

## Statistical Evaluation of Gridded Meteorological Datasets Aggregated Through Compromise Programming: A Case Study in Nineveh, Iraq

Khalid Qaraghuli<sup>a,b</sup>, Mohamad Fared Murshed<sup>a\*</sup>, Md Azlin Md Said<sup>a</sup>, Zulfaqar Sa'adi<sup>c</sup> & Jayanta Das<sup>d</sup>

<sup>a</sup>*School of Civil Engineering, Universiti Sains Malaysia, 14300, Nibong Tebal, Pulau Pinang, Malaysia,*

<sup>b</sup>*Al-Mussaib Technical Institute, Al-Furat Al-Awsat Technical University, Babil, Iraq*

<sup>c</sup>*Centre for Environmental Sustainability and Water Security, Research Institute for Sustainable Environment, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor Bahru, Malaysia.*

<sup>d</sup>*Department of Geography, Rampurhat College, PO- Rampurhat, Dist- Birbhum, 731224, India.*

\*Corresponding author: [cefaredmurshed@usm.my](mailto:cefaredmurshed@usm.my)

Received 11 December 2024, Received in revised form 2 May 2025

Accepted 2 June 2025, Available online 30 October 2025

### ABSTRACT

Gridded datasets are essential for climate monitoring in regions with sparse observational data, but they often face challenges in capturing local climatic variability and accuracy. This study evaluates three widely used gridded precipitation datasets (TerraClimate, CHIRPS, TAMSAT) and three potential evapotranspiration (PET) datasets (TerraClimate, MODIS, ERA5-Land) against observations from seven stations in Nineveh, Iraq. The primary objective is to assess the accuracy of these gridded products in replicating observed precipitation and PET values using key statistical metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Normalized RMSE (NRMSE), Percent Bias (PBIAS), Nash-Sutcliffe Efficiency (NSE), coefficient of determination (R<sup>2</sup>), and Kling-Gupta Efficiency (KGE). Compromise Programming (CP), a decision-making tool that integrates multiple statistical metrics into a unified composite score, was applied to rank the performance of the gridded datasets. The findings reveal that TerraClimate outperforms other products for precipitation and PET, with an average MAE of 30.54 for precipitation and 39.48 for PET, and KGE of 0.79 for precipitation and 0.84 for PET. CHIRPS and TAMSAT rank second and third for precipitation, while MODIS and ERA5-Land follow TerraClimate for PET. This study emphasizes the importance of evaluating gridded data to ensure its accuracy and reliability, particularly in regions with limited ground-based observations. The study's contribution lies in employing CP to aggregate multiple statistical metrics into a composite score, providing an effective framework for resolving discrepancies in ranking gridded datasets. This supports the climate impact assessments and environmental management in regions like Iraq with limited meteorological data.

**Keywords:** Climate monitoring; Compromise Programming; Gridded datasets; TerraClimate; CHIRPS

### INTRODUCTION

In recent decades, the impacts of global climate change have become increasingly evident, with compelling evidence pointing to the significant warming of the Earth's climate (Dheyaa et al. 2024; Hussan et al. 2024; Mat Daud et al. 2023; Mohd Salleh et al. 2023). Reliable, continuous meteorological data, particularly precipitation and reference evapotranspiration (PET) are essential for climate change research as they offer critical insights into the

evolving atmospheric and hydrological conditions (Khan et al. 2024; Santos et al. 2023). Precipitation plays a fundamental role in the Earth's hydrological cycle and energy balance, and precise rainfall measurements are indispensable for various applications such as hydrological modeling, agricultural practices, drought monitoring, water resource management, numerical weather forecasting, and moisture budget calculations (Bisht et al. 2024). Moreover, reliable rainfall data enhances our understanding of their wide-ranging effects across multiple disciplines (Saicharan

& Rangaswamy 2023; Yanfatriani et al. 2024). Reference evapotranspiration, a vital component of evaporation processes, serves as a key agrometeorological parameter in both climate and hydrological studies (Dong et al. 2020; Nasrollahi et al. 2021). It plays a crucial role in water balance hydrological models, crop evapotranspiration estimations for specific regions, drought analysis, climate change investigations, and the development of irrigation strategies and management plans (Samreen et al. 2023; Tigkas et al. 2020; Ucar et al. 2023). However, available research on PET trends in Iraq is limited by the short duration of analysis (Zhang et al. 2013). Weather variables such as temperature, wind speed, and sunshine hours all influence PET, impacting plant water needs and contributing to the assessment of climate variability. Numerous studies have highlighted the importance of accurately measuring these variables (Kirschbaum et al. 2020; Tanimu et al. 2024).

So far, ground-based meteorological stations are primary sources of direct climate observations (Saicharan & Rangaswamy 2023; Zambrano-Bigiarini et al. 2017). However, in many developing and conflict-affected regions, including Iraq, reliable long-term station data are often limited or unavailable (Abubakar 2024), posing significant challenges for the spatial analysis (Zambrano-Bigiarini et al. 2017). This is attributed to the scarcity or absence of radar networks and rain gauges, limited resources, inadequate infrastructure, lack of trained personnel and equipment, financial limitations, and insufficient efforts toward installation and maintenance (Abdourahamane 2021; Ogbu et al. 2020; Tanimu et al. 2024). Iraq's climate ranges from Mediterranean conditions in the north to semi-arid and arid climates in the south, but its meteorological data are scarce and poorly distributed, making climate and hydrological studies difficult. These challenges are particularly pressing given Iraq's growing environmental issues, including freshwater scarcity, increased vulnerability to drought, and frequent extreme weather events, which are exacerbated by inadequate water management and inconsistent precipitation data (Salman et al. 2019).

Advances in Earth observation technologies, particularly remote sensing, have opened new avenues for addressing data gaps in climate monitoring (Avtar et al. 2020; Barmpoutis et al. 2020). Climate reanalysis has emerged as a valuable approach for producing gridded meteorological datasets (Dalla Torre et al. 2024; Pelosi et al. 2020; Sun et al. 2018). These datasets are derived from retrospective numerical simulations of past atmospheric conditions, integrating ground-based and satellite observations through data assimilation techniques. Unlike interpolation methods, reanalysis reproduces the spatial and temporal patterns of meteorological variables, such as

temperature and precipitation, based on physical and dynamic principles, ensuring consistency across space and time over extended periods (Parker 2016). This makes them particularly beneficial in regions with sparse or unevenly distributed surface measurements (Dalla Torre et al. 2024; Essou et al. 2017; Tarek et al. 2020).

Multi-source climate data products have been developed, which include gauge-based, satellite-based, and merged satellite-gauge products (Ji et al. 2020; Tanimu et al. 2024). Researchers widely use the gridded data from these sources to enable studies on climate trends (Nashwan et al. 2019), drought characterization (Yan et al. 2023), and flood risk assessments in data-scarce regions (Funk et al. 2015). These gridded data products, known for their spatial and temporal continuity, are extensively used to support environmental planning, water resource management, and adaptation to climate change (Dalla Torre et al. 2024; Khan et al. 2024).

A wide range of gridded products, covering parameters like precipitation, temperature, and evapotranspiration at various resolutions, have been developed to meet the needs of climate research (Saicharan & Rangaswamy 2023). The accuracy of these products is critical, as these serve as fundamental inputs for numerous environmental applications (Sorooshian et al. 2011). However, the reliability of gridded climate data can vary significantly due to geographic and temporal climatic factors (Dalla Torre et al. 2024; Tanimu et al. 2024). Selecting an appropriate gridded dataset poses a considerable challenge in climatic research, especially in regions with sparse, unreliable, or short-term observational records (Tanimu et al. 2024). Therefore, rigorous evaluation and validation of these datasets are necessary to ensure that they represent meteorological conditions for specific location (Saicharan & Rangaswamy 2023). Many recent studies have evaluated gridded data performance on global and regional scales, confirming its potential as a valuable alternative to ground-based data (Sireesha et al. 2020) for assessing runoff (Wiwoho & Astuti 2022), precipitation (de Andrade et al. 2022) temperature (Yang et al. 2023) and drought data (Khan et al. 2024; Yan et al. 2023) are instances of these studies.

Despite recent evaluations of gridded precipitation data in regions surrounding Iraq (Salman et al. 2019), no detailed studies have been conducted to assess the suitability of precipitation and PET products at a regional scale for areas like Nineveh, Iraq. Various statistical measures are often used to assess how well gridded data replicate observed data in terms of the mean, variability, temporal patterns, and distribution, but conflicting results among these measures make it challenging to determine the best gridded product (Bisht et al. 2024; Muhammad et al. 2019; Tanimu et al. 2024). This underscores the need

to balance trade-offs among different evaluation metrics.

Compromise programming (CP), is a robust multi-criteria decision-making tool that identifies solutions closest to the ideal based on specific evaluation criteria (Bisht et al. 2024). Unlike other methods, CP determines the optimal solution by identifying the closest point to an ideal solution without needing any subjective input from decision-makers (Tanimu et al. 2024). CP has been proven effective in environmental decision-making (Bisht et al. 2024; Deepthi & Sivakumar 2022; Salman et al. 2019), where its flexibility and objectivity allow for the efficient identification of solutions in scenarios with multiple evaluation criteria (Muhammad et al. 2019).

One notable study by Salman et al. (2019) evaluated the performance of gridded precipitation data for the entire country of Iraq. However, validating datasets at the sub-divisional level is crucial in addition to evaluations conducted at national or political levels (Saicharan & Rangaswamy 2023). This study aims to evaluate and select the most suitable gridded data products for precipitation and PET in Nineveh, Iraq. To the best of our knowledge, this study is the first to compare gridded data at a regional (governorate) level, incorporating both precipitation and PET. This regional focus offers a more detailed and localized perspective, which can provide valuable insights for regional climate assessments, hydrological modeling, and water resource management, ultimately contributing to a deeper understanding of climate variability and its impacts on different areas within Iraq. For precipitation, three widely used datasets (TerraClimate, CHIRPS, and TAMSAT) were utilized to ensure robust spatial and temporal coverage. For PET, TerraClimate, MODIS, and ERA5-Land were incorporated, leveraging each dataset's unique contributions to evapotranspiration estimation. These datasets were chosen based on their extensive validation in arid and semi-arid regions and their established relevance to drought analysis (Du et al. 2024; P. Kumari et al. 2024; Rachidi et al. 2023; Suliman et al. 2024; C. Xu et al. 2024)

Various statistical metrics were employed to assess each dataset's ability to capture the mean, variability, temporal pattern, and distribution of observed data. CP was then applied to identify the best-performing dataset by integrating multiple performance metrics, aiming to find an optimal solution that closely aligns with the observed data. It is expected that selecting the most suitable gridded datasets based on these assessments will lead to an improved analysis of the climate change effects in the study area.

## STUDY AREA

Iraq, a Middle Eastern country in West Asia, spans latitudes 29°5'N to 38°25'N and longitudes 38°50'E to 48°50'E. Known for its unique climatic and geographical diversity, the country shares borders with Turkey to the north, Kuwait to the southeast, Iran to the east, Jordan to the west, Syria to the northwest, and Saudi Arabia to the south (Al-Hasani & Shahid 2024).

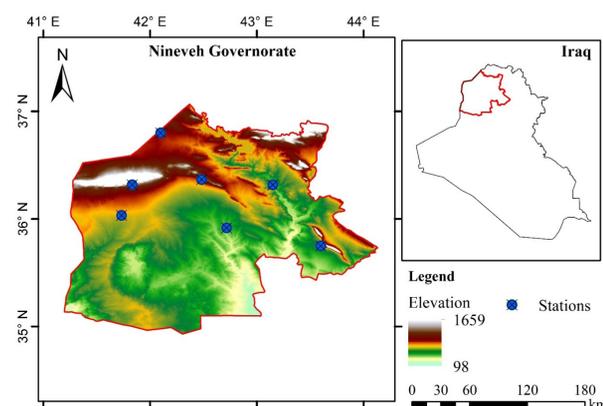


FIGURE 1. Study area and geographical location of the meteorological stations

As one of the countries situated in the West Asia and North Africa (WANA) region, Iraq is predominantly classified as arid, with approximately 95% of its area falling within the dry zones. This study focuses on the Nineveh Governorate, located in northwestern Iraq, encompassing an area of 32,308 km<sup>2</sup>. The governorate lies between longitudes 41° 25' E to 44° 15' E and latitudes 34° 15' N to 37° 30' N (Nadhim Al-neama et al. 2022; Shukur et al. 2021). Figure. 1, created using ArcGIS 10.8, illustrates the geographical locations of the meteorological stations analyzed in this research.

The climate of Nineveh Governorate is characterized by hot, dry summers and cold, rainy winters, significantly influenced by the region's varied topography. The Tigris River traverses the governorate, splitting it into eastern and western banks. Often referred to as Iraq's breadbasket, Nineveh plays a vital role in the large-scale cultivation of the rain-fed cereal crops. Mosul, the governorate's capital and Iraq's second-largest city straddles both sides of the Tigris River. The city's terrain differs between the two sides: on the right bank, the elevations range from 220 meters in the south to 240 meters in the north, with northern hills reaching heights of up to 289 meters. In contrast, the left bank is predominantly flat, interspersed with hills that range from 250 to 273 meters in elevation (Tanimu et al. 2024).

Long-term meteorological data from the Mosul station reveal that the majority of rainfall in Nineveh Governorate occurs during the winter months, with an average annual precipitation of 378 mm recorded between 1937 and 2010. The region experiences an average annual temperature of 21°C, with summer temperatures often reaching 40°C. However, the meteorological records from ground stations in Nineveh are frequently incomplete (Bisht et al. 2024), with data gaps caused by various factors, including operational disruptions, particularly during the security crises of 2014.

The limited number of meteorological stations and the incomplete records highlight the challenges of relying solely on ground-based observations in the region. Given Nineveh's significant role in agriculture and its diverse climatic conditions, addressing the issue of missing meteorological data is crucial (Qaraghuli et al. 2024). Leveraging gridded datasets can enhance the accuracy of weather forecasting and drought assessments, support agricultural planning, and contribute to improved economic stability and public safety in Iraq. This approach is particularly important for ensuring resilience in a region where reliable climate data is essential for sustainable development.

## DATA SOURCES AND DESCRIPTION

### STATION DATA

The study used key parameters, including Precipitation (Pre), Maximum Temperature (Tmax), Minimum Temperature (Tmin), Mean Temperature (Tmean), Relative Humidity (RH), Wind Speed (WS), and Sunshine Hours (Sun), as these variables are critical for evaluating precipitation and PET gridded datasets. Precipitation is directly assessed due to its pivotal role in hydro-climatological processes, while the parameters used for PET estimation were selected based on their inclusion in widely accepted models, such as the FAO-56 Penman-Monteith equation. These variables influence the accuracy of PET calculations by capturing essential atmospheric and climatic conditions, such as temperature, humidity, WS, and solar radiation. The choice of these parameters reflects their relevance in quantifying key hydrometeorological processes. The inclusion of well-established variables ensures a comprehensive and robust assessment. Stations like Sheikhan and Hamdaniyah were excluded due to incomplete records, which could have compromised the reliability of the results. This careful selection process helps ensure that the evaluation of the gridded products is both

representative and reliable. The geographical locations of the stations are illustrated in Figure. 1 and Table 1 provides detailed descriptions of each station.

TABLE 1. Description of meteorological stations

Station	Name	Lat (N)	Long (E)	Elevation
Station1	Al-Baaj	36° 02'	41° 48'	321
Station2	Makhmour	35° 46'	43° 35'	270
Station3	Mosul	36° 19'	43° 09'	223
Station4	Rabiah	36° 48'	42° 06'	382
Station5	Sinjar	36° 19'	41° 50'	465
Station6	Tel-Abta	35° 55'	42° 24'	200
Station7	Tel-Afar	36° 22'	42° 06'	273

## GRIDDED DATA

### TERRACLIMATE

TerraClimate is a comprehensive dataset providing monthly climate and climatic water balance data for global terrestrial surfaces from 1958 to the present. With a high spatial resolution of approximately 4 km (1/24th degree) and monthly temporal resolution, TerraClimate is designed to support ecological and hydrological studies requiring fine-scale and time-varying data (Al-Yaari et al. 2024). The dataset comprises primary climate variables, including the precipitation accumulation, and derived variables such as reference evapotranspiration (calculated using the ASCE Penman-Monteith method) (Abubakar 2024; Solaimani & Ahmadi 2024). These variables enable a detailed assessment of climatic and hydrological processes, supporting studies in drought monitoring, water resource management, and climate change impact assessments (de Andrade et al. 2022).

TerraClimate is created using a climatically aided interpolation method that integrates high-resolution climatological normals from the WorldClim dataset with time-varying data from the Climatic Research Unit's (CRU) Ts4.0 dataset and the Japanese 55-year Reanalysis (JRA55). This approach applies interpolated anomalies from CRU Ts4.0/JRA55 to the high-resolution WorldClim baseline, ensuring spatial precision while covering an extended temporal record (Abatzoglou et al. 2018; Saicharan & Rangaswamy 2023). For regions where CRU Ts4.0 lacks sufficient observational data (e.g., parts of Africa, South America, scattered islands, and Antarctica), JRA55 serves as the primary data source, particularly for variables like solar radiation and wind speed (Hanchane et al. 2023).

The accuracy of TerraClimate has been validated against station-based observations from various global networks, such as the Global Historical Climate Network (GHCN), SNOTEL, and RAWS. The validation demonstrated improved spatial realism and lower error metrics compared to its parent CRU Ts4.0 data. TerraClimate's annual reference evapotranspiration fields align well with station-based FLUXNET measurements, while its interannual runoff estimates correlate strongly with the measured streamflow data across numerous global watersheds. This robust validation underscores the reliability of TerraClimate as a high-quality dataset for analyzing historical and future climate and hydrological conditions (Abatzoglou et al. 2018). TerraClimate monthly data in NetCDF file format were downloaded from the official TerraClimate website (<https://www.climatologylab.org/terraclimate.html>), and the data for each station in the study area were extracted using ArcGIS 10.8.

### CHIRPS

The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) is a globally recognized dataset designed to overcome the challenges of sparse ground-based precipitation measurements, particularly in data-limited regions (Abdulahi et al. 2024; de Andrade et al. 2022). Developed through a collaboration between the Climate Hazards Group (CHG) at the University of California, Santa Barbara, and the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center, CHIRPS combines satellite-derived observations with in-situ rain gauge data to deliver high-resolution precipitation estimates (Alsumaiti et al. 2024; Saicharan & Rangaswamy 2023). The dataset spans over 35 years (1981 to near-present) and provides global coverage between 50°N and 50°S at a fine spatial resolution of 0.05° (~5 km). This extensive temporal and spatial coverage makes CHIRPS a valuable resource for global and regional climate analyses (Bisht et al. 2024; Zambrano-Bigiarini et al. 2017).

Widely validated against station-based observations, CHIRPS has demonstrated reliability in numerous applications, including drought early warning systems, seasonal drought monitoring, and trend analysis. Its high spatial and temporal resolution, coupled with its long historical record, makes it an indispensable tool for global hydrological and climate studies. Notably, CHIRPS has played a pivotal role in supporting the USAID Famine Early Warning Systems Network (FEWS NET) by providing critical data for assessing drought severity and contextualizing rainfall deficits within historical norms (Abubakar 2024; Zambrano-Bigiarini et al. 2017).

Through its comprehensive approach to precipitation monitoring, CHIRPS supports diverse applications, including agricultural forecasting (Fernandes et al. 2020; Harrison et al. 2022), water resource management (Du et al. 2024; Kibii & Du Plessis 2024), and climate change impact assessments (Arfasa et al. 2024; Banerjee et al. 2024). Its robust methodologies and extensive validation ensure that CHIRPS remains a cornerstone dataset for addressing global environmental challenges (Bisht et al. 2024). This study utilized CHIRPS v2.0 monthly data in the NetCDF file format, downloaded from the official CHIRPS website (<https://www.chc.ucsb.edu/data/chirps>). The monthly data for each station in the study area were extracted using ArcGIS 10.8.

### TAMSAT

TAMSAT (Tropical Applications of Meteorology using SATellite data) is a satellite-based rainfall product developed by the University of Reading. TAMSAT provides rainfall estimates across the African continent, including Madagascar, at a spatial resolution of 0.0375° x 0.0375° (~4 km) (Addisu et al. 2024; Boluwade 2023; Rachidi et al. 2023). The rainfall estimates are derived using the cloud-index method, which compares cold cloud duration (CCD) to a predetermined temperature threshold. CCD is the length of time showing that a satellite pixel is colder than the specified threshold. The algorithm calibrates CCD using parameters that are spatially and seasonally variable, but constant from year to year. This approach ensures that inter-annual variations in rainfall are driven primarily by satellite observations, making TAMSAT a valuable tool for monitoring precipitation in regions with sparse ground-based weather stations (Addisu et al. 2024; Kabite Wedajo et al. 2021).

TAMSAT data are available at multiple temporal resolutions, including daily, pentadal (5-day), decadal (10-day), monthly, and seasonal (DJF, MAM, JJA, SON) intervals, providing flexibility for different types of analysis (Maidment et al. 2017). The dataset spans from 1983 to the present, offering a long-term record of rainfall patterns across Africa. Data are regularly updated and released on the 1st, 6th, 11th, 16th, 21st, and 26th of each month (Datti et al. 2024; Wedajo et al. 2021). These data are publicly available for operational, research, and commercial use under a Creative Commons license via the TAMSAT website ([www.tamsat.org.uk](http://www.tamsat.org.uk)). This study utilizes the monthly precipitation data from TAMSAT v3.1, which were downloaded from the official TAMSAT website (<https://research.reading.ac.uk/tamsat/>). The monthly data for each station in the study area were extracted from the website directly.

## ERA5-LAND

ERA5-Land is a reanalysis dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) that provides a high-resolution, consistent view of land surface variables over several decades (Dalla Torre et al. 2024; de Andrade et al. 2022). It is based on the ERA5 climate reanalysis, with enhanced resolution achieved by replaying the land component to capture a more detailed depiction of surface processes (Pelosi et al. 2020). Reanalysis combines the model data with global observations, creating a consistent and physically based dataset that extends back several decades, offering an accurate description of past climate conditions (Chang et al. 2024; Muñoz-Sabater et al. 2021).

ERA5-Land covers the period from 1950 to the present, with a temporal resolution of Monthly averaged reanalysis (Dalla Torre et al. 2024). The native spatial resolution of the dataset is 9 km, with data gridded to a  $0.1^\circ \times 0.1^\circ$  regular Lat-Lon grid in the Climate Data Store (CDS). This high resolution allows for a detailed analysis of the water and energy cycles at the surface level (Tan et al. 2023; J. Xu et al. 2022). Daily PET data were obtained in the NetCDF format from the University of Bristol repository (<https://data.bris.ac.uk/data/dataset/qb8ujazzda0s2aykkv0oq0ctp>). The data corresponding to the study stations were extracted and subsequently aggregated into monthly values using R programming.

## MODIS

The Moderate Resolution Imaging Spectroradiometer (MODIS) is a key instrument aboard NASA's Terra and Aqua satellites, delivering critical data for monitoring Earth's surface and atmospheric systems (Zhao et al. 2024). Among its diverse suite of products, the MOD16A2 Version 105 provides 8-day global potential evapotranspiration estimates at a 1 km spatial resolution (Banerjee et al. 2023; Luo & Shao 2022). Evapotranspiration, which encompasses both evaporation and plant transpiration from the Earth's surface to the atmosphere, is a fundamental variable for understanding the interactions between the water, energy, and carbon cycles (Faisol et al. 2020; Running et al. 2019).

The MOD16A2 product, produced by the Numerical Terradynamic Simulation Group (NTSG) at the University of Montana in collaboration with NASA's Earth Observing System, uses the Penman-Monteith equation to estimate both Actual Evapotranspiration and Potential Evapotranspiration (Mpakairi et al. 2024; Mu et al. 2011). This approach integrates MODIS-derived spectral data with meteorological inputs such as surface temperature, vapor pressure deficit, and net radiation, ensuring

consistency across the global landscapes (Kumari et al. 2021). The long-term availability of MOD16A2 data, spanning from 2000 onward, allows for the quantification of changes in the climate, land use, and ecosystem disturbances, offering valuable insights for environmental management and climate change studies (Astuti et al. 2022; Mpakairi et al. 2024).

In this study, the MODIS MOD16A2 dataset (MODIS Global Terrestrial Evapotranspiration, 8-Day, 1 km resolution) was utilized to retrieve Potential Evapotranspiration (PET) data for each ground station within the study area. Data spanning the period from 2000 to 2013 were extracted using Google Earth Engine (GEE), ensuring accurate spatial and temporal alignment with the study's requirements.

## METHODOLOGY

This study was designed to evaluate the performance of three gridded precipitation datasets (TerraClimate, CHIRPS, TAMSAT) and three potential evapotranspiration (PET) datasets (TerraClimate, MODIS, ERA5-Land) by comparing them with ground station observations from the Nineveh region of Iraq, spanning the period from 1992 to 2013. The primary objective was to identify the most accurate datasets for hydrometeorological applications in data-scarce regions. The methodology is outlined as follows:

1. **Data Collection:** Monthly data for precipitation and key meteorological variables (maximum temperature ( $T_{max}$ ), minimum temperature ( $T_{min}$ ), relative humidity (RH), wind speed (WS), and sun hours) were obtained from seven ground stations in Nineveh for the entire study period.
2. **PET Calculation:** PET for each station was calculated using the FAO Penman-Monteith equation, implemented through the "SPEI" package in R. These station-level PET values were then compared with corresponding gridded PET datasets (TerraClimate, MODIS, ERA5-Land) to assess their accuracy.
3. **Gridded Data Extraction:** Precipitation and PET data from the selected gridded datasets (TerraClimate, CHIRPS, TAMSAT, MODIS, and ERA5-Land) were downloaded for the entire study period. A point-to-pixel extraction method was employed to align the station coordinates with the corresponding grid points. The time series data from the ground stations were compared with the respective pixel values from

the gridded datasets.

4. **Statistical Evaluation:** The performance of each gridded dataset was quantitatively evaluated using seven statistical metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Normalized Root Mean Squared Error (NRMSE), Percent Bias (PBIAS), Nash-Sutcliffe Efficiency (NSE), R-squared ( $R^2$ ), and Kling-Gupta Efficiency (KGE). These metrics were selected to assess the accuracy, efficiency, and bias of the gridded datasets in replicating the observed data from the ground stations.
5. **Composite Index for Ranking:** To rank the datasets, the Compromise Programming (CP) method was applied. This method integrates the individual statistical metric scores into a composite index, where datasets closer to the ideal solution (i.e., those with lower CP scores) are considered to perform better.
6. **Visualization:** To complement the statistical analysis, Probability Density Function (PDF) plots were generated to visually compare the distribution of precipitation and PET between the observed data and the gridded datasets. Additionally, scatter plots were constructed to illustrate the relationship between observed and gridded values, providing further insights into the datasets' accuracy and consistency.

## PERFORMANCE EVALUATION OF THE GRIDDED PRODUCT DATASETS

To evaluate the performance of the gridded monthly precipitation and PET datasets used in this study, we employed several evaluation metrics. These metrics quantitatively measure the accuracy and reliability of the gridded datasets by comparing them against ground-based observations (Saicharan & Rangaswamy 2023). Each metric offers unique insights into different aspects of the model performance, ensuring a thorough evaluation. The calculations for these metrics were performed using R programming. The metrics are explained below:

### 1. Mean Absolute Error (MAE)

MAE is a widely used metric for measuring the average magnitude of errors in a set of predictions, without considering their direction (Hanchane et al. 2023; Tanimu et al. 2024). It is defined as the average

of the absolute differences between the predicted values and the observed values. Mathematically, MAE is expressed as follows (Solaimani & Ahmadi 2024):

$$MAE = \frac{1}{n} \sum_{i=1}^n |P_i - O_i|$$

where  $P_i$  represents the value derived from the gridded dataset corresponding to the  $i$ -th observation,  $O_i$  is the observed value, and  $n$  is the number of observations. MAE provides a straightforward interpretation of error magnitude, making it useful for understanding the typical deviation between the gridded product dataset and the ground truth (Hassan et al. 2020). The MAE ranges from 0 to  $\infty$ , where 0 indicates a perfect match between the gridded product and observed values. Lower MAE values signify greater accuracy and better performance of the dataset in replicating observed conditions (Addisu et al. 2024).

### 2. Root Mean Square Error (RMSE)

RMSE quantifies the differences between the predicted and observed values by taking the square root of the average of the squared differences (Hanchane et al. 2023; Mohamad Hamzah et al. 2022). It is defined as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2}$$

RMSE is sensitive to larger errors due to the squaring of the differences, making it particularly useful for identifying gridded datasets that may have significant outliers or large deviations from observations. Like MAE, lower RMSE values signify better model performance (Saicharan & Rangaswamy 2023), but RMSE places more emphasis on larger errors.

### 3. Normalized Root Mean Square Error (NRMSE)

NRMSE is a metric used to assess the accuracy of model predictions (gridded) relative to observed values, normalized by the mean of the observed data (Hanchane et al. 2023). It calculates the distance between observed and gridded data, summarizing the magnitude of errors over various times (Sireesha et al. 2020). The NRMSE expresses the error as a percentage, making it easier to interpret in the context

of the data range. Lower NRMSE values indicate that the gridded values are closer to the observed values, while higher values suggest poor gridded performance. It is calculated as:

$$NRMSE = \frac{RMSE}{\bar{O}} \times 100\%$$

where  $\bar{O}$  represents the average of the observed values. This version of NRMSE is useful when we seek to compare the gridded accuracy relative to the overall mean of the observed dataset.

#### 4. The Percentage Bias (PBIAS)

PBIAS is a metric used to evaluate the overall bias in the predictions of a model (gridded dataset) compared to the observed values (Hanchane et al. 2023). It is calculated as the difference between the predicted values  $P_i$  and the observed values  $O_i$ , expressed as a percentage of the sum of the observed values (Mamat & Mohd Razali 2023). The formula for PBIAS is:

$$PBIAS = \frac{\sum_{i=1}^n (P_i - O_i)}{\sum_{i=1}^n O_i} \times 100\%$$

PBIAS quantifies the tendency of the gridded product to overestimate or underestimate the observed data (Addisu et al. 2024; Sireesha et al. 2020). A PBIAS ranges from  $-\infty$  to  $\infty$ ; a value of 0 indicates a perfect agreement between the gridded and observed data, while positive values indicate an overall overestimation of the observed data and negative values indicate an underestimation. Smaller absolute values of PBIAS signify better model performance in terms of accurately predicting the observed conditions, with a value closer to zero indicating minimal bias in the dataset (Hanchane et al. 2023; Saicharan & Rangaswamy 2023).

#### 5. Coefficient of Determination (R2)

The coefficient of determination (R2) is a widely used metric to assess the strength of the relationship between observed and predicted values (Addisu et al. 2024). It measures the proportion of variance in the observed data that can be explained by the predicted (gridded) data (Hanchane et al. 2023). Its values range from 0 to 1, with higher values indicating a stronger

agreement between the observed and gridded data. A value of  $R^2 = 1$  indicates a perfect replication of the observed data by the gridded values, while  $R^2 = 0$  indicates no correlation (Abdulahi et al. 2024). The formula for R2 is expressed as:

$$R^2 = \frac{(\sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P}))^2}{\sum_{i=1}^n (O_i - \bar{O})^2 \sum_{i=1}^n (P_i - \bar{P})^2}$$

where  $O_i$  and  $P_i$  are the observed and gridded values, respectively, and  $\bar{O}$  and  $\bar{P}$  represent their respective means.  $n$  denotes the total number of observations. Although R2 provides a valuable insight into the predictive power of the model, it does not account for bias or systematic errors and is often used in conjunction with other metrics (Hanchane et al. 2023), such as Nash-Sutcliffe Efficiency (NSE), for a more comprehensive evaluation of the model performance.

#### 6. Nash-Sutcliffe Efficiency (NSE)

NSE is a normalized statistics that determines the relative magnitude of the residual variance compared to the variance of the observed data (Sireesha et al. 2020). It is defined as:

$$NSE = 1 - \frac{\sum_{i=1}^n (P_i - O_i)^2}{\sum_{i=1}^n (P_i - \bar{O})^2}$$

NSE values range from  $-\infty$  to 1, where a value of 1 indicates a perfect match between the gridded dataset and observed data (Abdulahi et al. 2024). Values ranging from 0 to 1 indicate that the gridded dataset offers better predictions than the mean of the observed data, while negative values suggest that the gridded dataset performs worse than simply using the observed mean (Saicharan & Rangaswamy 2023). NSE is particularly useful for assessing the predictive capability of the gridded datasets and hydrological models in capturing the variability of the observed data.

#### 7. The Kling-Gupta Efficiency (KGE)

KGE developed by (Gupta et al. 2009), is a robust metric that evaluates the performance of the gridded datasets by assessing the agreement between gridded

values  $P_i$  and observed values  $O_i$ . The KGE combines three components (correlation, bias, and variability) to provide a comprehensive assessment of the gridded performance (Deepthi & Sivakumar 2022). The formula for KGE is:

$$KGE = 1 - \sqrt{(r - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2}$$

Where  $r$  is the Pearson correlation coefficient between  $P_i$  and  $O_i$ ,  $\beta$  is the ratio of the mean gridded value to the mean observed value ( $\beta = \frac{\bar{P}}{\bar{O}}$ ), which measures bias, and  $\gamma$  is the ratio of the standard deviation of the gridded values to the standard deviation of the observed values ( $\gamma = \frac{\sigma_P}{\sigma_O}$ ), which represents variability (Deepthi & Sivakumar 2022).

The KGE score ranges from  $-\infty$  to 1, where a value of 1 indicates a perfect agreement between the gridded and observed data. A KGE value closer to 1 reflects higher accuracy, with optimal performance achieved when  $r = 1$ ,  $\beta = 1$ , and  $\gamma = 1$ . Negative KGE values indicate poor performance (Addisu et al. 2024). This metric is particularly useful in hydrology and climate studies, as it accounts for multiple facets of the model accuracy, including the ability to replicate the magnitude and variability of the observed conditions.

## COMPROMISE PROGRAMMING

CP is a distance-based method within the MCDM framework that identifies the best dataset based on the minimum distance of each alternative from an ideal solution in the available set (Bisht et al. 2024). The statistical metrics described above were used to rank and select the best gridded precipitation and PET datasets using CP. The Compromise Programming Index (CPI) is calculated by measuring the distance as follows (Deepthi & Sivakumar 2022; Sa'adi et al. 2024):

$$CPI = \left[ \sum_{j=1}^m w_j |x_{ji} - x_j^*|^p \right]^{1/p}$$

where  $x_{ij}$  is the normalized value of the  $j$ -th metric for the  $i$ -th dataset,  $x_j^*$  is the normalized ideal value of the  $j$ -th metric,  $w_j$  is the weight assigned to the  $j$ -th metric, and  $p$  is the distance parameter,  $p = 1$  for linear distance and  $p = 2$  for squared Euclidean distance (Deepthi & Sivakumar 2022; Muhammad et al. 2019). In this study, a linear distance measure  $p = 1$  was used, ensuring equal importance across all metrics (Salman et al. 2019). The CPI can take

any positive value, where a lower CPI indicates that the gridded dataset is closer to the observed data and is thus more suitable.

## GRAPHICAL COMPARISON

In addition to using the statistical methods, graphical techniques were utilized to visually compare both the observed and gridded datasets. These methods enable a direct assessment of how well the gridded data replicate observed values, providing valuable insights into their performance (Legates & McCabe 1999). Graphical comparisons are essential for effective evaluation, as they complement numerical metrics by highlighting patterns, biases, and the alignment between the datasets (Hanchane et al. 2023). The graphical methods include the Probability Density Function (PDF) and scatter plot analysis.

The PDFs of the observed and gridded datasets were overlaid to visually assess the alignment of their statistical distributions. This method evaluates how accurately the gridded datasets capture the variability and central tendencies of the observed data, providing a clear visual representation of their agreement (Sireesha et al. 2020; Solaimani & Ahmadi 2024). Scatter plots were utilized to examine the relationship between the observed and gridded datasets. By plotting the gridded values against the actual observed values, these plots emphasize correlations, biases, and outliers, offering insights into the reliability and accuracy of the gridded data (Salman et al. 2019; Solaimani & Ahmadi 2024).

## RESULTS

### GRIDDED DATASETS EVALUATION THROUGH STATISTICAL METRICS

In this study, we evaluated the performance of three gridded precipitation products (TerraClimate, CHIRPS, and TAMSAT) and three gridded reference evapotranspiration (PET) products (TerraClimate, ERA5-Land, and MODIS) by comparing them to the observed data from seven stations in the Nineveh governorate. Seven statistical metrics were employed to evaluate each gridded product's accuracy in replicating observed precipitation and PET. These metrics included MAE, RMSE, NRMSE, PBIAS, NSE,  $R^2$ , and KGE. The results are summarized in Table 2 for precipitation and Table 3 for PET. For precipitation, TerraClimate exhibits the best performance, with the lowest average MAE of 14.20, indicating higher accuracy. Its MAE values range from 11.95 to 16.49, giving a range of

4.54, which reflects relatively consistent performance across stations. CHIRPS shows a slightly higher average MAE of 15.26, suggesting slightly lower accuracy compared to TerraClimate. The MAE values for CHIRPS span from 12.45 to 17.38, resulting in a range of 4.93, which is comparable in variability to TerraClimate. TAMSAT, on the other hand, has the highest average MAE at 18.75, indicating the least accuracy among the three products. Its MAE values are relatively uniform, ranging from 17.52 to 20.34, with a range of 2.82, demonstrating more consistent performance, albeit at a higher error level.

TerraClimate also demonstrates the best overall performance with the lowest average RMSE of 22.75 mm and NRMSE of 68.6%, indicating higher accuracy in precipitation replication. The RMSE for TerraClimate ranges from 19.65 mm to 26.35 mm, resulting in a range of 6.70 mm, while NRMSE spans from 58.6% to 79.1%, with a range of 20.5%, reflecting consistent performance. CHIRPS has a higher average RMSE of 24.33 mm and NRMSE of 73.84%, indicating slightly less accuracy compared to TerraClimate. Its RMSE values range from 19.73 mm to 27.13 mm, giving a range of 7.40 mm, and NRMSE ranges from 58.6% to 98.4%, with a broader range of 39.8%, showing greater variability in performance across stations. TAMSAT, on the other hand, exhibits the least accuracy with the highest average RMSE of 30.65 mm and NRMSE of 92.93%. The RMSE values for TAMSAT vary from 27.64 mm to 33.44 mm, resulting in a range of 5.80 mm, while NRMSE spans from 78.2% to 114.9%, yielding a wide range of 36.7%. TAMSAT has relatively consistent RMSE values, where its higher NRMSE indicates a significant overestimation in normalized terms.

With an average PBIAS of 34.99% and NSE of 0.52, TerraClimate demonstrates superior performance overall, indicating relatively better accuracy and model efficiency. The PBIAS values for TerraClimate range from 21.5% to 52.7%, resulting in a range of 31.2%, while NSE spans from 0.37 to 0.66, with a range of 0.29, reflecting consistency in performance. CHIRPS has an average PBIAS of 27.61%, which is slightly better than TerraClimate, but its lower average NSE of 0.44 suggests reduced efficiency in reproducing observed precipitation variability. CHIRPS exhibits PBIAS ranging from 8.3% to 58.2%, resulting in a range of 49.9%, and NSE values from 0.03

to 0.66, with a range of 0.63, indicating greater variability in performance across stations. TAMSAT, on the other hand, shows the weakest performance, with the highest average PBIAS of 48.63%, indicative of significant bias, and the lowest average NSE of 0.24, reflecting poor model efficiency. Its PBIAS ranges from 22.4% to 78.5%, with a range of 56.1%, while NSE values vary widely, from -0.32 to 0.39, resulting in a range of 0.71, further emphasizing its lower consistency and accuracy.

In terms of R2 and KGE, TerraClimate exhibits the highest performance overall, with an average R2 of 0.52 and KGE of 0.59, indicating better agreement with observed data and stronger model efficiency. The R2 values for TerraClimate range from 0.37 to 0.66, yielding a range of 0.29, while KGE spans from 0.40 to 0.72, resulting in a range of 0.32, reflecting relatively consistent performance across stations. CHIRPS has a slightly lower average R2 of 0.44, similar to TerraClimate's average KGE of 0.59, suggesting comparable model efficiency but reduced explained variability. CHIRPS R2 values range widely, from 0.03 to 0.66, with a range of 0.63, while KGE varies from 0.30 to 0.73, giving a range of 0.43, indicating greater variability in its performance across stations. TAMSAT shows the weakest performance, with the lowest average R2 of 0.24 and KGE of 0.39, reflecting poor agreement with observed data and reduced model efficiency. The R2 values for TAMSAT range from -0.32 to 0.39, resulting in a range of 0.71, while KGE ranges from 0.08 to 0.59, yielding a range of 0.51, highlighting significant inconsistencies.

In summary, TerraClimate outperforms both CHIRPS and TAMSAT in replicating observed precipitation, exhibiting the lowest average errors, RMSE, NRMSE, and the highest model efficiency, with moderate variability across stations. CHIRPS follows closely, showing slightly higher errors and greater variability while maintaining a comparable model efficiency. TAMSAT, though more consistent in its predictions, demonstrates the least accuracy, with the highest MAE, RMSE, NRMSE, and bias, as well as the lowest model efficiency. These results indicate that TerraClimate offers the most reliable and consistent performance, while CHIRPS and TAMSAT face challenges in replicating observed precipitation accurately, with TAMSAT struggling the most due to its higher error margins and lower efficiency.

TABLE 2. Statistical performance comparison of gridded precipitation products against observation data

Product	Station	MAE	RMSE	NRMSE	PBIAS	NSE	R2	KGE
TerraClimate	Station01	11.95	19.65	69.90	35.30	0.51	0.51	0.59
	Station02	13.52	21.95	68.60	31.10	0.53	0.53	0.62
	Station03	14.89	23.72	63.60	28.00	0.59	0.59	0.67
	Station04	14.34	23.38	62.20	25.10	0.61	0.61	0.69
	Station05	14.68	23.19	58.60	21.50	0.66	0.66	0.72
	Station06	13.52	21.02	79.10	51.20	0.37	0.37	0.43
	Station07	16.49	26.35	78.20	52.70	0.39	0.39	0.40
	Average	14.20	22.75	68.60	34.99	0.52	0.52	0.59
CHIRPS	Station01	13.55	21.48	76.40	29.00	0.41	0.41	0.59
	Station02	17.38	27.13	84.80	45.80	0.28	0.28	0.46
	Station03	14.99	24.68	66.10	8.30	0.56	0.56	0.71
	Station04	16.04	24.45	65.10	30.20	0.58	0.58	0.65
	Station05	16.41	26.71	67.50	10.60	0.54	0.54	0.69
	Station06	16.03	26.16	98.40	58.20	0.03	0.03	0.30
	Station07	12.45	19.73	58.60	11.20	0.66	0.66	0.73
	Average	15.26	24.33	73.84	27.61	0.44	0.44	0.59
TAMSAT	Station01	17.52	27.64	98.30	52.50	0.03	0.03	0.35
	Station02	20.34	33.44	104.50	69.30	-0.10	-0.10	0.20
	Station03	17.92	29.53	79.10	29.90	0.37	0.37	0.59
	Station04	19.47	32.05	85.30	41.70	0.27	0.27	0.49
	Station05	19.64	30.97	78.20	22.40	0.39	0.39	0.59
	Station06	18.50	30.53	114.90	78.50	-0.32	-0.32	0.08
	Station07	17.83	30.37	90.20	46.10	0.18	0.18	0.43
	Average	18.75	30.65	92.93	48.63	0.24	0.24	0.39

For PET, in comparing the performance of TerraClimate, ERA5-Land, and MODIS in replicating observed PET, TerraClimate demonstrates the best overall performance, with an average MAE of 30.54. The MAE values for TerraClimate range from 15.25 to 61.54, with a range of 46.29, indicating moderate variability across stations. ERA5-Land follows with a higher average MAE of 50.8, suggesting a lower accuracy compared to TerraClimate. The MAE values for ERA5-Land range from 25.89 to 93.86, resulting in a range of 67.97, indicating significant variability in its performance across stations. MODIS shows an average MAE of 47.96, which is similar to ERA5-Land but slightly lower in value. The MAE values for MODIS range from 33.63 to 68.16, giving a range of 34.53, reflecting moderate variability.

With an average RMSE of 39.48 mm and an average NRMSE of 38.67%, TerraClimate demonstrates relatively better accuracy. Its RMSE values range from 19.59 mm to 76.52 mm, with a range of 56.93 mm, while its NRMSE

spans from 27.6% to 61.6%, reflecting a range of 34%. ERA5-Land, in comparison, has a higher average RMSE of 61.59 mm and an even higher average NRMSE of 60.36%. The RMSE values for ERA5-Land range from 31.74 mm to 112.73 mm, resulting in a range of 81.0 mm, and its NRMSE varies from 35.8% to 90.8%, with a broad range of 55%. MODIS, while showing an average RMSE of 53.28 mm and an average NRMSE of 60.14%, falls between TerraClimate and ERA5-Land. Its RMSE values range from 40.03 mm to 72.26 mm, giving a range of 32.23 mm, and its NRMSE spans from 38.9% to 99.4%, reflecting a wide range of 60.5%.

In terms of PBIAS and NSE, TerraClimate has an average PBIAS of 13.16% and an average NSE of 0.84. Its PBIAS values range from -29.4% to 7.6%, with a range of 37%, while its NSE values vary from 0.62 to 0.92, reflecting a range of 0.30. These results indicate that TerraClimate generally provides a good balance between bias and model efficiency. In contrast, ERA5-Land shows

higher bias, with an average PBIAS of 28.29% and a lower NSE of 0.60, suggesting poorer accuracy and model efficiency in comparison to TerraClimate. The PBIAS for ERA5-Land spans from -45.3% to -13.8%, resulting in a range of 31.5%, and the NSE ranges from 0.17 to 0.87, with a range of 0.70. This wider range in both PBIAS and NSE indicates greater variability in ERA5-Land's performance across stations. MODIS shows an average

PBIAS of 22.53% and an average NSE of 0.58, placing it between TerraClimate and ERA5-Land. Its PBIAS values range from -2.8% to 50.5%, giving a range of 53.3%, and its NSE values vary from 0.01 to 0.85, with a range of 0.84. MODIS's higher PBIAS and lower NSE values suggest that while it performs well at certain stations, it exhibits a significant overestimation and variability in model efficiency.

TABLE 3. Statistical performance comparison of gridded reference evapotranspiration products against observation data

Product	Station	MAE	RMSE	NRMSE	PBIAS	NSE	R2	KGE
TerraClimate	Station01	19.12	26.06	29.40	-5.60	0.91	0.91	0.92
	Station02	38.80	49.79	44.00	-18.60	0.81	0.81	0.75
	Station03	16.08	22.97	31.10	7.60	0.90	0.90	0.81
	Station04	15.25	19.59	27.60	0.00	0.92	0.92	0.87
	Station05	31.93	40.18	39.10	-16.50	0.85	0.85	0.77
	Station06	31.09	41.27	37.90	-14.40	0.86	0.86	0.81
	Station07	61.54	76.52	61.60	-29.40	0.62	0.62	0.59
	Average	30.54	39.48	38.67	13.16	0.84	0.84	0.79
ERA5-Land	Station01	25.89	31.74	35.80	-13.80	0.87	0.87	0.84
	Station02	74.28	87.75	77.50	-37.50	0.40	0.40	0.48
	Station03	27.62	33.55	45.50	-20.50	0.79	0.79	0.73
	Station04	28.99	35.10	49.40	-21.70	0.76	0.76	0.72
	Station05	60.06	72.04	70.00	-34.70	0.51	0.51	0.52
	Station06	44.93	58.22	53.50	-24.50	0.71	0.71	0.65
	Station07	93.86	112.73	90.80	-45.30	0.17	0.17	0.35
	Average	50.80	61.59	60.36	28.29	0.60	0.60	0.61
MODIS	Station01	48.88	54.03	65.80	31.40	0.56	0.56	0.67
	Station02	38.29	44.08	39.20	4.80	0.85	0.85	0.68
	Station03	68.16	72.26	99.40	50.50	0.01	0.01	0.48
	Station04	60.18	63.04	87.60	43.80	0.23	0.23	0.55
	Station05	33.63	40.03	38.90	7.30	0.85	0.85	0.74
	Station06	44.27	48.76	47.90	17.10	0.77	0.77	0.70
	Station07	42.31	50.75	42.20	-2.80	0.82	0.82	0.64
	Average	47.96	53.28	60.14	22.53	0.58	0.58	0.64

Based on R<sup>2</sup> and KGE, TerraClimate again demonstrates the highest overall performance. TerraClimate has an average R<sup>2</sup> of 0.84 and an average KGE of 0.79, with R<sup>2</sup> values ranging from 0.62 to 0.92, and KGE values spanning from 0.59 to 0.92. This indicates a strong agreement with the observed data and relatively high model efficiency across most stations. In contrast, ERA5-Land exhibits a lower average R<sup>2</sup> of 0.60 and a KGE of 0.61. The R<sup>2</sup> values for ERA5-Land range from 0.17 to 0.87, reflecting a broader variability, while the KGE values range from 0.35 to 0.84, indicating less consistency and efficiency compared

to TerraClimate. MODIS shows the lowest average R<sup>2</sup> at 0.58 and an average KGE of 0.64. Its R<sup>2</sup> values vary from 0.01 to 0.85, and the KGE values range from 0.48 to 0.74. The wide range in both R<sup>2</sup> and KGE for MODIS suggests significant variability in its ability to replicate PET, particularly with lower R<sup>2</sup> values at certain stations.

In summary, TerraClimate outperforms both ERA5-Land and MODIS across the studied metrics in replicating observed PET. TerraClimate consistently shows lower MAE, RMSE, and NRMSE, indicating smaller errors and better accuracy. It also demonstrates strong model

efficiency with the best PBIAS and NSE values. Additionally, TerraClimate has the highest  $R^2$  and KGE, reflecting a better agreement with observed data. In comparison, ERA5-Land shows higher biases and weaker performance, with lower NSE and  $R^2$  values, while MODIS, though performing better than ERA5-Land in some metrics, still lags behind TerraClimate overall.

### BEST-GRIDDED DATASET BASED ON COMPROMISE PROGRAMMING

Although TerraClimate generally outperforms the other products in replicating observed precipitation and PET, a detailed assessment reveals varying performance across stations and metrics. This highlights the challenge of identifying and confirming a single best product, as performance discrepancies are evident depending on the specific station and evaluation metric. For instance, TerraClimate was generally superior but did not perform consistently across all stations or metrics. Similarly, CHIRPS excelled in some cases but lagged in others, and TAMSAT's performance varied widely. These inconsistencies underscore the need for advanced techniques to systematically evaluate and rank gridded products, ensuring a more robust and objective assessment. To address this discrepancy, CP was used to rank the gridded datasets for precipitation and PET objectively. This approach calculates the relative distance of each dataset from the ideal solution across multiple statistical metrics. The ideal values for the metrics were determined based on their optimal performance criteria: RMSE, NRMSE, and PBIAS were minimized to 0, while NSE and  $R^2$  were maximized to 1.

The novelty of using CP in this context lies in its ability to aggregate multiple statistical metrics into a single composite score, allowing for a more balanced and objective evaluation of gridded datasets. Unlike traditional methods that may prioritize one metric over another, CP resolves the discrepancies among various performance indicators, providing a comprehensive ranking of the datasets. This methodology improves the robustness of the evaluation, ensuring that the most suitable product is selected for both precipitation and PET across different stations and metrics.

For precipitation, the CP results indicated that TerraClimate had the smallest relative distance to the ideal solution (CP = 0.3509), making it the best-performing product. This was followed by CHIRPS (CP = 0.5671) and TAMSAT (CP = 2.6458), which showed greater variability in performance across stations and metrics. For PET, the CP analysis ranked the datasets as TerraClimate (CP = 0),

MODIS (CP = 2.2880), and ERA5-Land (CP = 2.5960). TerraClimate CP score of 0 reflects its close alignment with the ideal values, demonstrating its superior performance across most stations. MODIS and ERA5-Land provided competitive results but exhibited slightly higher deviations from the ideal solution.

### COMPARATIVE ANALYSIS USING PROBABILITY DISTRIBUTION PLOTS

The comparative analysis using the probability distribution plots assessed the accuracy of the gridded datasets (TerraClimate, CHIRPS, TAMSAT, ERA5\_Land, and MODIS) in representing monthly precipitation and PET distributions relative to the observed data across several stations as shown in Figure. 2 and Figure. 3. The x-axis in these plots shows a range of precipitation and PET intensity in mm/month, while the y-axis indicates the frequency of events corresponding to the respective intensity range. The density of monthly data was estimated using the Gaussian kernel (Sireesha et al. 2020). For precipitation, TerraClimate showed the closest alignment with observed station data, demonstrating similar peak density values and distribution patterns, followed by CHIRPS, which diverged slightly in lower intensity ranges, while TAMSAT displayed a broader spread and tended to overestimate higher precipitation levels, especially at Station 07. For PET, TerraClimate again aligned well with the observed data, particularly at Stations 01, 04, and 07, whereas MODIS exhibited a broader spread and occasional overestimation across multiple stations. ERA5-Land generally underestimated the PET values, indicated by a noticeable peak shift in density. Overall, TerraClimate emerged as the most consistent dataset for accurately capturing both precipitation and PET distributions, which underscores its suitability for applications in drought monitoring and climate impact assessment where high data fidelity is essential. This analysis highlights the variability in gridded data representations and demonstrates the utility of PDF as a statistical method for visually and quantitatively evaluating the dataset performance, thus facilitating more informed decisions on the dataset selection in environmental research.

### ASSESSMENT THROUGH SCATTER PLOT ANALYSIS

The scatter plot analysis was conducted to evaluate the performance of multiple gridded datasets (TerraClimate, CHIRPS, TAMSAT for precipitation and TerraClimate,

ERA5, MODIS for PET) against the observed data across several stations as shown in Figure. 4 and Figure. 5. In these plots, the x-axis represents observed monthly values for precipitation and PET, while the y-axis shows the corresponding values from the gridded datasets. A closer clustering of data points around the 1:1 line signifies a better alignment with observed values, indicating higher accuracy and consistency of the gridded datasets.

For precipitation, TerraClimate generally demonstrated the highest correlation with observed data, as seen by its

closer clustering around the 1:1 line across most stations, indicating a higher accuracy in capturing the observed precipitation patterns. CHIRPS exhibited a moderate level of alignment, albeit with some deviations from the 1:1 line, especially at higher precipitation values, suggested an occasional underestimation or overestimation. TAMSAT showed the least agreement, with a wider spread and more frequent deviations, indicating greater variability and less consistency with observed precipitation values.

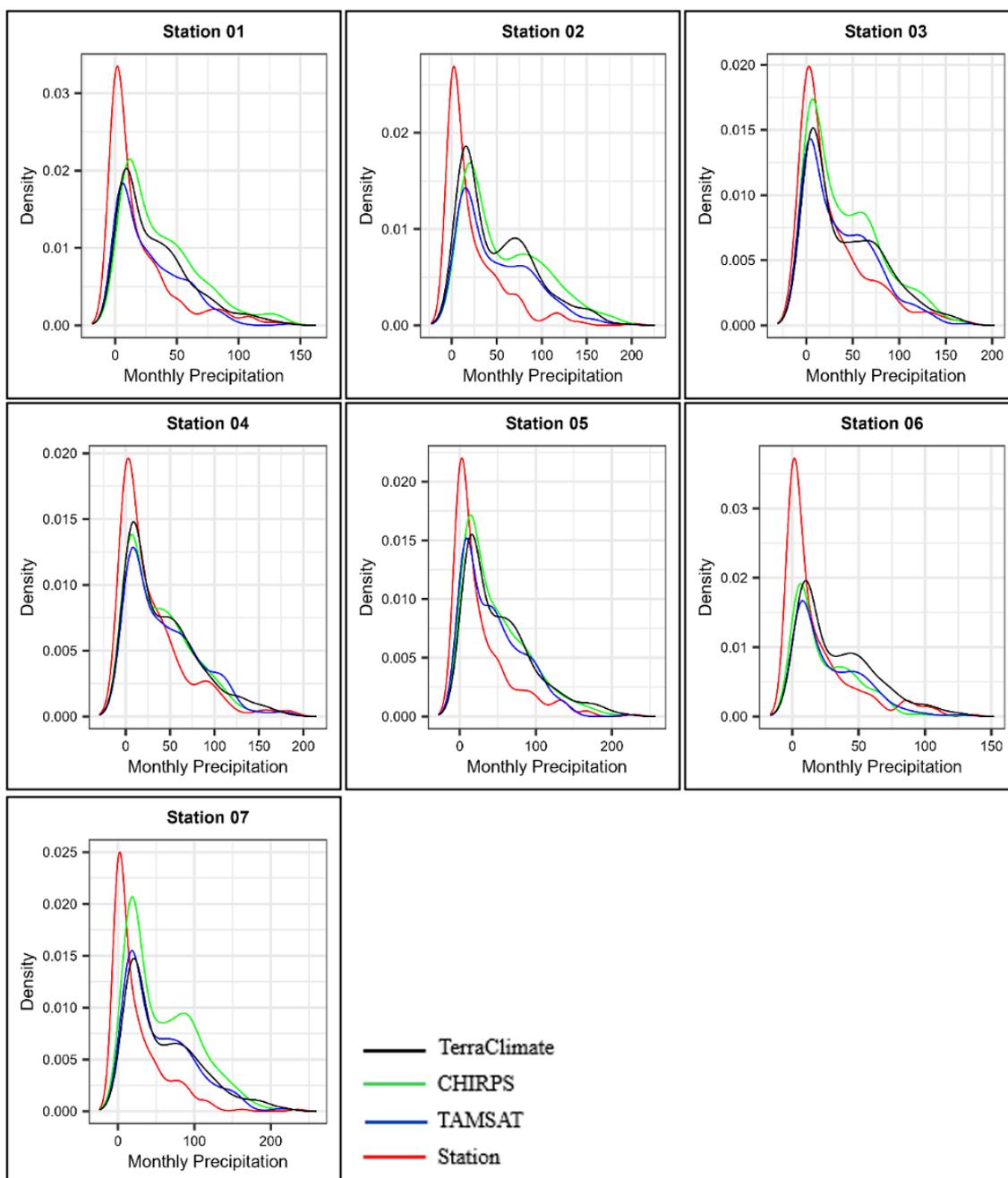


FIGURE 2. PDF plots of monthly precipitation (observed and gridded data)

In terms of PET, TerraClimate also emerged as the most reliable dataset, displaying a strong alignment with observed data, particularly evident from its tight clustering around the 1:1 line. MODIS showed a moderate correlation, with some scatter and deviations, particularly at higher PET values, which points to a tendency for slight overestimation in those ranges. ERA5 demonstrated the weakest correlation among the PET datasets, with points more widely dispersed and showing significant deviations from the 1:1 line, indicating a tendency to underestimate observed PET values.

The scatter plot analysis thus highlights TerraClimate as the most reliable dataset for both precipitation and PET, followed by CHIRPS and MODIS for precipitation and PET, respectively. TAMSAT for precipitation and ERA5 for PET showed greater discrepancies from the observed values, underscoring the importance of the dataset selection based on the specific variable and study requirements. This comprehensive analysis underscores the utility of scatter plots as a visual tool to assess systematic biases and performance across gridded datasets in replicating observed data.

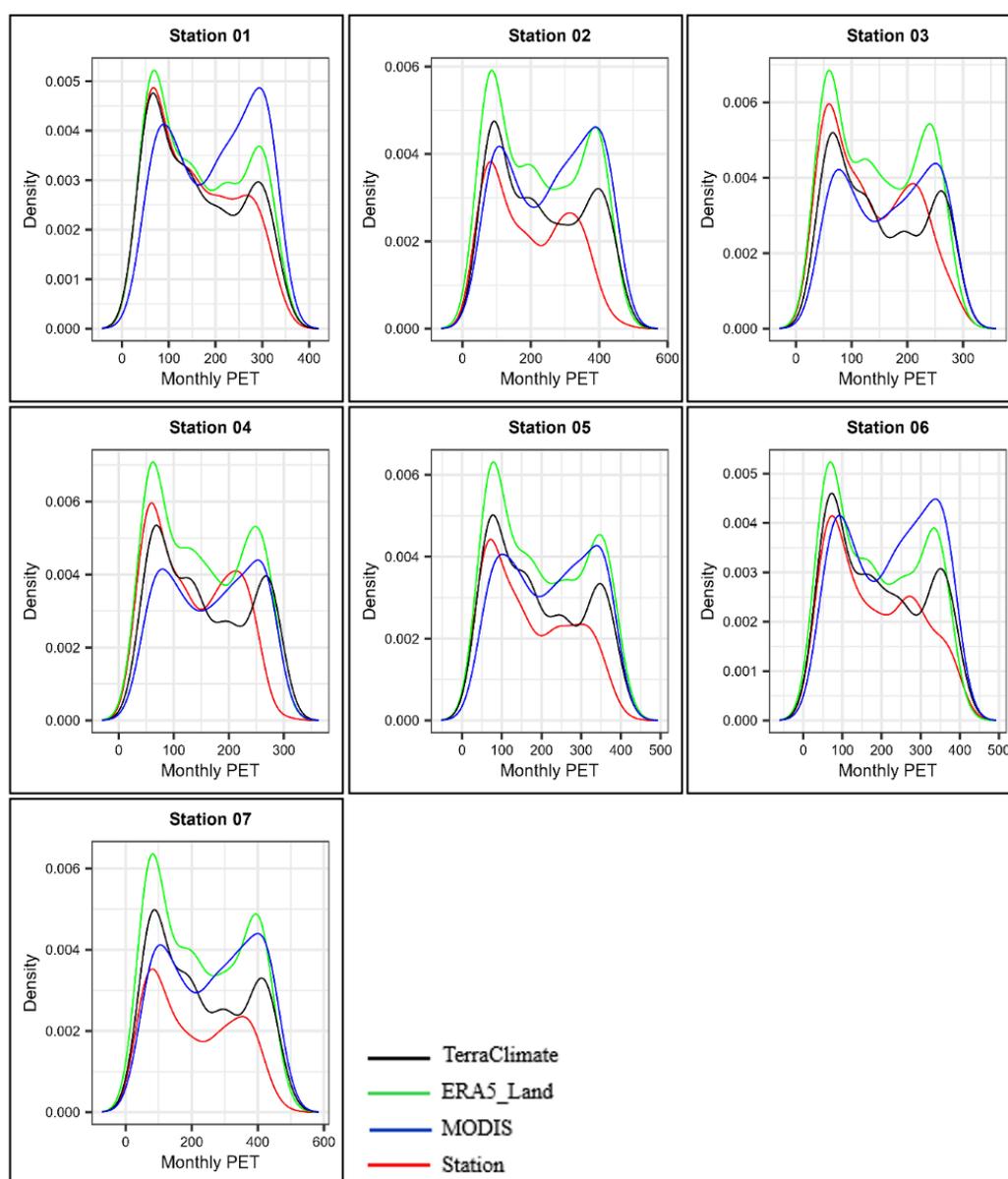


FIGURE 3. PDF plots of monthly reference evapotranspiration (observed and gridded data)

FIGURE 3. PDF plots of monthly reference evapotranspiration (observed and gridded data)

DISCUSSION

This study evaluates the performance of various gridded datasets (e.g., TerraClimate, CHIRPS, TAMSAT, MODIS, and ERA5-Land) in replicating observed precipitation and

PET across multiple ground stations in the Nineveh Governorate. The results suggest that, while gridded datasets show varying degrees of accuracy in representing observed data, they generally offer valuable alternatives for regions with limited or sparse ground station data.

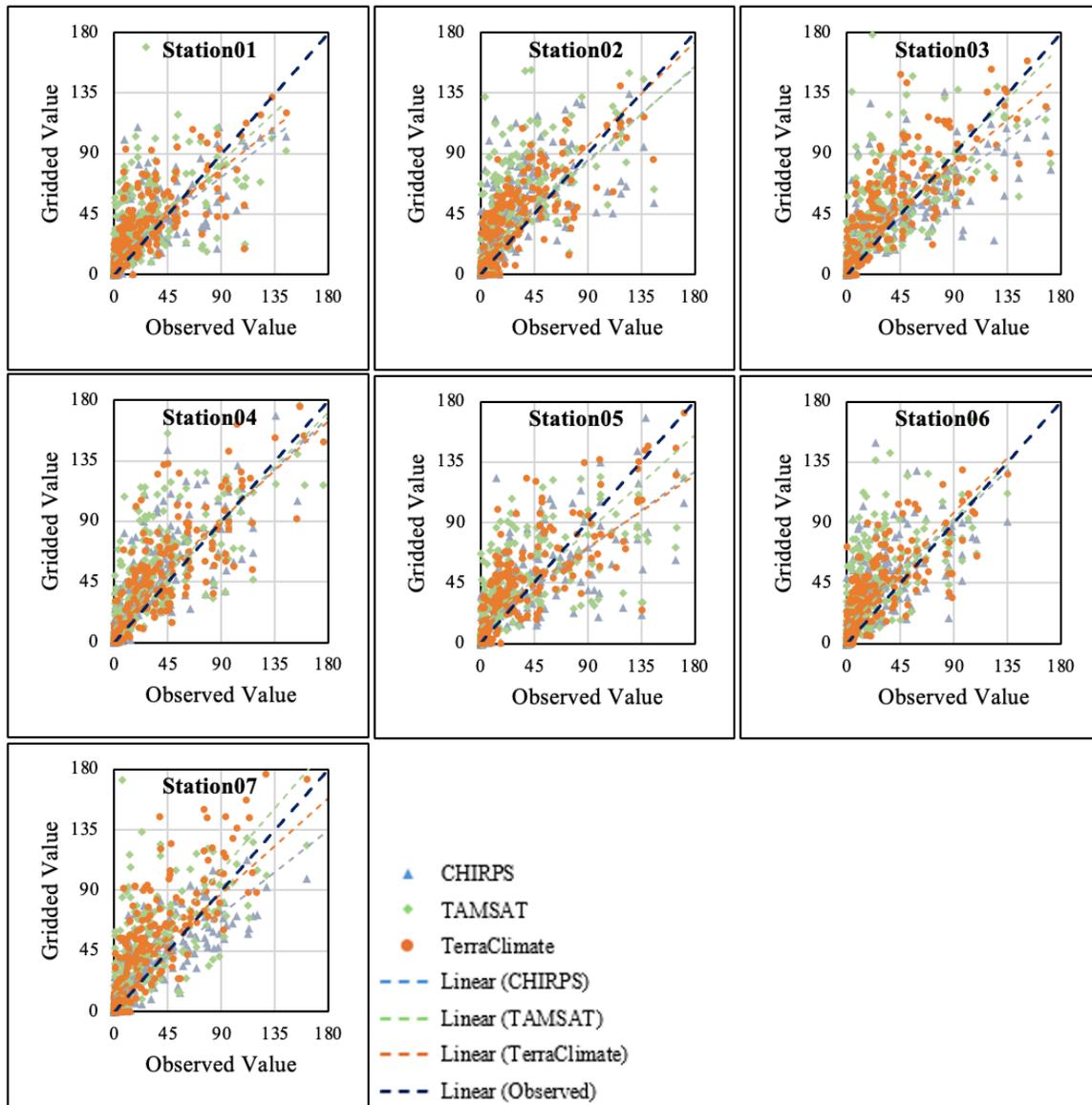


FIGURE 4. Scatter plots for observed and gridded precipitation data (mm/month) for studied stations

The statistical analysis revealed that different gridded datasets performed differently across various metrics. This underscores a common challenge in the dataset evaluation: a dataset excelling in one metric may perform poorly in others, resulting in conflicting conclusions. Previous studies have primarily relied on expert subjectivity and general assessments to evaluate various gridded datasets against observational networks (Araghi et al. 2023; Cepeda

Arias & Cañon Barriga 2022; Rachidi et al. 2023). However, this approach lacks the precision needed to account for the complexities and variability inherent in spatial and temporal data. Objective assessments, based on a more comprehensive set of performance metrics, are essential to provide a robust and unbiased evaluation. Such assessments allow for a more accurate comparison across different datasets, addressing potential inconsistencies, and

improving the reliability of the results. Without a detailed, objective evaluation, conclusions drawn from subjective

assessments may be misleading, particularly in regions where gridded datasets play a crucial role in data-scarce areas.

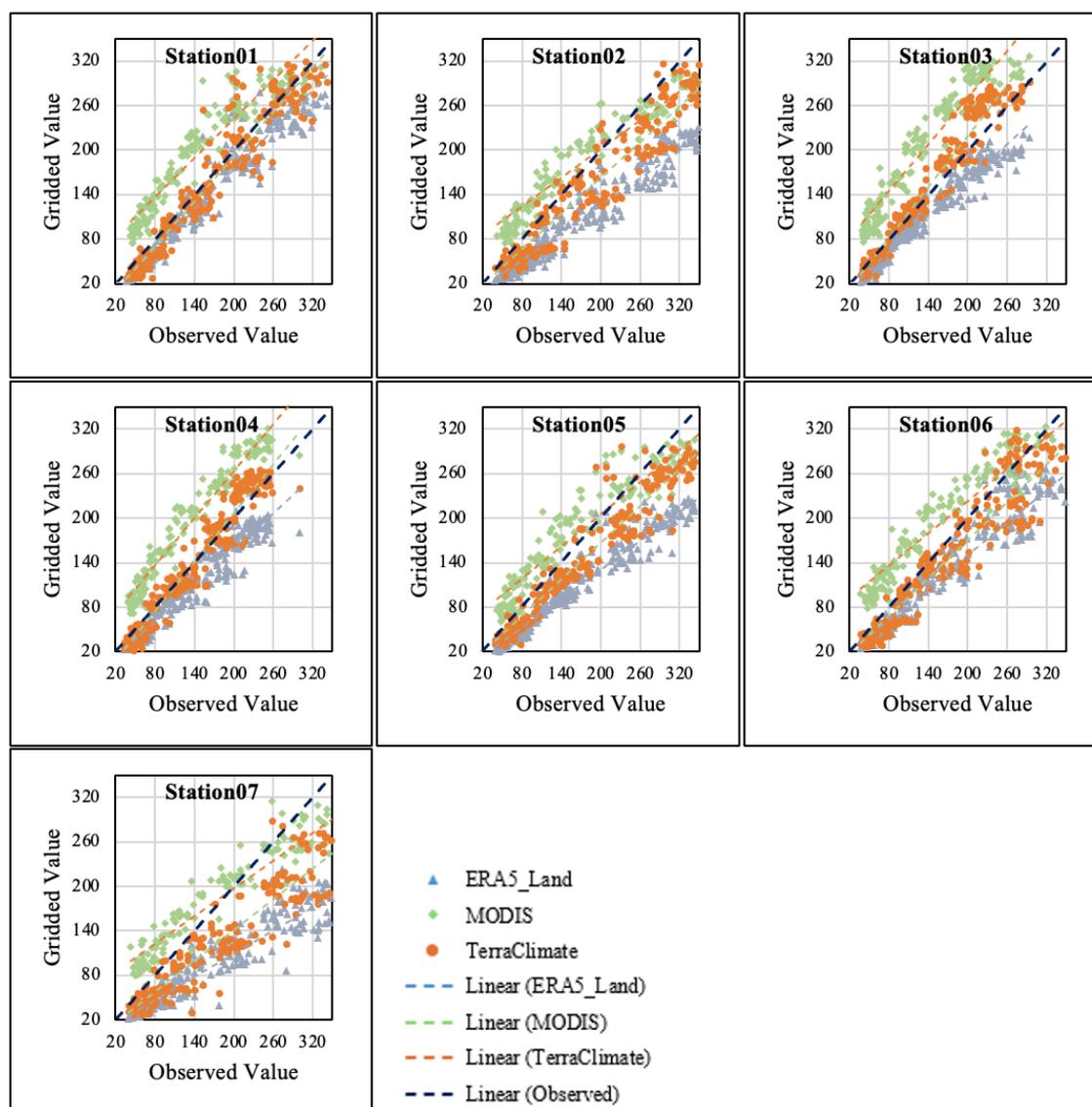


FIGURE 5. Scatter plots for observed and gridded reference evapotranspiration data (mm/month) for studied stations

To address this issue, compromise programming (CP) proves to be essential, as it integrates multiple evaluation metrics into a unified decision-making framework, effectively balancing these conflicts. CP facilitated the selection of the most suitable gridded dataset by providing a comprehensive assessment of overall performance, emphasizing its critical role in resolving metric conflicts. Employing CP alongside multiple statistical metrics, such as  $R^2$ , RMSE, and PBIAS, ensures a robust and balanced evaluation process, as supported by previous studies (Deepthi & Sivakumar 2022; Hazhir & Foroughi 2024; Muhammad et al. 2019; Salman et al. 2019). Salman et al.

(2019) conducted a comprehensive analysis by integrating multiple statistical metrics using the CP approach. Their study revealed that, among the various datasets analyzed, the gauge-based Global Precipitation Climatology Centre (GPCC) precipitation data demonstrated the highest accuracy in replicating observed precipitation across Iraq. Similarly, (Tanimu et al. 2024) evaluated the performance of gridded climate datasets for Nigeria using CP and four statistical criteria, ranking CRU as the best, followed by CHELSA, TERRA, ERA5, and CPC for replicating in-situ rainfall, and temperature data across the country. This demonstrates how the CP approach effectively combines

the statistical metrics to identify the most accurate gridded climate datasets for replicating observed climate variables.

Consistent with research in other regions, such as Iran (Araghi et al. 2023; Hamarash et al. 2022; Solaimani & Ahmadi 2024) and Brazil (Filgueiras et al. 2022), this study underscores the potential of gridded datasets to deliver reliable estimates of precipitation and PET, even in areas with sparse or poorly distributed observational data. Among the evaluated datasets, TerraClimate demonstrated the highest accuracy and stability, closely aligning with ground station observations. These findings align with earlier studies, such as (Kolling Neto et al. 2024; Solaimani & Ahmadi 2024; Tanimu et al. 2024), which reported TerraClimate's superior performance across diverse climate regions, including neighboring areas like Iran. Similarly, (Rachidi et al. 2023) highlighted TerraClimate's capability to replicate the precipitation patterns accurately, while (Dumont et al. 2022) emphasized its long-term stability and effectiveness for temporal monitoring and water balance evaluations. Hamarash et al. (2022), in their study on meteorological drought in the semi-arid regions of Iran, also concluded that TerraClimate data serves as a reliable alternative in areas where in-situ data is impractical, particularly in desert, arid, and semi-arid regions.

TerraClimate's superior performance can be attributed to its advanced interpolation method, which integrates high-resolution climatological normals from WorldClim with coarser, time-varying data from CRU Ts4.0 and JRA55. The CRU dataset, based on daily observational data from over 5,000 weather stations (Zhao et al. 2024), provides a high-resolution global grid dating back to 1901, with no missing values and robust interpolation using angular distance weighting (ADW) (Harris et al. 2020). CRU data have been widely applied in climate change detection and compound event analysis. Similarly, WorldClim delivers very high-resolution climatology for global land areas, offering a wide range of climate variables derived from reliable weather station records, making it invaluable for ecological and environmental research (Fierke et al. 2024; Hemp & Hemp 2024). By leveraging these proven datasets' comprehensive coverage, reliable observational data, and advanced interpolation methods, TerraClimate achieves superior accuracy and stability in capturing precipitation and PET patterns, as demonstrated in this study, more accurately than other gridded products. Although CHIRPS and TAMSAT are widely used for precipitation estimation, their reliance on satellite data can be hindered by the lack of ground-based observations, affecting their accuracy in capturing local climatic variations, particularly in arid regions like Nineveh.

In Nineveh, where rainfed agriculture is essential, TerraClimate's reliable PET estimates are crucial. Given the region's highly variable and often insufficient

precipitation, accurate PET data is essential for effective water management. TerraClimate's precise PET estimations help optimize irrigation schedules and improve water use efficiency, which is vital in this water-scarce area.

In this study area, TerraClimate, followed by CHIRPS for precipitation and MODIS for PET, emerged as reliable options for analyzing climate conditions in the Nineveh Governorate. Future studies should explore their performance across different climate zones and extended time periods to further refine their applicability for long-term monitoring and decision-making.

## CONCLUSION

A recent study assessed the performance of gridded datasets for the Nineveh Governorate in Iraq, where limited observational data present a significant challenge for hydrological and climatic analyses. This research marks a critical step forward by evaluating multiple gridded datasets, including TerraClimate, CHIRPS, TAMSAT, MODIS, and ERA5\_Land, for their ability to replicate precipitation and potential evapotranspiration (PET). The study represents a pioneering effort to apply compromise programming (CP) on a regional scale, offering a methodological solution for addressing conflicting results from individual statistical metrics, such as correlation coefficient ( $R^2$ ), RMSE, and Bias.

The results demonstrated that TerraClimate was the most accurate and stable dataset, owing to its integration of high-quality observational data from sources like the Climatic Research Unit (CRU) and WorldClim. This dataset consistently aligned with ground station observations, outperforming others in capturing precipitation and PET patterns. CHIRPS and MODIS also emerged as reliable options for specific variables. The study highlights the potential of CP to integrate diverse evaluation metrics, rank datasets based on performance, and facilitate a robust and objective selection process.

The methodology proposed in this research underscores the value of gridded datasets for addressing data gaps in arid and semi-arid regions like Iraq. As climate variability intensifies, such datasets can serve as vital tools for drought monitoring, water resource management, and climate impact studies. Future research is encouraged to extend the evaluation to other regions and datasets, explore different time periods, and incorporate advanced decision-making methods. The CP approach is highly adaptable, allowing it to evaluate a wide range of climate variables, such as temperature, wind speed, and humidity, across different regions. This flexibility arises from CP's capacity to aggregate and assess multiple performance metrics,

making it suitable for diverse datasets. Unlike methods that rely on a single evaluation criterion, CP incorporates several key metrics, which can be tailored to the specific characteristics of each climate variable. By ranking datasets based on their relative performance, CP ensures a comprehensive and objective evaluation framework that can be generalized across various regions and datasets, overcoming geographic and climate-specific challenges. Additionally, as extreme weather events such as droughts and floods increase, the assessment of daily gridded data products may prove crucial for evaluating weather extremes and enhancing preparedness in the region.

### ACKNOWLEDGEMENT

The authors are deeply indebted to the School of Civil Engineering at Universiti Sains Malaysia for their support and encouragement throughout this research. They also extend their heartfelt thanks to the Iraqi Meteorological Organization and Seismology for providing meteorological data that have made this study possible.

### DECLARATION OF COMPETING INTEREST

None.

### REFERENCES

- Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A. & Hegewisch, K. C. 2018. TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958-2015. *Scientific Data* 5: 1–12. doi:10.1038/sdata.2017.191
- Abdourahamane, Z. S. 2021. Evaluation of fine resolution gridded rainfall datasets over a dense network of rain gauges in Niger. *Atmospheric Research* 252(July 2020): 105459. doi:10.1016/j.atmosres.2021.105459
- Abdulahi, S. D., Husen, S. B. & Muleta, A. H. 2024. Comparison and evaluation of hydrologic performance of satellite, reanalysis and climate model-based precipitation products in the Upper Awash River Basin, Ethiopia. *Water Practice and Technology* 19(7): 2473–2491. doi:10.2166/wpt.2024.134
- Abubakar, H. B. 2024. Evaluation of high-resolution precipitation datasets CHIRPS, TerraClimate and TAMSAT over the Enkangala Escarpment of South Africa.
- Addisu, S., Aniley, E., Gashaw, T., Kelemu, S. & Fetene Demessie, S. 2024. Evaluating the performances of gridded satellite products in simulating the rainfall characteristics of Abay Basin, Ethiopia. *Sustainable Environment* 10(1). doi:10.1080/27658511.2024.2381349
- Al-Hasani, A. A. J. & Shahid, S. 2024. Assessing the effect of climate change on spatiotemporal variations in reference evapotranspiration across Iraq. *Theoretical and Applied Climatology* 259(January): 188–228. doi:10.1007/s00704-024-05217-w
- Al-Yaari, A., Condom, T., Anthelme, F., Cauvy-Fraunié, S., Dangles, O., Junquas, C., Moret, P., et al. 2024. Warming-induced cryosphere changes predict drier Andean eco-regions. *Environmental Research Letters* 19(10). doi:10.1088/1748-9326/ad6ea6
- Alsumaiti, T. S., Hussein, K. A., Ghebreyesus, D. T., Petchprayoon, P., Sharif, H. O. & Abdalati, W. 2024. Development of Intensity–Duration–Frequency (IDF) Curves over the United Arab Emirates (UAE) Using CHIRPS Satellite-Based Precipitation Products. *Remote Sensing* 16(1). doi:10.3390/rs16010027
- Araghi, A., Martinez, C. J. & Adamowski, J. F. 2023. Evaluation of TerraClimate gridded data across diverse climates in Iran. *Earth Science Informatics* 16(2): 1347–1358. doi:10.1007/s12145-023-00967-z
- Arfasa, G. F., Owusu-Sekyere, E. & Doke, D. A. 2024. Climate Change Projections and Impacts on Future Temperature, Precipitation, and Stream flow in the Veia Catchment, Ghana. *Environmental Challenges* 14(October 2023): 100813. doi:10.1016/j.envc.2023.100813
- Astuti, I. S., Wiwoho, B. S., Purwanto, P., Wagistina, S., Deffinika, I., Sucahyo, H. R., Herlambang, G. A., et al. 2022. An Application of Improved MODIS-Based Potential Evapotranspiration Estimates in a Humid Tropic Brantas Watershed—Implications for Agricultural Water Management. *ISPRS International Journal of Geo-Information* 11(3). doi:10.3390/ijgi11030182
- Avtar, R., Komolafe, A. A., Kouser, A., Singh, D., Yunus, A. P., Dou, J., Kumar, P., et al. 2020. Assessing sustainable development prospects through remote sensing: A review. *Remote Sensing Applications: Society and Environment* 20(September): 100402. doi:10.1016/j.rsase.2020.100402
- Banerjee, A., Ariz, D., Turyasingura, B., Pathak, S., Sajjad, W., Yadav, N. & Kirsten, K. L. 2024. Long-term climate change and anthropogenic activities together with regional water resources and agricultural productivity in Uganda using Google Earth Engine. *Physics and Chemistry of the Earth, Parts A/B/C* 134: 103545. doi:https://doi.org/10.1016/j.pce.2024.103545

- Banerjee, A., Kang, S., Meadows, M. E., Xia, Z., Sengupta, D. & Kumar, V. 2023. Quantifying climate variability and regional anthropogenic influence on vegetation dynamics in northwest India. *Environmental Research* 234(July): 116541. doi:10.1016/j.envres.2023.116541
- Barmpoutis, P., Papaioannou, P., Dimitropoulos, K. & Grammalidis, N. 2020. A review on early forest fire detection systems using optical remote sensing. *Sensors (Switzerland)* 20(22): 1–26. doi:10.3390/s20226442
- Bisht, D. S., Chowdhury, B., Rawat, S. S. & Pottakkal, J. G. 2024. Performance ranking of global precipitation estimates over data scarce Western Himalayan Region of India. *Theoretical and Applied Climatology* 155(8): 7515–7537. doi:10.1007/s00704-024-05069-4
- Boluwade, A. 2023. Spatial-Temporal Evaluation of Satellite-Derived Rainfall Estimations for Water Resources Applications in the Upper Congo River Basin. *Research square*.
- Cepeda Arias, E. & Cañon Barriga, J. 2022. Performance of high-resolution precipitation datasets CHIRPS and TerraClimate in a Colombian high Andean Basin. *Geocarto International* 37(27): 17382–17402. doi:10.1080/10106049.2022.2129816
- Chang, Y., Qi, Y. & Wang, Z. 2024. Comprehensive evaluation of IMERG, ERA5-Land and their fusion products in the hydrological simulation of three karst catchments in Southwest China. *Journal of Hydrology: Regional Studies* 52(November 2023). doi:10.1016/j.ejrh.2024.101671
- Dalla Torre, D., Di Marco, N., Menapace, A., Avesani, D., Righetti, M. & Majone, B. 2024. Suitability of ERA5-Land reanalysis dataset for hydrological modelling in the Alpine region. *Journal of Hydrology: Regional Studies* 52(February). doi:10.1016/j.ejrh.2024.101718
- Datti, A. D., Zeng, G., Tarnavsky, E., Cornforth, R., Pappenberger, F., Abdullahi, B. A. & Onyejuruwa, A. 2024. Evaluation of Satellite-Based Rainfall Estimates against Rain Gauge Observations across Agro-Climatic Zones of Nigeria, West Africa. *Remote Sensing* 16(10). doi:10.3390/rs16101755
- de Andrade, J. M., Ribeiro Neto, A., Bezerra, U. A., Moraes, A. C. C. & Montenegro, S. M. G. L. 2022. A comprehensive assessment of precipitation products: Temporal and spatial analyses over terrestrial biomes in Northeastern Brazil. *Remote Sensing Applications: Society and Environment* 28(June). doi:10.1016/j.rsase.2022.100842
- Deepthi, B. & Sivakumar, B. 2022. Performance assessment of general circulation models: application of compromise programming method and global performance indicator technique. *Stochastic Environmental Research and Risk Assessment* 36(6): 1761–1778. doi:10.1007/s00477-021-02124-8
- Dheyaa, M. A., Al-Mukhtar, M. M. & Shemal, K. 2024. Analyzing the Future Climate Change Impacts on Meteorological Parameters Using the LARS-WG Model. *Civil Engineering Journal (Iran)* 10(11): 3754–3778. doi:10.28991/CEJ-2024-010-11-019
- Dong, Q., Wang, W., Shao, Q., Xing, W., Ding, Y. & Fu, J. 2020. The response of reference evapotranspiration to climate change in Xinjiang, China: Historical changes, driving forces, and future projections. *International Journal of Climatology* 40(1): 235–254. doi:10.1002/joc.6206
- Du, H., Tan, M. L., Zhang, F., Chun, K. P., Li, L. & Kabir, M. H. 2024. Evaluating the effectiveness of CHIRPS data for hydroclimatic studies. *Theoretical and Applied Climatology* 155(3): 1519–1539. doi:10.1007/s00704-023-04721-9
- Dumont, M., Saadi, M., Oudin, L., Lachassagne, P., Nugraha, B., Fadillah, A., Bonjour, J. L., et al. 2022. Assessing rainfall global products reliability for water resource management in a tropical volcanic mountainous catchment. *Journal of Hydrology: Regional Studies* 40(February). doi:10.1016/j.ejrh.2022.101037
- Essou, G. R. C., Brissette, F. & Lucas-Picher, P. 2017. The use of reanalyses and gridded observations as weather input data for a hydrological model: Comparison of performances of simulated river flows based on the density of weather stations. *Journal of Hydrometeorology* 18(2): 497–513. doi:10.1175/JHM-D-16-0088.1
- Faisol, A., Indarto, Novita, E. & Budiyono. 2020. An evaluation of MODIS global evapotranspiration product (MOD16A2) as terrestrial evapotranspiration in East Java-Indonesia. *IOP Conference Series: Earth and Environmental Science* 485(1). doi:10.1088/1755-1315/485/1/012002
- Fernandes, K., Muñoz, A. G., Ramirez-Villegas, J., Agudelo, D., Llanos-Herrera, L., Esquivel, A., Rodriguez-Espinoza, J., et al. 2020. Improving seasonal precipitation forecasts for agriculture in the orinoquia Region of Colombia. *Weather and Forecasting* 35(2): 437–449. doi:10.1175/WAF-D-19-0122.1
- Fierke, J., Joelson, N. Z., Loguercio, G. A., Putzenlechner, B., Simon, A., Wyss, D., Kappas, M., et al. 2024. Assessing uncertainty in bioclimatic modelling: a comparison of two high-resolution climate datasets in northern Patagonia. *Regional Environmental Change* 24(3): 110. doi:10.1007/s10113-024-02278-5
- Filgueiras, R., Venancio, L. P., Aleman, C. C. & Cunha, F. F. da. 2022. Comparison and calibration of terraclimate climatological variables over the Brazilian territory. *Journal of South American Earth Sciences* 117: 103882. doi:https://doi.org/10.1016/j.jsames.2022.103882

- Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., et al. 2015. The climate hazards infrared precipitation with stations - A new environmental record for monitoring extremes. *Scientific Data* 2: 1–21. doi:10.1038/sdata.2015.66
- Gupta, H. V., Kling, H., Yilmaz, K. K. & Martinez, G. F. 2009. Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology* 377(1–2): 80–91. doi:10.1016/j.jhydrol.2009.08.003
- Hamarash, H., Hamad, R. & Rasul, A. 2022. Meteorological drought in semi-arid regions: A case study of Iran. *Journal of Arid Land* 14(11): 1212–1233. doi:10.1007/s40333-022-0106-9
- Hanchane, M., Kessabi, R., Krakauer, N. Y., Sadiki, A., El Kassoui, J. & Aboubi, I. 2023. Performance Evaluation of TerraClimate Monthly Rainfall Data after Bias Correction in the Fes-Meknes Region (Morocco). *Climate* 11(6). doi:10.3390/cli11060120
- Harris, I., Osborn, T. J., Jones, P. & Lister, D. 2020. Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. *Scientific Data* 7(1): 1–18. doi:10.1038/s41597-020-0453-3
- Harrison, L., Landsfeld, M., Husak, G., Davenport, F., Shukla, S., Turner, W., Peterson, P., et al. 2022. Advancing early warning capabilities with CHIRPS-compatible NCEP GEFS precipitation forecasts. *Scientific Data* 9(1): 1–13. doi:10.1038/s41597-022-01468-2
- Hassan, I., Kalin, R. M., White, C. J. & Aladejana, J. A. 2020. Evaluation of Daily Gridded Meteorological Datasets over the Niger Delta Region of Nigeria and Implication to Water Resources Management. *Atmospheric and Climate Sciences* 10(01): 21–39. doi:10.4236/acs.2020.101002
- Hazhir, M. M. & Foroughi, A. A. 2024. A compromise programming approach for cross efficiency measurement in basic two-stage network system. *Expert Systems with Applications* 252(PA): 124205. doi:10.1016/j.eswa.2024.124205
- Hemp, A. & Hemp, J. 2024. Weather or not—Global climate databases: Reliable on tropical mountains? *PLoS ONE* 19(3 March): 1–12. doi:10.1371/journal.pone.0299363
- Hussan, W. H., Khazaa, S. T. & Al-Shammari, M. H. 2024. Effect of Climate Change on Wetland Areas in West Iraq Using Satellite Data and GIS Techniques. *Civil Engineering Journal (Iran)* 10(9): 2966–2978. doi:10.28991/CEJ-2024-010-09-013
- Ji, X., Li, Y., Luo, X., He, D., Guo, R., Wang, J., Bai, Y., et al. 2020. Evaluation of bias correction methods for APHRODITE data to improve hydrologic simulation in a large Himalayan basin. *Atmospheric Research* 242(February): 104964. doi:10.1016/j.atmosres.2020.104964
- Kabite Wedajo, G., Kebede Muleta, M. & Gessesse Awoke, B. 2021. Performance evaluation of multiple satellite rainfall products for Dhidhessa River Basin (DRB), Ethiopia. *Atmospheric Measurement Techniques* 14(3): 2299–2316. doi:10.5194/amt-14-2299-2021
- Khan, H. M., Aslam, M. F., Waseem, M., Jalil Abbasi, H. K., Iftikhar, A. & Haq, F. U. 2024. Evaluating satellite-based precipitation products for spatiotemporal drought analysis. *Journal of Arid Environments* 224(July): 105225. doi:10.1016/j.jaridenv.2024.105225
- Kibii, J. K. & Du Plessis, J. A. 2024. Applicability of CHIRPS-based Pitman model for simulation of climate change flows. *Physics and Chemistry of the Earth* 135(May): 103643. doi:10.1016/j.pce.2024.103643
- Kirschbaum, D., Kapnick, S. B., Stanley, T. & Pascale, S. 2020. Changes in extreme precipitation and landslides over high mountain Asia. *Geophysical Research Letters* 47(4): 1–9. doi:10.1029/2019GL085347
- Kolling Neto, A., Ribeiro, R. B., Fraga, M. de S. & Pruski, F. F. 2024. Estimating water balance in a Brazilian semiarid watershed using different spatial data. *Journal of South American Earth Sciences* 140: 104930. doi:https://doi.org/10.1016/j.jsames.2024.104930
- Kumari, N., Srivastava, A. & Dumka, U. C. 2021. A long-term spatiotemporal analysis of vegetation greenness over the himalayan region using google earth engine. *Climate* 9(7): 1–20. doi:10.3390/cli9070109
- Kumari, P., Shaik, R., Vannam, S. C. & Singh, S. K. 2024. Drought evaluation using various evapotranspiration models over semi-arid river basins. *Journal of Water and Climate Change* 15(8): 3582–3601. doi:10.2166/wcc.2024.699
- Legates, D. R. & McCabe, G. J. 1999. Evaluating the use of “goodness-of-fit” measures in hydrologic and hydroclimatic model validation. *Water Resources Research* 35(1): 233–241. doi:10.1029/1998WR900018
- Luo, Z. & Shao, Q. 2022. A modified hydrologic model for examining the capability of global gridded PET products in improving hydrological simulation accuracy of surface runoff, streamflow and baseflow. *Journal of Hydrology* 610(January): 127960. doi:10.1016/j.jhydrol.2022.127960
- Maidment, R. I., Grimes, D., Black, E., Tarnavsky, E., Young, M., Greatrex, H., Allan, R. P., et al. 2017. A new, long-term daily satellite-based rainfall dataset for operational monitoring in Africa. *Scientific Data* 4. doi:10.1038/sdata.2017.63
- Mamat, N. & Mohd Razali, S. F. 2023. Comparisons of Various Imputation Methods for Incomplete Water Quality Data: A Case Study of The Langat River, Malaysia. *Jurnal Kejuruteraan* 35(1): 191–201. doi:10.17576/jkukm-2023-35(1)-18

- Mat Daud, N., Daud, N. F., Abu Bakar, A. A., Abd Aziz, N., Badrealam, S. & Dollah, Z. 2023. Performance of a Rainwater Harvesting Tank Under Varying Non-Potable Demand: Case Study in Kubang Semang, Penang. *Jurnal Kejuruteraan* 35(6): 1481–1486. doi:10.17576/jkukm-2023-35(6)-21
- Mohamad Hamzah, F., Tajul Ariffin, A. N., Othman, H., Abd Rahman, N., Kamarudin, M. K. A., Rusiman, M. S. & Ahmad Rusmili, S. H. 2022. A Forecast of Surface Ozone Using Analytical Models. *Jurnal Kejuruteraan* 35(2): 35–45. doi:10.17576/jkukm-2022-si5(2)-04
- Mohd Salleh, S. H., Wan Mohtar, W. H. M., Abdul Maulud, K. N. & Al-Ani, I. 2023. Hydrodynamic Modelling: Estuary Dynamic Implication to Morphological Changes. *Jurnal Kejuruteraan* 35(3): 635–645. doi:10.17576/jkukm-2023-35(3)-11
- Mpakairi, K. S., Dube, T., Sibanda, M. & Mutanga, O. 2024. Remote sensing crop water productivity and water use for sustainable agriculture during extreme weather events in South Africa. *International Journal of Applied Earth Observation and Geoinformation* 129(April): 103833. doi:10.1016/j.jag.2024.103833
- Mu, Q., Zhao, M. & Running, S. W. 2011. Improvements to a MODIS global terrestrial evapotranspiration algorithm. *Remote Sensing of Environment* 115(8): 1781–1800. doi:10.1016/j.rse.2011.02.019
- Muhammad, M. K. I., Nashwan, M. S., Shahid, S., Ismail, T. bin, Song, Y. H. & Chung, E. S. 2019. Evaluation of empirical reference evapotranspiration models using compromise programming: A case study of Peninsular Malaysia. *Sustainability (Switzerland)* 11(16). doi:10.3390/su11164267
- Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., et al. 2021. ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth System Science Data* 13(9): 4349–4383. doi:10.5194/essd-13-4349-2021
- Nadhim Al-neama, S., Yang, S. & Muneer Yahya, B. 2022. Evaluation of surface run-off potential of basins in Nineveh governorate, Iraq based on morphometric analysis, using RS and GIS. *Materials Today: Proceedings* 60: 1753–1768. doi:10.1016/j.matpr.2021.12.313
- Nashwan, M. S., Shahid, S. & Abd Rahim, N. 2019. Unidirectional trends in annual and seasonal climate and extremes in Egypt. *Theoretical and Applied Climatology* 136(1–2): 457–473. doi:10.1007/s00704-018-2498-1
- Nasrollahi, M., Zolfaghari, A. A. & Yazdani, M. R. 2021. Spatial and Temporal Properties of Reference Evapotranspiration and Its Related Climatic Parameters in the Main Agricultural Regions of Iran. *Pure and Applied Geophysics* 178(10): 4159–4179. doi:10.1007/s00024-021-02806-y
- Ogbu, K. N., Houngouè, N. R., Gbode, I. E. & Tischbein, B. 2020. Performance evaluation of satellite-based rainfall products over Nigeria. *Climate* 8(10): 1–23. doi:10.3390/cli8100103
- Parker, W. S. 2016. Reanalyses and observations: What's the Difference? *Bulletin of the American Meteorological Society* 97(9): 1565–1572. doi:10.1175/BAMS-D-14-00226.1
- Pelosi, A., Terribile, F., D'Urso, G. & Chirico, G. B. 2020. Comparison of ERA5-Land and UERRA MESCAN-SURFEX reanalysis data with spatially interpolated weather observations for the regional assessment of reference evapotranspiration. *Water (Switzerland)* 12(6). doi:10.3390/W12061669
- Qaraghuli, K., Murshed, M. F., M. Said, M. A., Mokhtar, A. & Rousta, I. 2024. Univariate and multivariate imputation methods evaluation for reconstructing climate time series data: A case study of Mosul station-Iraq. *Journal of Agrometeorology* 26(3): 318–323. doi:10.54386/jam.v26i3.2657
- Rachidi, S., El Mazoudi, E. H., El Alami, J., Jadoud, M. & Er-Raki, S. 2023. Assessment and Comparison of Satellite-Based Rainfall Products: Validation by Hydrological Modeling Using ANN in a Semi-Arid Zone. *Water (Switzerland)* 15(11). doi:10.3390/w15111997
- Running, S.W., Mu, Q., Zhao, M. & Moreno, A. 2019. MODIS Global Terrestrial Evapotranspiration (ET) Product (NASA MOD16A2/A3) Algorithm Theoretical Basis Document Collection 6 (March): 1–40.
- Sa'adi, Z., Al-Suwaiyan, M. S., Yaseen, Z. M., Tan, M. L., Goliatt, L., Heddam, S., Halder, B., et al. 2024. Observed and future shifts in climate zone of Borneo based on CMIP6 models. *Journal of Environmental Management* 360(February): 121087. doi:10.1016/j.jenvman.2024.121087
- Saicharan, V. & Rangaswamy, S. H. 2023. A Comparison and Ranking Study of Monthly Average Rainfall Datasets with IMD Gridded Data in India. *Sustainability (Switzerland)* 15(7). doi:10.3390/su15075758
- Salman, S. A., Shahid, S., Ismail, T., Al-Abadi, A. M., Wang, X. jun & Chung, E. S. 2019. Selection of gridded precipitation data for Iraq using compromise programming. *Measurement: Journal of the International Measurement Confederation* 132: 87–98. doi:10.1016/j.measurement.2018.09.047
- Samreen, T., Ahmad, M., Baig, M. T., Kanwal, S., Nazir, M. Z. & Sidra-Tul-Muntaha. 2023. Remote Sensing in Precision Agriculture for Irrigation Management 31. doi:10.3390/envirosciproc2022023031

- Santos, P. A. B. dos, Schwerz, F., Carvalho, L. G. de, Baptista, V. B. da S., Marin, D. B., Ferraz, G. A. e. S., Rossi, G., et al. 2023. Machine Learning and Conventional Methods for Reference Evapotranspiration Estimation Using Limited-Climatic-Data Scenarios. *Agronomy* 13(9). doi:10.3390/agronomy13092366
- Shukur, O. B., Ali, S. H. & Saber, L. A. 2021. Climatic Temperature Data Forecasting in Nineveh Governorate Using the Recurrent Neural Network Method. *International Journal on Advanced Science, Engineering and Information Technology* 11(1): 113–123. doi:10.18517/ijaseit.11.1.14083
- Sireesha, C., Roshni, T. & Jha, M. K. 2020. Insight into the precipitation behavior of gridded precipitation data in the Sina basin. *Environmental Monitoring and Assessment* 192(11). doi:10.1007/s10661-020-08687-3
- Solaimani, K. & Ahmadi, S. B. 2024. Evaluation of TerraClimate gridded data in investigating the changes of reference evapotranspiration in different climates of Iran. *Journal of Hydrology: Regional Studies* 52: 101678. doi:10.1016/j.ejrh.2024.101678
- Sorooshian, S., Aghakouchak, A., Arkin, P., Eylander, J., Foufoula-Georgiou, E., Harmon, R., Hendrickx, J. M. H., et al. 2011. Advanced concepts on remote sensing of precipitation at multiple scales. *Bulletin of the American Meteorological Society* 92(10): 1353–1357. doi:10.1175/2011BAMS3158.1
- Suliman, A. H. A., Rajab, J. M. & Shahid, S. 2024. Evaluating the accuracy of APHRODITE and CHIRPS satellite-based Precipitation products for meteorological drought monitoring. *Theoretical and Applied Climatology* 155(7): 6567–6579. doi:10.1007/s00704-024-05015-4
- 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(1): 79–107. doi:10.1002/2017RG000574
- Tan, M. L., Armanuos, A. M., Ahmadianfar, I., Demir, V., Heddami, S., Al-Areeq, A. M., Abba, S. I., et al. 2023. Evaluation of NASA POWER and ERA5-Land for estimating tropical precipitation and temperature extremes. *Journal of Hydrology* 624(April): 129940. doi:10.1016/j.jhydrol.2023.129940
- Tanimu, B., Hamed, M. M., Bello, A. A. D., Abdullahi, S. A., Ajibike, M. A. & Shahid, S. 2024. Selecting the optimal gridded climate dataset for Nigeria using advanced time series similarity algorithms. *Environmental Science and Pollution Research* 31(10): 15986–16010. doi:10.1007/s11356-024-32128-0
- Tarek, M., Brissette, F. P. & Arsenault, R. 2020. Evaluation of the ERA5 reanalysis as a potential reference dataset for hydrological modelling over North America. *Hydrology and Earth System Sciences* 24(5): 2527–2544. doi:10.5194/hess-24-2527-2020
- Tigkas, D., Vangelis, H. & Tsakiris, G. 2020. Implementing crop evapotranspiration in RDI for farm-level drought evaluation and adaptation under climate change conditions. *Water Resources Management* 34(14): 4329–4343. doi:10.1007/s11269-020-02593-6
- Ucar, Y., Kocięcka, J., Liberacki, D. & Rolbiecki, R. 2023. Analysis of crop water requirements for apple using dependable rainfall. *Atmosphere* 14(1). doi:10.3390/atmos14010099
- Wiwoho, B. S. & Astuti, I. S. 2022. Runoff observation in a tropical Brantas watershed as observed from long-term globally available TerraClimate data 2001–2020. *Geoenvironmental Disasters* 9(1). doi:10.1186/s40677-022-00214-5
- Xu, C., Wang, W., Hu, Y. & Yongwei, L. 2024. Evaluation of ERA5, ERA5-Land, GLDAS-2.1, and GLEAM potential evapotranspiration data over mainland China. *Journal of Hydrology: Regional Studies* 51(September 2023): 101651. doi:10.1016/j.ejrh.2023.101651
- Xu, J., Ma, Z., Yan, S. & Peng, J. 2022. Do ERA5 and ERA5-land precipitation estimates outperform satellite-based precipitation products? A comprehensive comparison between state-of-the-art model-based and satellite-based precipitation products over mainland China. *Journal of Hydrology* 605(December 2021): 127353. doi:10.1016/j.jhydrol.2021.127353
- Yan, N., Zhu, W., Wu, B., Tuvdendorj, B., Chang, S., Mishigdorj, O. & Zhang, X. 2023. Assessment of the grassland carrying capacity for winter-spring period in Mongolia. *Ecological Indicators* 146(June 2022): 109868. doi:10.1016/j.ecolind.2023.109868
- Yanfatriani, E., Marzuki, M., Vonnisa, M., Razi, P., Hapsoro, C. A., Ramadhan, R. & Yusnaini, H. 2024. Extreme rainfall trends and hydrometeorological disasters in tropical regions: Implications for climate resilience. *Emerging Science Journal* 8(5): 1860–1874. doi:10.28991/ESJ-2024-08-05-012
- Yang, A., Liu, C., Yang, D. & Lu, C. 2023. Electric vehicle adoption in a mature market: A case study of Norway. *Journal of Transport Geography* 106(November 2022): 103489. doi:10.1016/j.jtrangeo.2022.103489
- Zambrano-Bigiarini, M., Nauditt, A., Birkel, C., Verbist, K. & Ribbe, L. 2017. Temporal and spatial evaluation of satellite-based rainfall estimates across the complex topographical and climatic gradients of Chile. *Hydrology and Earth System Sciences* 21(2): 1295–1320. doi:10.5194/hess-21-1295-2017

- Zhang, D., Liu, X. & Hong, H. 2013. Assessing the effect of climate change on reference evapotranspiration in China. *Stochastic Environmental Research and Risk Assessment* 27(8): 1871–1881. doi:10.1007/s00477-013-0723-0
- Zhao, B., E, M. X. & Chong, S. L. 2024. Spatiotemporal Distribution Pattern of Surface Evapotranspiration in Gannan Prefecture, China Based on Mod16. *Applied Ecology and Environmental Research* 22(3): 2107–2120. doi:10.15666/aer/2203\_21072120
- Zhao, Xiong, S., Tian, Y., Wu, Y., Li, B. & Chen, X. 2024. Compound dry and hot events over major river basins of the world from 1921 to 2020. *Weather and Climate Extremes* 44(May): 100679. doi:10.1016/j.wace.2024.100679