tests, Res	——
23	RainSim	[37]	2018	USA, Australia, and Vietnam	1961–1990	Daily, monthly	P	Mean, average, maximum, minimum, standard deviation, skewness, (Q-Q) plots, Wilcoxon tests, KS-test, NSE, and MAE	——
24	R-GENERAT-PREC	[38]	2017	Australia	1923-2012	Daily, monthly	P	CV, SD, REs, and R	——
25	R-GLIM-CLIM	[39]	2017	USA	1958–2015 1959–2016	Daily, monthly	P, T, W.S	Mean, average, maximum, minimum, standard deviation, RMSEs, and Wilcoxon tests	——
26	R-MAW-GEN	[40]	2016	Italy	1961 -1990	Daily	P	Mean, maximum, minimum, standard deviation, (Q-Q) plots, and (K-S) test	——

27	RWG	[9]	2021	Germany and Switzerland	1951-2003	Daily	P	Mean, average	undefined, but use 53 years
28	SDSM	[58]	2019	Iraq	1961-1990	Daily	p, T_{max}, T_{min}	Mean, maximum, minimum, R^2, NSE, and RMSE	2011-2040 2041-2070 2071-2099
29	SHArP	[59]	2018	USA	1950–2005	Daily	P, T	Mean, average, variation, maximum, minimum, standard deviation, and (Q-Q) plots	1950–2100
30	SIMMETEO	[41]	2003	Iran	1966–1995	Daily, monthly	p, T_{max}, T_{min}, S.RAD	Mean, average, maximum, minimum, standard deviation, T-test, F-test, and Se	undefined, but use 30 years
31	SPAGETTA	[60]	2019	eight European regions	1961–1990	Daily	P, T	Mean, average, maximum, minimum, standard deviation, R	2071–2100
32	TCRG	[42]	2017	Malaysia	1953–2012	Daily	P	Mean, average, maximum, minimum, standard deviation, skewness coefficient, Scatter plots, MAPE, (K–S) test, Wilcoxon test, Squared ranks tests, and k	——
33	UKCP09	[61]	2015	United Kingdom	1961-2000	Daily	P, P_{ET}	Mean, average, maximum, minimum, and skewness coefficient	2010-2099
34	UWG	[62]	2022	France	2003	Hourly, monthly	T, R.H, W.S	Mean, average, and variation	2040-2070
35	VCWG	[63]	2023	Canada	2020, 2021, 2022	Hourly, Daily, Monthly	T	Mean, average, variation, maximum, minimum, and standard deviation	2020-2100
36	WACS-Gen	[43]	2010	France	1973-1992	Daily	p, T_{max}, T_{min}, G.RAD, W.S	Mean, average, maximum, minimum, standard deviation, skewness, R, and (Q-Q) plots	——
37	WeaGets	[44]	2012	Canada	1891-2008 1947-2006	Daily, monthly, yearly	p, T_{max}, T_{min}	Mean, average, variation, maximum, minimum, standard deviation, MAREs, and R	undefined, but use 10 years
38	WeatherMan	[37]	2018	USA, Australia, and Vietnam	1961–1990	Daily, monthly	P	Mean, average, maximum, minimum, standard deviation, skewness, (Q-Q) plots, Wilcoxon tests, KS-test, NSE, and MAE	——
39	WGEN	[45]	2014	Brazil	1961-2011	Daily, monthly	p, T_{max}, T_{min}	Mean, average, maximum, minimum, standard deviation, RMS, Monte Carlo test, and correlation of Pearson coefficient	undefined, but use 50 years

5..DISCUSSION

The main objective of this research is to provide relevant information on various weather generators, as previously classified in the present research based on previous studies and research. For a variety of reasons, the operation of a weather generator must be accurate to be used in the management of water resources efficiently. At that point, the models could also be implemented in the diagnosis of future weather and climate by analyzing them within hydrological, climatic, and agricultural indicators, as well as drought indicators. Furthermore, the calculation of water budgets and the analysis of water balances, particularly in arid environments where rainfall and temperatures fluctuate, in addition to the other parameters included in the calculations of weather forecasting and climate change, might be further analyzed. As a result, decision-makers have greatly benefited from using weather generators that provide them with a clear scientific understanding. This paper reviews studies and research on weather generators, which were investigated in depth, according to the types and categories indicated in the research. The papers included in this study demonstrated an increasing trend toward using high-accuracy methodologies that provide plausible and close-to-real-world outcomes through verification and mathematical, statistical, and programming testing. Furthermore, worldwide climate change websites have been improved by showing the data and models used to analyze previous data as inputs for weather generators, thereby producing future data. This survey stands out from many earlier studies because of its distinctiveness and concentration on the literature on weather generators and their relationship to climate change. The evolution of the classification of published works imposes a structure on the mass of publications. On the other hand, the categorization structure provides scientists with important context for their study. It starts with identifying prospective paths of inquiry in the region. Second, the classification might show research gaps that may be used to determine prospective future directions. This research classified weather generators into two categories: Richardson-type and serial approach. In the first type, a Markov chain defines a particular day's state as "wet" or "dry" and specifies the relationship between the current and prior days' states. Most of the Markov chain models are first-order models. Although the first-order model is satisfying, the findings of the longer simulated drought wave were somewhat shorter than the observed results, which might be due to the short-term memory of the first-order Markov model [64]. To solve this constraint, it is recommended to utilize a second or higher-order Markov chain. In tropical locations, the second-order Markov chain has an optimal value for forecasting monthly rainfall, whereas the third-order is the best for calculating yearly rainfall [65]. In subtropical locations with four seasons, the forecast of daily rainfall in the summer is better than in the other seasons [66]. Parametric probabilities, i.e., single parameters such as exponential [64] or multiparameters, such as gamma [64,65,67–69], Weibull [64,70], normal/Gaussian [69,71], lognormal [65], mixed exponential [64,65,70], hybrid exponential [64,65,72], and skew-normal [64,65] are typically used to generate rainfall quantities. Meanwhile, the K-nearest neighbor is commonly used as a non-parametric probability [73]. Most researchers suggest that the three-parameter distribution produces better results than alternative models [64,70]. Three-parameter distributions, such as the mixed exponential distribution, are more effective in reproducing daily precipitation variance in the subtropics. In contrast, the skewed normal and Weibull distributions better reflect the features of excessive rainfall at the >95th percentile [64]. In the tropics, the mixed exponential (three parameters) is highly suited for predicting the mean and maximum values on the hourly scale, in comparison to Weibull (two parameters) [70]. Spatiotemporal fluctuations also impact the distribution model's applicability; therefore, not all three-parameter distributions are preferable. Statistical testing showed an insignificant difference in the performance of one-, two-, and three-parameter distributions [65]. The exponential (one parameter) and lognormal (two parameters) distributions outperform other distributions at high values [65], while the double gamma distribution (two parameters) may represent both heavy and average rainfall at the same time [68]. The most prevalent types of weather generators employ Markov chain techniques, including WGEN, CLIMGEN, CLIGEN, WeaGETS, and MulGETS. In several studies, Chen and Brissett [74] evaluated SWGs to generate data on rainfall in China's Loss Plateau region. By using WGEN, CLIGEN, and CLIMGEN, 2-state of first-order Markov chains are used to generate events of precipitation. WGEN utilizes gamma, CLIMGEN uses Weibull, and CLIMGEN employs a skewed distribution to calculate precipitation. WeaGETS employs a third-order Markov chain and a mixed exponential distribution. Weather generators based on three parameters, like CLIGEN and WEAGETS, often outperform two-parameter distributions, like CLIMGEN and WGEN, for modeling daily precipitation levels, particularly when simulating extreme rainfall.

6.CONCLUSIONS

A comprehensive review of previously published literature on applying weather generators models around the world was conducted in this study to provide a better understanding of the models' capabilities. The drawbacks and shortcomings of each model type, i.e., the Richardson type and the serial one, were also discussed. The reviewed papers were addressed in terms of time scales, methodologies, and climate parameters. The review revealed that the major objectives for utilizing stochastic weather generators models are either to reproduce climatic data, statistical downscaling, projecting future data trends, or evaluating extreme values. The stochastic climate model is considered the most common tool utilized for data creation and statistical downscaling. These stochastic models' performance varies based on the study area, weather conditions, and length of the span. Spatiotemporal variations and parameter selection might all explain the disparities in model findings. The stochastic weather generator model is simple and effective, and the spatial and temporal scale, as well as the model type, may be tailored to the study objectives. The more collection of models used, the more favorable the results. Generally, the stochastic model is highly adaptable to the demands of the user despite some application shortcomings and drawbacks. However, by adapting cutting-edge machine learning methods, such as deep learning approaches along with the weather generators, it is anticipated that the performance of the stochastic generators will be enhanced, providing more accurate reanalyzed or future data. The machine learning methods should be the future trend studies for the sake of the development of weather generators implementations.

ACKNOWLEDGEMENTS

The authors are grateful for the financial support received from the Ministry of Water Resources - The General Commission for Irrigation and Reclamation Projects during this study period, Postgraduate Research Grant No. 3024 (5/3/2024).

ABBREVIATIONS

(ANOVA) test	Analysis of Variance
(KS) test	Kolmogorov-Smirnov test
(K-S) test	Kolmogorov-Smirnov tests
(Q-Q) plots	Quantile-quantile plots
AEs	Absolute Errors
CFs	Change Factors

CGP	Conditional Gaussian Process
CMIP	Climate Model Intercomparison Project
CV	Coefficient of Variation
DS	Relative Difference in Standard Deviation
$\bar{e}$	Bias
ET	Evapotranspiration
FAO	Food and Agriculture Organization of the United Nations
F-test	F-Test Statistic
G.RAD	Global Radiation
GCM	Global Climate Model
GEV	Generalized Extreme Value
H	Humidity
IPCC	Intergovernmental Panel on Climate Change
k	Kurtosis Coefficient
KT	Correction coefficient
L-moments	L-statistics
LS-error	Least Squares Error
MAE	Mean Absolute Error
MAEs	Mean Absolute Errors
MAREs	Mean Absolute Relative Errors
MBE	Mean Bias Error
MBE	Mean Bias Error
MedAE	Median Absolute Error
MOS	Mean Opinion Score tests
MX.5P	Mean Daily Maximum 30-min
NASA	National Aeronautics and Space Administration
NMSE	Normalized Mean Square Error
NOAA	National Oceanic and Atmospheric Administration
NRMSE	Normal Square Root Mean Error
NSE	Nash-Sutcliff Efficiency
P	Precipitation
P(W|D)	Dry Day Probability
P(W|W)	Wet Day Probability
P.BIAS	Percent Bias
P_{atm}	Atmospheric Pressure
PE	Percent Error Estimate
P_{ET}	Potential Evapotranspiration
Pr	Partial Correlation Coefficient
PSNR	Peak Signal-to-Noise Ratio
P_{vapor}	Vapor Pressure
QUMP	Quantifying Uncertainty in Model Predictions
R	Correlation Coefficient
R.H	Relative Humidity
R^2	Determination Coefficient
r^2	Determination Coefficient
Ra	Solar radiation
Rb	Relative Bias
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
REs	Relative Errors
RMSE	Root Mean Square Error
Rs	Relative Standard Error
S.RAD	Solar Radiation
SDEV	Standard Deviation
Se	Standard Error
SE	Standard Error
SKEW	Skewness Coefficient
SSIM	Structural Similarity Index
SVM	Support Vector Machines
SWG	Stochastic Weather Generator
T	Temperature
T_{air}	Air Temperature
TimePk	Peak Time
T_{max}	Maximum Temperature
T_{min}	Minimum Temperature
t-test	Hypothesis Test Statistic
W.S.	Wind Speed
WCRP	World Climate Research Programme
WG	Weather Generator
μ	Mean
σ	Standard Deviation
X	Variable Value
Γ	Gamma Function
λ	Estimated Parameter
β	Scale Parameter
α	Shape Parameter
t	Day Number
P_r	Transitional Probability
s	State of Precipitation of the Next Day
q	State of Precipitation of the Previous Day

REFERENCES

[1] Core Writing Team, Pachauri RK, Meyer LA. **Climate Change 2014: Synthesis Report**. IPCC, Geneva, Switzerland; 2014.

[2] Diffenbaugh NS, Field CB. **Changes in Ecologically Critical Terrestrial Climate Conditions**. *Science* 2013; **341**(6145): 486–492.

[3] Hsiang SM, Burke M, Miguel E. **Quantifying the Influence of Climate on Human Conflict**. *Science* 2013; **341**(6151): 1235367.

[4] Ansari A, Pranesti A, Telaumbanua M, Alam T, Taryono, Wulandari RA, et al. **Evaluating the Effect of Climate Change on Rice Production in Indonesia Using Multimodelling Approach**. *Heliyon* 2023; **9**(9): e19539.

[5] Diffenbaugh NS, Swain DL, Touma D, Lubchenco J. **Anthropogenic Warming Has Increased Drought Risk in California**. *Proceedings of the National Academy of Sciences of the United States of America* 2015; **112**(13): 3931–3936.

[6] Easterling DR, Meehl GA, Parmesan C, Changnon SA, Karl TR, Mearns LO. **Climate Extremes: Observations, Modeling, and Impacts**. *Science* 2000; **289**(5487): 2068–2074.

[7] Duan Z, Song X. **Mapping Cover and Management Factor Based on Weather Generator and Remote Sensing**. *International Workshop on Education Technology and Training & International Workshop on Geoscience and Remote Sensing*; 2008; Shanghai, China; pp. 464–467.

[8] Hong NM, Lee TY, Chen YJ. **Daily Weather Generator with Drought Properties by Copulas and Standardized Precipitation Indices**. *Environmental Monitoring and Assessment* 2016; **188**(6): 335.

[9] Ullrich SL, Hegnauer M, Nguyen DV, Merz B, Kwadijk J, Vorogushyn S. **Comparative Evaluation of Two Types of Stochastic Weather Generators for Synthetic Precipitation in the Rhine Basin**. *Journal of Hydrology* 2021; **601**: 126588.

[10] Collados-Lara AJ, Pardo-Igúzquiza E, Pulido-Velazquez D. **Assessing the Impact of Climate Change – and Its Uncertainty – on Snow Cover Areas by Using Cellular Automata Models and Stochastic Weather Generators**. *Science of the Total Environment* 2021; **788**: 147693.

[11] Li Y, Sun Y. **A Multi-Site Stochastic Weather Generator for High-Frequency Precipitation Using Censored Skew-Symmetric Distribution**. *Spatial Statistics* 2021; **41**: 100484.

[12] Farhani N, Carreau J, Kassouk Z, Mougenot B, Le Page M, Lili-Chabaane Z, et al. **Sub-Daily Stochastic Weather Generator Based on Reanalyses for Water Stress Retrieval in Central Tunisia**. *HAL* 2020; hal-02902163.

[13] Ahn KH. **Coupled Annual and Daily Multivariate and Multisite Stochastic Weather Generator to Preserve Low- and High-Frequency Variability to Assess Climate Vulnerability**. *Journal of Hydrology* 2020; **581**: 124396.

[14] Verdin A, Rajagopalan B, Kleiber W, Podestá G, Bert F. **A Conditional Stochastic Weather Generator for Seasonal to Multi-Decadal Simulations**. *Journal of Hydrology* 2018; **556**: 835–846.

[15] Hashmi MZ, Shamseldin AY, Melville BW. **Downscaling of Future Rainfall Extreme Events: A Weather Generator Based Approach**. *18th World IMACS Congress and MODSIM 2009 - International Congress on Modelling and Simulation: Interfacing Modelling and Simulation with Mathematical and Computational Sciences, Proceedings*; 2009; pp. 3928–3934.

[16] Al-Mukhtar M, Dunger V, Merkel B. **Evaluation of the Climate Generator Model CLIGEN for Rainfall Data Simulation in Bautzen Catchment Area, Germany**. *Hydrology Research* 2014; **45**(4–5): 615–630.

[17] Ibeje AO, Osuagwu JC, Onosakponome OR. **A Markov Model for Prediction of Annual Rainfall**. *International Journal of Scientific Engineering and Applied Science (IJSEAS)* 2018; **4**(3): 1–7.

[18] Ng JL, Abd Aziz S, Huang YF, Wayayok A, Rowshon M. **Generation of a Stochastic Precipitation Model for the Tropical Climate**. *Theoretical and Applied Climatology* 2018; **133**(1–2): 489–509.

[19] Dastidar AG, Ghosh D, Dasgupta S, De UK. **Higher Order Markov Chain Models for Monsoon Rainfall over West Bengal, India**. *Indian Journal of Radio and Space Physics* 2010; **39**(1): 39–44.

[20] Abreu MC, de Souza A, Lyra GB, de Oliveira-Júnior JF, Pobocikova I, de Almeida LT, et al. **Assessment and Characterization of the Monthly Probabilities of Rainfall in Midwest Brazil Using Different Goodness-of-Fit Tests as Probability Density Functions Selection Criteria**. *Theoretical and Applied Climatology* 2023; **151**(1–2): 491–513.

[21] Mahgoub Mohamed T, Abd Allah Ibrahim A. **Fitting Probability Distributions of Annual Rainfall in Sudan**. *SUST Journal of Engineering and Computer Sciences (JECS)* 2016; **17**(2): 21–30.

[22] Ye L, Hanson LS, Ding P, Wang D, Vogel RM. **The Probability Distribution of Daily Precipitation at the Point and Catchment Scales in the United States**. *Hydrology and Earth System Sciences* 2018; **22**(12): 6519–6531.

[23] Richardson CW. **Stochastic Simulation of Daily Precipitation, Temperature, and Solar Radiation**. *Water Resources Research* 1981; **17**(1): 182–190.

[24] Racsko P, Szeidl L, Semenov M. **A Serial Approach to Local Stochastic Weather Models**. *Ecological Modelling* 1991; **57**(1–2): 27–41.

[25] Yiou P. **AnaWEGE: A Weather Generator Based on Analogues of Atmospheric Circulation**. *Geoscientific Model Development* 2014; **7**(2): 531–543.

[26] Mairech H, López-Bernal Á, Testi L, Villalobos FJ. **ClimaSG: A Weather Generator for Crop Modelling and Water Requirements Studies**. *Agricultural Water Management* 2022; **271**: 107789.

[27] Saha A, Ravela S. **Downscaling Extreme Rainfall Using Physical-Statistical Generative Adversarial Learning**. *Journal of Advances in Modeling Earth Systems* 2022; **14**(9): e2022MS003120.

[28] Gilewski P. **Application of Global Environmental Multiscale (GEM) Numerical Weather Prediction (NWP) Model for Hydrological Modeling in Mountainous Environment**. *Atmosphere* 2022; **13**(9): 1367.

[29] Sommer PS, Kaplan JO. **A Globally Calibrated Scheme for Generating Daily Meteorology from Monthly Statistics: Global-WGEN (GWGEN) v1.0**. *Geoscientific Model Development* 2017; **10**(10): 3771–3791.

[30] Vallam P, Qin XS. **Multi-Site Rainfall Simulation at Tropical Regions: A Comparison of Three Types of Generators**. *Meteorological Applications* 2016; **23**(3): 425–437.

[31] Hartkamp AD, White JW, Hoogenboom G. **Comparison of Three Weather Generators for Crop Modeling: A**

Case Study for Subtropical Environments. *Agricultural Systems* 2003; **76**(2): 539–560.

[32] Hernández-Bedolla J, Solera A, Paredes-Arquiola J, Sanchez-Quispe ST, Domínguez-Sánchez C. **A Continuous Multisite Multivariate Generator for Daily Temperature Conditioned by Precipitation Occurrence**. *Water* 2022; **14**(21): 3525.

[33] Nesrine Farhani, Julie Carreau, Zeineb Kassouk, Bernard Mougenot, Michel Le Page, Zohra Lili-Chabaane, Rim Zitouna-Chebbi GB. **Regional Sub-Daily Stochastic Weather Generator Based on Reanalyses for Surface Water Stress Estimation in Central Tunisia**. *Environmental Modelling & Software* 2022; **155**: 105446.

[34] Mehrotra R, Li J, Westra S, Sharma A. **A Programming Tool to Generate Multi-Site Daily Rainfall Using a Two-Stage Semi Parametric Model**. *Environmental Modelling and Software* 2015; **63**: 230–239.

[35] Hermann N' V, Bi G, Adjakpa TT, Allechy FB, Youan Ta M, Yapi AF, et al. **Performance of Multi-Site Stochastic Weather Generator MulGETS: Application to the Lobo Watershed (Western Center of Côte d'Ivoire)**. *International Journal of Innovative Science and Research Technology* 2020; **5**(12): 1274–1279.

[36] Fodor N, Dobi I, Mika J, Szeidl L. **Applications of the MVWG Multivariable Stochastic Weather Generator**. *The Scientific World Journal* 2013; **2013**: 348547.

[37] Vu TM, Mishra AK, Konapala G, Liu D. **Evaluation of Multiple Stochastic Rainfall Generators in Diverse Climatic Regions**. *Stochastic Environmental Research and Risk Assessment* 2018; **32**(5): 1337–1353.

[38] Vu TM, Mishra AK, Konapala G, Liu D. **Generation of Multi-Site Stochastic Daily Rainfall with Four Weather Generators a Case Study of Gloucester Catchment in Australia**. *Stochastic Environmental Research and Risk Assessment* 2018; **32**(5): 1337–1353.

[39] Emanuele Cordano EE. **The Stationarity of Two Statistical Downscaling Methods for Precipitation Under Different Choices of Cross-Validation Periods**. *Italian Journal of Agrometeorology* 2016; **21**(3): 17–30.

[40] Cordano E, Eccel E. **Tools for Stochastic Weather Series Generation in R Environment**. *Italian Journal of Agrometeorology* 2016; **21**(3): 31–42.

[41] Soltani A, Hoogenboom G. **Minimum Data Requirements for Parameter Estimation of Stochastic Weather Generators**. *Climate Research* 2003; **25**: 109–119.

[42] Ng JL, Abd Aziz S, Huang YF, Wayayok A, Rowshon MK. **Stochastic Modelling of Seasonal and Yearly Rainfalls with Low-Frequency Variability**. *Stochastic Environmental Research and Risk Assessment* 2017; **31**(9): 2215–2233.

[43] Flecher C, Naveau P, Allard D, Brisson N. **A Stochastic Daily Weather Generator for Skewed Data**. *Water Resources Research* 2010; **46**(7): W07519.

[44] Chen J, Brissette FP, Leconte R. **WeaGETS – A Matlab-Based Daily Scale Weather Generator for Generating Precipitation and Temperature**. *Procedia Environmental Sciences* 2012; **13**: 2222–2235.

[45] Muza MN. **Application of Weather Generation to High Frequency and High Resolution Gridded Datasets in Sao Paulo**. *Advances in Plants & Agriculture Research* 2014; **1**(2): 00009.

[46] Qian B, Gameda S, De Jong R, Falloon P, Gornall J. **Comparing Scenarios of Canadian Daily Climate Extremes Derived Using a Weather Generator**. *Climate Research* 2010; **41**(2): 131–149.

[47] Xiaoying Yang, Ruimin He, Jinyin Ye, Mou Leong Tan, Xiyan Ji, Lit Tan GW. **Integrating an Hourly Weather Generator with an Hourly Rainfall SWAT Model for Climate Change Impact Assessment in the Ru River Basin, China**. *Atmospheric Research* 2020; **244**: 105059.

[48] Vesely FM, Paleari L, Movedi E, Bellocchi G, Confalonieri R. **Quantifying Uncertainty Due to Stochastic Weather Generators in Climate Change Impact Studies**. *Scientific Reports* 2019; **9**(1): 11011.

[49] Timothy J. Osborn, Craig J. Wallace ICH& TMM. **Pattern Scaling Using ClimGen Monthly-Resolution Future Climate Scenarios Including Changes in the Variability of Precipitation**. *Climatic Change* 2016; **134**(3): 353–369.

[50] Forsythe N, Fowler HJ, Blenkinsop S, Burton A, Kilsby CG, Archer DR, Harpham MZH. **Application of a Stochastic Weather Generator to Assess Climate Change Impacts in a Semi-Arid Climate: The Upper Indus Basin**. *Journal of Hydrology* 2014; **517**: 1019–1034.

[51] Xu YP, Ma C, Pan SL, Zhu Q, Ran QH. **Evaluation of a Multi-Site Weather Generator in Simulating Precipitation in the Qiantang River Basin, East China**. *Journal of Zhejiang University: Science A (Applied Physics & Engineering)* 2014; **15**(3): 219–230.

[52] Doaa R. Mohammed RKM. **Climate Change's Impacts on Drought in Upper Zab Basin, Iraq: A Case Study**. *Tikrit Journal of Engineering Science* 2024; **31**(1): 161–171.

[53] Ahmadi M, Etedali HR, Elbeltagi A. **Evaluation of the Effect of Climate Change on Maize Water Footprint under RCPs Scenarios in Qazvin Plain, Iran**. *Agricultural Water Management* 2021; **254**: 106963.

[54] Shagega FP, Munishi SE, Kongo VM. **Prediction of Future Climate in Ngerengere River Catchment, Tanzania**. *Physics and Chemistry of the Earth* 2019; **112**: 200–209.

[55] Chisanga CB, Phiri E, Chinene VRN. **Statistical Downscaling of Precipitation and Temperature Using Long Ashton Research Station Weather Generator in Zambia: A Case of Mount Makulu Agriculture Research Station**. *American Journal of Climate Change* 2017; **06**(03): 487–512.

[56] Osman Y, Al-Ansari N, Abdellatif M, Aljawad SB, Knutsson S. **Expected Future Precipitation in Central Iraq Using LARS-WG Stochastic Weather Generator**. *Engineering* 2014; **06**(13): 948–959.

[57] Liu J, Williams JR, Wang X, Yang H. **Using MODAWEC to Generate Daily Weather Data for the EPIC Model**. *Environmental Modelling and Software* 2009; **24**(5): 655–664.

[58] Al-Mukhtar M, Qasim M. **Future Predictions of Precipitation and Temperature in Iraq Using the Statistical Downscaling Model**. *Arabian Journal of Geosciences* 2019; **12**(2): 1–15.

[59] Smith K, Strong C, Rassoul-Agha F. **Multisite Generalization of the SHArP Weather Generator**. *Journal of Applied Meteorology and Climatology* 2018; **57**(9): 2113–2127.

[60] Martin Dubrovsky, Radan Huth HD& MWR. **Parametric Gridded Weather Generator for Use in Present and Future Climates - Focus on Spatial Temperature Characteristics**. *Theoretical and Applied Climatology* 2020; **139**(3–4): 1031–1044.

[61] Glenis V, Pinamonti V, Hall JW, Kilsby CG. **A Transient Stochastic Weather Generator Incorporating Climate Model Uncertainty**. *Advances in Water Resources* 2015; **85**: 14–26.

[62] Obaidullah Yaqubi, Auline Rodler, Sihem Guernouti MM. **Creation and Application of Future Typical Weather Files in the Evaluation of Indoor Overheating in Free-Floating Buildings**. *Building and Environment* 2022; **216**: 109008.

[63] Aliabadi AA, Chen X, Yang J, Madadizadeh A, Siddiqui K. **Retrofit Optimization of Building Systems for Future Climates Using an Urban Physics Model**. *Building and Environment* 2023; **243**: 110654.

[64] Li Z, Brissette F, Chen J. **Assessing the Applicability of Six Precipitation Probability Distribution Models on the Loess Plateau of China**. *International Journal of Climatology* 2014; **34**(2): 462–471.

[65] Ng JL, Abd Aziz S, Huang YF, Wayayok A, Rowshon M. **Generation of a Stochastic Precipitation Model for the Tropical Climate**. *Theoretical and Applied Climatology* 2018; **133**(1–2): 489–509.

[66] Wei W, Yan Z, Jones PD. **Potential Predictability of Seasonal Extreme Precipitation Accumulation in China**. *Journal of Hydrometeorology* 2017; **18**(4): 1071–1080.

[67] Chowdhury AK, Kar KK, Shahid S, Chowdhury R, Rashid MM. **Evaluation of Spatio-Temporal Rainfall Variability and Performance of a Stochastic Rainfall Model in Bangladesh**. *International Journal of Climatology* 2019; **39**(11): 4256–4273.

[68] Gao C, Booij MJ, Xu YP. **Development and Hydrometeorological Evaluation of a New Stochastic Daily Rainfall Model: Coupling Markov Chain with Rainfall Event Model**. *Journal of Hydrology* 2020; **589**: 125118.

[69] Mehrotra R, Sharma A, Kumar DN, Reshmidevi TV. **Assessing Future Rainfall Projections Using Multiple GCMS and a Multi-Site Stochastic Downscaling Model**. *Journal of Hydrology* 2013; **488**: 84–100.

[70] Abas N, Daud ZM, Yusof F. **A Comparative Study of Mixed Exponential and Weibull Distributions in a Stochastic Model Replicating a Tropical Rainfall Process**. *Theoretical and Applied Climatology* 2014; **118**(3): 597–607.

[71] Long Y, Tang R, Wang H, Jiang C. **Monthly Precipitation Modeling Using Bayesian Non-Homogeneous Hidden Markov Chain**. *Hydrology Research* 2019; **50**(2): 562–576.

[72] Patidar S, Tanner E, Soundharajan BS, Sengupta B. **Associating Climatic Trends with Stochastic Modelling of Flow Sequences**. *Geosciences* 2021; **11**(6): 263.

[73] Lee T, Singh VP. **Discrete k-Nearest Neighbor Resampling for Simulating Multisite Precipitation Occurrence and Model Adaption to Climate Change**. *Geoscientific Model Development* 2019; **12**(3): 1189–1207.

[74] Chen J, Brissette FP. **Comparison of Five Stochastic Weather Generators in Simulating Daily Precipitation and Temperature for the Loess Plateau of China**. *International Journal of Climatology* 2014; **34**(10): 3089–3105.