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A Comprehensive review of global precipitation Products: Availability and application for flood inundation mapping

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सार – यह अध्ययन कालिक स्तर पर वर्षा के तीस उत्पादों का मूल्यांकन किया गया जिसमें गेज, उपग्रह-व्युत्पन्न और पुनःविश्लेषण प्रकार शामिल हैं। CRU, GPCC और CPC-Global जैसे गेज उत्पादों वर्षा गेज माप पर निर्भर करता है हालाँकि, गेज के वितरण के कारण उन्हें चुनौतियों का सामना करना पड़ता है। PERSIANN-CCS, TRMM 3B42, और GPCP जैसे उपग्रह-आधारित उत्पाद स्थानिक और कालिक विभेदन देते हैं खास तौर पर उन इलाकों में जहां गेजिंग स्टेशन नहीं हैं। फिर भी, ये उपग्रह-आधारित डेटासेट अप्रत्यक्ष हैं और इनमें अनिश्चितताओं की संभावना रहती है। NCEP1, ERA-Interim और MERRA जैसे पुनःविश्लेषित उत्पाद, वायुमंडलीय डेटासेट देने के लिए प्रेक्षणीय डेटा स्रोतों को एकीकृत करते हैं, जो जलवायु अध्ययन के लिए बहुत महत्वपूर्ण हैं। फिर भी, डेटा आत्मसात प्रक्रियाओं और मॉडल पूर्वाग्रहों की वजह से उनमें सीमाएँ होती हैं। शोधकर्ताओं को जलवायु और जलविज्ञान आकलन करते समय हर डेटासेट के इस्तेमाल और सीमाओं पर विचार करना चाहिए। हालांकि GSMaP और IMERG जैसे उपग्रह उत्पाद ERA-5 और MERRA-2 जैसे पुनःविश्लेषित उत्पादों के साथ बाढ़ मानचित्रण के लिए ज़रूरी हैं, लेकिन बाढ़ मॉडलिंग में उनके इस्तेमाल से पहले पूर्वाग्रह समायोजन लागू करना ज़रूरी है।

ABSTRACT. The study evaluates thirty precipitation products across temporal scales, encompassing gauge, satellite-derived, and reanalysis types. Gauge products such as CRU, GPCC, and CPC-Global depend on rain gauge measurements; however, they encounter challenges due to the distribution of gauges. Satellite-based products such as PERSIANN-CCS, TRMM 3B42, and GPCP offer temporal and spatial resolution, especially in regions lacking gauging stations. Nevertheless, these satellite-based datasets are indirect and prone to uncertainties. Reanalysis products, including NCEP1, ERA-Interim, and MERRA, integrate observational data sources to provide atmospheric datasets, which are invaluable for climate studies. Yet, they possess limitations owing to data assimilation processes and model biases. Researchers must consider the applications and limitations of each dataset when conducting climate and hydrological assessments. Although satellite products such as GSMaP and IMERG, along with reanalysis products such as ERA-5 and MERRA-2, are vital for flood mapping, it is essential to apply bias adjustments before their utilization in flood modelling.

Key words – IMERG, TRMM, GSMaP, NCEP, Flood inundation.

1. Introduction

Substantial evidence supports ongoing climate change, highlighting the significant impact of human activities, particularly through increasing levels of atmospheric carbon dioxide and other greenhouse gases, as major contributors to this phenomenon (Mitchell & Jones, 2005). Climate change impacts both natural and anthropogenic systems from local to global scales (Feng et al., 2004). The intricate link between the global water cycle and climate system is characterized by precipitation (Thornes et al., 2010; Eltahir & Bras, 1996). Precipitation affects various aspects of human life across multiple sectors, including disaster preparedness, water resources management, agriculture, energy production, and the economy. By understanding precipitation patterns and trends (Kidd & Huffman, 2011), societies can better adapt to changing weather conditions and develop strategies for sustainable well-being.

Accurate and reliable precipitation data are crucial for forecasting weather, climate, and hydrological conditions, which are essential for water resource management and researching climate trends and variability (Jiang et al., 2012; Liu et al., 2017). Gauge readings have been the predominant method for in situ observations of precipitation (Kidd, 2001), providing comprehensive climate data sets with varied temporal resolutions. However, this approach has limitations, particularly in maritime regions and sparsely populated areas where coverage is insufficient (Kidd et al., 2017; Rana et al., 2014). To overcome these gaps, satellite observations offer more consistent geographical coverage and high temporal data using advanced infrared (IR) and microwave (MW) sensors (Kidd & Levizzani, 2010; Xie et al., 2003a). Available satellite-derived datasets for operational use include CPC, CMORPH, TRMM, and PERSIANN.

Additionally, products that integrate gauge and satellite observations have been developed to enhance the accuracy of climate variable measurements. This approach leverages the strengths of both data types, aiming to maximize their respective advantages (Huffman et al., 1995; Xie et al., 2003a). A prominent example is The Global Precipitation Climatology Project (GPCP) monthly precipitation analysis, widely used in climate research to understand global precipitation patterns and trends by combining multiple data sources for comprehensive accuracy (Adler et al., 2003). These diverse precipitation datasets have proven invaluable across various study domains. They facilitate the quantification and demonstration of local and global climate change trends using varied data sources.

Precipitation data is essential for running and calibrating hydrological and ecological models. Although numerous high-resolution climate datasets are used extensively in research, inconsistencies still exist among them (Tapiador et al., 2017). These discrepancies can be attributed to inherent flaws in the data sources and differences in methodologies during their creation (Gehne et al., 2016; Jiang et al., 2012; Kidd et al., 2012; Miao et al., 2015; Sun et al., 2014). The World Meteorological Organization (WMO) highlights the necessity for at least 30 years of historical data in climate studies. While long-term precipitation records are often found in gauge-based and reanalysis datasets. The satellite-derived datasets are relatively newer with shorter durations (from 2000 onwards), they provide essential insights into meteorological processes, drought monitoring, and hydrological assessments. We aim to conduct a review of gauge, satellite, and reanalysis datasets the outline of the shown in the Figure 1.

2. Data and methodology

2.1 *Gauge-Based Precipitation Products*

Creating a comprehensive, integrated global dataset for climate research requires compiling data from various countries. Since its establishment in 1873, the World Meteorological Organization (WMO) has been pivotal as a global entity, bringing together 191 member governments and regions. The organization's primary goal is to address the growing demand for climate observations and ensure that collected data is accessible to all nations. The Global Climate Observing System (GCOS) plays an essential role in advancing climate research through promoting transparency and cooperation in data collection and dissemination (Spence & Townshend, 1995). Despite the presence of numerous gauge-based observation systems, it's important to recognize that not all have been used consistently or simultaneously. Variability in data availability and continuity from these gauge systems poses challenges when attempting to construct a comprehensive and uninterrupted dataset for climate studies (Kidd et al., 2017).

Data gridding is essential in climate research due to the uneven distribution of observation stations. Interpolation techniques are used to create a continuous spatial representation of climate variables from these irregularly spaced data points. The Climate Research Unit (CRU) data set, known for its detailed spatial resolution and extensive historical coverage, includes precipitation among other climate factors. It compiles information from various sources such as gauge readings, satellite observations, and reanalysis datasets. By integrating diverse data, the CRU dataset provides insights into long-term precipitation patterns, supporting climate modeling and agricultural research.

The Global Precipitation Climatology Centre (GPCC) specializes in collecting, quality-checking, and analyzing data from global rain gauges. Its database comprises data from 158 countries and 31 regional providers, with national meteorological agencies being the primary source of information. Additionally, the GPCC receives monthly climate and daily surface synoptic data via the World Meteorological Organization's Global Telecommunication System (WMO GTS). The GPCC

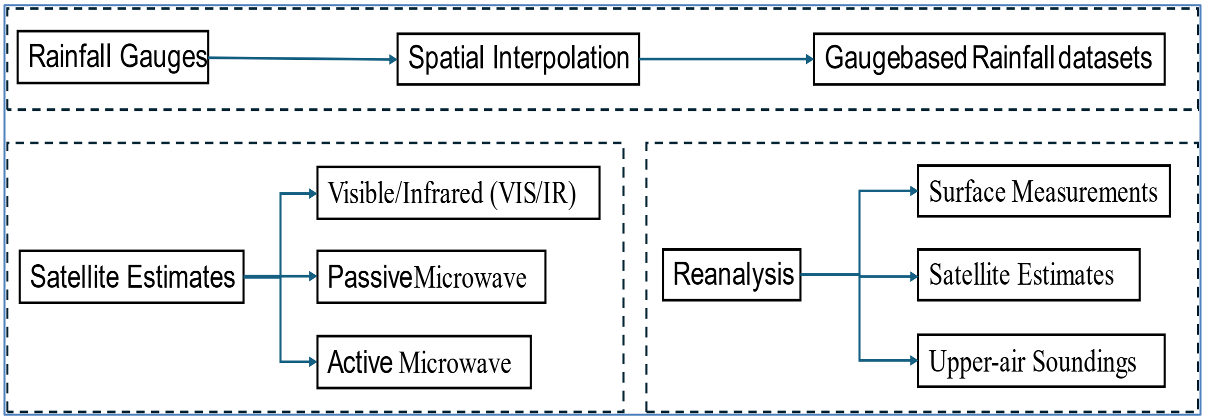

Fig. 1. Flowchart showing different sources of precipitation dataset

also integrates data from global collections such as those by the Climate Research Unit (CRU) with data from 11,800 stations, the Food and Agriculture Organization (FAO) with 13,500 stations, and the Global Historical Climatology Network (GHCN), which includes data from 34,800 stations through both GHCN2 and GHCN daily datasets. Data from various regional initiatives by international organizations further enhance the GPCC database. This extensive compilation uses information from over 85,000 stations worldwide, covering more than two centuries.

The CPC-Global product aggregates precipitation data from around 30,000 stations worldwide, incorporating gauge reports from various sources such as the GTS, the Cooperative Observer Network, and national meteorological agencies. This comprehensive dataset offers reliable daily global precipitation information valuable to climate researchers and meteorologists for understanding trends and enhancing analyses. However, a key challenge lies in the variability of observation timings across different national networks, which can lead to untagged multiday accumulations affecting data comparability with other sources (Viney & Bates, 2004).

Gauged rainfall products depend on historical observations collected by ground stations, with initial datasets often being similar across various databases. Consequently, these datasets have generally shown consistency in their spatial and temporal dimensions. However, there has been a significant decline in the number of instruments used to collect this data over time. In 1901, approximately 10,900 usable stations existed worldwide, according to the GPCC Full Data Reanalysis Version 7.0. This number increased to about 49,470 by July 1970 but subsequently decreased to around 30,000 in 2005 and further down to roughly 10,000 by 2012. The decline in ground-based observations affects all climatic data, not just precipitation measurements.

Several factors contribute to this reduction, including the rising costs associated with operating these stations and maintaining personnel (Strangeways, 2006). Additionally, restrictions on data release from national meteorological agencies (NMAs), site abandonment, migration, and economic or political considerations have further compounded the issue. Traditionally, precipitation measurement has relied heavily on ground-based gauges, which offer localized temporal precision but fail to accurately represent spatial variability due to their uneven distribution. This is particularly problematic in emerging nations where such instruments are often unavailable (Xie & Xiong, 2011). The gauge-based global rainfall products are summarized in Table 1.

2.2 *Satellite Estimates*

Satellites are essential for providing real-time data on precipitation-producing clouds using technologies such as infrared sensors, precipitation radar, and passive microwave radiometers. These tools enhance global observation and analysis of rainfall patterns (Sun et al., 2018). The sensors can be divided into three groups: passive MW (PMW), active MW, and visible/IR (VIS/IR) sensors on geostationary (GEO) and low-earth orbit (LEO) satellites (Michaelides et al., 2009; Prigent, 2010).

The Visible/Infrared (VIS/IR) approach in meteorology examines the relationship between cold, bright cloud tops and convection processes. In this method, colder cloud tops are indicative of substantial vertical development within clouds, which is often associated with more intense rainfall events. A primary advantage of VIS/IR satellite observations lies in their extensive coverage capabilities, especially over tropical regions where ground-based data may be sparse. Additionally, these satellites offer high temporal resolution, enabling frequent and timely updates on weather conditions.

Table 1

Gauge-based Rainfall Products

Data Set	Resolution	Frequency	Period	References
CRU	0.5° × 0.5°	Monthly	1901–2015	(Harris et al., 2014) (New et al., 2001)
GHCN-M	5° × 5°	Monthly	1900–present	(Peterson & Vose, 1997)
GHCN-M	0.5° × 0.5°, 1.0° × 1.0°, 2.5° × 2.5°	Monthly	1901–2013	(Schneider et al., 2013)
GPCC	0.5° × 0.5°, 1.0° × 1.0°, 2.5° × 2.5°	Daily	1988–2013	(Schamm et al., 2014)
GPCC-daily	1.0° × 1.0°,	Monthly	1948–2012	(Chen et al., 2002)
PREC	0.5° × 0.5°, 1.0° × 1.0°, 2.5° × 2.5°	Monthly	1948–present	(Willmott & Matsuura, 1995)
CPC-Global	0.5° × 0.5°	Daily	1979–2005	(Xie et al., 2007)

The Precipitation Measuring Microwave (PMW) techniques offer a direct method for measuring precipitation by being sensitive to the size of precipitation particles, thus providing more accurate estimates than other methods. One significant advantage is their ability to penetrate cloud cover, unlike Visible/Infrared (VIS/IR) observations, which allows for improved global monitoring and quantification of precipitation (Hollinger et al., 1987). The launch of the Tropical Rainfall Measuring Mission (TRMM), including the PMW TRMM Microwave Imager in 1997, marked a significant advancement in tropical precipitation analysis (Kummerow et al., 1998). Various strategies, such as probabilistic, physical, and iterative algorithms, have been developed to estimate rainfall effectively (Petty, 1994; Bauer et al., 2001; Pierdicca et al., 1996; Wentz & Spencer, 1998), with the Goddard PROFiling scheme being a widely used method for assessing instantaneous rainfall and its vertical structure (Kummerow et al., 2001).

While PMW-based methods can accurately estimate instantaneous rainfall, they are currently limited to Low Earth Orbit (LEO) satellites, resulting in relatively poor temporal sampling compared to Geostationary (GEO) satellite IR instruments that provide rapid updates every 30 minutes or less (Hong et al., 2012). LEO satellites with PMW sensors offer near-complete global coverage approximately every three hours. The Climate Prediction Center Morphing (CMORPH) method leverages motion vectors from GEO satellite Infrared imagery, sampled at 30-minute intervals, to enhance precipitation estimates derived from Passive Microwave data (Joyce et al., 2004).

The introduction of the first spaceborne precipitation radar with TRMM in 1997 enabled Active Microwave observations for precipitation estimation (Kummerow et al., 2000). The Global Precipitation Measurement (GPM) project was established to further advance rainfall and snowfall observations, providing updated space-based measurements that led to improved global precipitation products. These advancements resulted from more precise instantaneous precipitation estimates and unified retrieval approaches using a constellation of MW radiometers (Hou et al., 2014). By combining motion-based methods like CMORPH with advanced MW radiometers in initiatives such as GPM has significantly enhanced the understanding of global precipitation patterns.

The Climate Prediction Center Morphing (CMORPH) method integrates data from Passive Microwave (PMW) sensors and Visible/Infrared (IR) satellites to produce high-quality precipitation estimates. When updated PMW data are unavailable, CMORPH relies on IR data to propagate existing MW-derived precipitation features, running analyses every 30 minutes with an 8 km grid resolution. A critical aspect of this method is its time-weighted linear interpolation between successive PMW sensor scans, which ensures temporally and spatially complete precipitation estimates by modifying the shape and intensity of precipitation characteristics. This approach provides a continuous and coherent representation of precipitation patterns, maintaining consistent data quality even when direct MW observations are missing. By leveraging both PMW and IR technologies, CMORPH effectively enhances the monitoring and prediction of rainfall events across different temporal and spatial scales.

The Global PERSIANN Cloud Classification System (PERSIANN-CCS) is designed to determine detailed rainfall distribution by leveraging infrared (IR) brightness temperature data from geostationary Earth orbit (GEO) satellites and passive microwave (PMW) measurements from low Earth orbit (LEO) satellites. This method extracts informative features to perform variable-threshold cloud segmentation, grouping cloud patches based on similarity in selected features. Rainfall mapping is then conducted for each detected cloud cluster using histogram matching and exponential regression techniques. By fitting curves to plots of pixel brightness temperature against rainfall rate, PERSIANN-CCS achieves more precise rainfall distribution estimates (Hong et al., 2007). Extending the data period from 1983 to the present, the PERSIANN Climate Data Record (PERSIANN-CDR) offers daily precipitation predictions at a finer resolution of 0.25° by applying the PERSIANN algorithm on GridSat-B1 IR satellite data. To enhance accuracy, an artificial neural network is trained using Stage IV hourly precipitation data from the National Centers for Environmental Prediction (NCEP). High-resolution PERSIANN estimates are further adjusted to reduce bias using Global Precipitation Climatology Project (GPCP) data with a resolution of 2.5° (Ashouri et al., 2015).

The Global Satellite Mapping of Precipitation (GSMaP) project, supported by the Japan Science and Technology Agency from 2002 to 2007, aims to develop precise algorithms for microwave radiometers and produce high-resolution global precipitation maps. While rain gauges offer accurate and reliable precipitation data at specific locations, they face limitations over sparsely inhabited or marine areas and can be affected by sampling errors. In contrast, satellite-based estimates provide uniform spatial coverage but may contain random errors and biases due to the indirect relationship between satellite observations and precipitation and issues like insufficient sampling and algorithmic flaws. To leverage the strengths of different approaches, efforts have been made to merge various data sources for improved precipitation analysis with regularly gridded fields. One prominent example is the CPC Merged Analysis of Precipitation (CMAP), which combines data from multiple sources for a more comprehensive global precipitation representation (Xie & Arkin, 1997). Another key product is the GPCP Version 2, introduced in 2002 as an enhancement over its original version from 1997. It integrates Microwave (MW), Infrared (IR), and gauge data through successive fusion. After correcting satellite estimates for gauge bias, it merges these with rain gauge measurements over land using an inverse error variance algorithm (Adler et al., 2003). This product is widely used in climate research, hydrological modeling, and other precipitation-related fields. Despite differences in source data and merging techniques, there are only minor variances between GPCP and CMAP analyses (Yin et al., 2004).

The TRMM 3B43 monthly fields are generated by integrating multi-satellite and gauge analyses using inverse random-error variance weighting. This process involves scaling each 3-hourly combined Passive Microwave-Infrared (PWM-IR) field to match the values of the 3B43 grid box, ensuring consistency between different data sources. The GPCP 1° daily precipitation analysis (GPCP 1dd), as noted by G. J. Huffman et al. (2001), is valuable for driving land-surface models, fulfilling initialization requirements in numerical models, addressing precipitation advance and retreat, and validating model forecasts.

The Multi-Source Weighted-Ensemble Precipitation (MSWEP) dataset is a significant advancement in global precipitation monitoring, offering high-resolution data with a 3-hourly temporal resolution and a spatial granularity of 0.25°. As described by Beck et al. (2017), MSWEP integrates inputs from rain gauges, satellite observations, and atmospheric model projections to provide the best available precipitation estimates in terms of timing and geography. This comprehensive approach leverages the strengths of diverse data sources: ground-based gauge measurements offer reliable validation points, satellites deliver extensive spatial coverage even over remote areas, and atmospheric models contribute temporal consistency by filling gaps when direct observations are unavailable. By combining these elements, MSWEP aims to overcome the limitations inherent in each individual source, producing more accurate and reliable precipitation estimates that are crucial for a wide range of applications, including climate research, hydrological modeling, and weather forecasting. However, careful consideration must be given to potential biases and limitations associated with each dataset. Table 2 illustrates a summary of discussed satellite precipitation products.

Table 2

Satellite-based Rainfall Products

Data Set	Resolution	Frequency	Period	Coverage	References
GPCP	2.5°	Monthly	1979–present	Global	(Adler et al., 2003)
GPCP 1dd	1.0°	Daily	1996–present	Global	(G. Huffman & Bolvin, 2013)
GPCP_PEN_v2.2	2.5°	5-daily	1979–2014	Global	(Xie et al., 2003b)
CMAP	2.5°	Monthly	1979–present	Global	(Xie et al., 2003b) (Xie & Arkin, 1997)
CPC-Global	0.5°	Daily	2006–present	Global	(Xie et al., 2007)
TRMM 3B43	0.25°	Monthly	1998–present	50°S–50°N	(G. J. Huffman et al., 2007)
TRMM 3B42	0.25°	3 h/Daily	1998–present	50°S–50°N	(G. J. Huffman et al., 2007)
GSMaP	0.1°	1 h/daily	2002–2012	60°S–60°N	(Ushio et al., 2009)
PERSIANN-CCS	0.04°	30 min/3, 6 h	2003–present	60°S–60°N	(Sorooshian et al., 2000)
PERSIANN-CDR	0.25°	3,6 h/Daily	1983–present	60°S–60°N	(Ashouri et al., 2015)
CMORPH	0.25°/8 km	30 min/3 h/Daily	2002–present	60°S–60°N	(Joyce et al., 2004)
GPM	0.1°	30 min/3 h/daily	2015–present	60°S–60°N	(Hou et al., 2014) (Skofronick-Jackson et al., 2018)
MSWEP	0.1°/0.5°	3 h/daily	1979–2017	Global	(Beck et al., 2017)

2.3 *Reanalysis*

Reanalysis systems provide a synthesized estimate of Earth's atmospheric state by integrating diverse observational data—such as satellite measurements, surface station records, and upper-air readings—with advanced numerical models that encapsulate various physical and dynamic processes. These systems create comprehensive and consistent datasets that merge historical observations with modern assimilation techniques and improved model capabilities, offering spatial homogeneity, temporal continuity, and a multidimensional hierarchy. The primary goal of reanalysis is to support climate research, enhance weather forecasting accuracy, and facilitate the study of long-term atmospheric trends and variability by producing climatic variables rooted in physically sound foundations, often available with minimal delay. However, it's important to note that precipitation forecasts generated by these systems are influenced by factors such as data input quality, model parameterizations, and complex interactions between models and observations, underscoring the need for continuous refinement and validation of reanalysis methodologies.

In this study, we focus on several global reanalysis systems, including the NCEP/NCAR reanalysis systems (NCEP1 and NCEP2), ERA-40 and ERA-Interim from the European Centre for Medium-Range Weather Forecasts (ECMWF), Japanese 55-year reanalysis (JRA-55), NCEP Climate Forecast System Reanalysis, Twenty-First Century Reanalysis System (20CRv2), and MERRA (Modern-Era Retrospective Analysis for Research and Application). Although NCEP2 was intended as an enhanced version of NCEP1 with corrections for human

Table 3

Reanalysis of Rainfall Global Products

Data Set	Resolution	Frequency	Period	Coverage	References
NCEP1	2.5° × 2.5°	Monthly/Daily/6 hourly	1948–present	Global	(Kalnay et al., 1996)
NCEP2	1.875°×1.875°	Monthly/6 hourly	1979–present	Global	(Kanamitsu et al., 2002)
ERA 40	2.5° × 2.5°/ 1.125°×1.125°	Monthly/6 hourly	1957–2002	Global	(Uppala et al., 2005)
ERA Interim	1.5° × 1.5°/ 0.75°×0.75°	Monthly/6 hourly	1979–present	Global	(Dee et al., 2011)
20CRv2	2.0° × 2.0°	Monthly/daily/6 hourly	1871–2012	Global	(Compo et al., 2011)
JRA-55	60 km	Monthly/3 hourly/6 hourly	1958–present	Global	(Ebita et al., 2011)
MERRA	0.5° × 0.67°	Daily	1979–present	Global	(Rienecker et al., 2011)
MERRA Land	0.5° × 0.67°	Monthly/Daily/1hourly	1980–present	Global	(Reichle et al., 2011)
CFSR	38 km	6 hourly	1979–2010	Global	(Saha et al., 2010)

errors while maintaining equivalent input data and vertical resolution (Kanamitsu et al., 2002), several assessments have found minimal differences in their performance. To address certain data assimilation challenges present in ERA-40, the ECMWF developed ERA-Interim. The ERA-40 dataset, covering 1958 to 2001, was known for overstating rainfall over tropical oceans; thus, ERA-Interim was created as an improved version with updated convective and boundary layer cloud methods that better represent atmospheric cloud processes (Dee et al., 2011). These improvements include adjustments in atmospheric comprehensive integrated ocean-land-atmosphere model, as described by Saha et al. (2010). This system, along with MERRA (Modern-Era Retrospective Analysis for Research and Applications), employs distinct data assimilation methodologies to produce their respective reanalysis datasets. Another notable dataset is the NOAA 20th Century Reanalysis (20CR), which provides a continuous record of various atmospheric variables spanning the entire 20th century, offering an extensive historical perspective on climate patterns.

Meanwhile, significant advancements have been made by the Japan Meteorological Agency in its reanalysis capabilities. Initially, they launched the Japanese 25-year reanalysis project, which subsequently evolved into the more comprehensive Japanese 55-year

stability and reduced precipitation estimates. More recent reanalysis efforts have resulted in datasets like 20CRv2, CFSR (Climate Forecast System Reanalysis), and MERRA, which feature higher spatial resolutions and more advanced numerical models and data assimilation techniques.

The Climate Forecast System Reanalysis (CFSR) assimilates and forecasts atmospheric conditions using numerical weather prediction techniques based on a

Reanalysis (JRA-55) in 2010, as detailed by Ebita et al. (2011). These efforts reflect ongoing improvements and refinements in global reanalysis systems aimed at enhancing our understanding of past climate conditions. Table 3 summarizes the discussed reanalysis rainfall products, providing a comparative overview of their characteristics and capabilities, although specific details from the table are not included here.

2.4 *Application of global rainfall products for flood inundation modeling*

In a comprehensive evaluation of satellite-derived precipitation datasets, Chen et al., (2020) identified GPM-IMERG as the most reliable on a global scale among its peers. Conversely, GSMaP displayed less favorable performance, characterized by higher BIAS values (>28%) and RMSE values (>1.39 mm hourly and >9.41 mm daily). Compared to the TRMM dataset, GPM-IMERG significantly reduces precipitation underestimation across most regions worldwide. However, while IMERG generally outperforms TMPA, it still encounters challenges in accurately capturing precipitation in areas with complex topography.

The ability of Satellite-Derived Precipitation Products (SPPs) to capture light precipitation events remains a significant limitation. Specifically, all SPPs exhibit deficiencies in these scenarios, with Root Mean Square Error (RMSE) values surpassing 2 mm for daily assessments and 0.5 mm for hourly evaluations. In terms of hydrological performance, GSMaP generally outperforms IMERG and CHIRPS, with the latter showing relatively poorer results (Masood et al., 2023). Tam et al., (2019) demonstrated that GSMaP-NRT could reliably generate a flood inundation model using the Rainfall-Runoff Inundation approach. However, for simulating discharge and flood extent more accurately, other SRPs such as PERSIANN-CCS, IMERG-E, and IMERG-L should be considered after applying necessary bias adjustments.

Uncertainty in flood modelling is influenced by several key factors: rainfall estimates, spatial resolution, and temporal resolution. Rainfall estimates are important because inaccuracies can lead to deviations in predicting flood extents; they depend on the quality and density of available meteorological data, which may vary across different regions. Spatial resolution pertains to the level of detail at which geographical features and land elevations are represented within a model. Higher resolutions provide more detailed representations, whereas lower resolutions may overlook critical topographical features that affect water flow. Temporal resolution involves the frequency with which data is updated or collected over time; finer temporal resolutions allow for capturing rapid changes in rainfall intensity and runoff dynamics, leading to more accurate flood predictions. Together, these factors contribute to the uncertainty inherent in flood inundation models, affecting their reliability and accuracy in forecasting flood scenarios.

To thoroughly assess rainfall uncertainty, it is recommended to incorporate ERA-5, CFSR, and MERRA-2 datasets alongside satellite products. These datasets collectively offer a more comprehensive perspective on precipitation patterns and uncertainties (McClean et al., 2023). MSWEP stands out for its favorable performance across various statistical metrics and spatio-temporal resolution, making it highly recommended for hydrometeorological applications. Given that product effectiveness can vary by region, further research is essential to evaluate both new and existing reanalysis and satellite-derived rainfall products for flood modeling across a broader range of climatic regions.

3. Conclusions

Reliable and accurate precipitation estimates are essential across various fields such as climate variability studies, water resource management, agriculture, weather forecasting, climate modeling, and hydrological assessments. Capturing the full spectrum of precipitation patterns presents challenges due to the variability in intensity, duration, and spatial extent of rainfall events. Addressing these challenges necessitates integrating diverse observational platforms like ground-based weather stations, satellites, radars, and other remote sensing instruments. Advanced data assimilation techniques and sophisticated numerical models are crucial for combining these varied data sources into reliable precipitation estimates. However, the declining availability of rain gauges could hinder our ability to monitor future changes in precipitation patterns effectively.

At a temporal scale, gauge-based precipitation products generally offer only monthly sampling, which limits their usefulness for real-time research or monitoring short-term extreme events such as floods. To produce gridded precipitation datasets that cover the Earth's terrain, gauge readings are spatially interpolated. While this approach provides broader coverage, it may smooth out extreme values and distort representations of short-term variations in precipitation. These limitations make it difficult to compare and integrate precipitation estimates from different sources, impacting the accuracy of climate and hydrological analyses.

Integrating various data sources, such as satellite observations, radar data, and gauge measurements, can enhance the accuracy and resolution of precipitation estimates. This integration facilitates better monitoring and understanding of weather patterns and climate variability. Satellite precipitation products like GSMaP, IMERG, CHIRPS, PERSIANN-CCS, MSWEP, along with reanalysis products ERA-5, CFSR, and MERRA-2, play significant roles in flood inundation mapping. The outcomes of studies leveraging these datasets can greatly benefit government agencies or departments responsible for issuing early flood warnings and predicting flood situations, particularly in regions where hydrometeorological stations are sparse and satellite images may not be readily accessible.

It is also suggested that relying solely on direct use of satellite-based precipitation products for flood modeling is inadequate. Instead, incorporating a bias correction step can significantly enhance the accuracy of these products. This approach will improve our understanding of how to effectively utilize satellite-based precipitation data even in areas with limited data availability, contributing to more accurate and timely flood forecasting efforts.

Conflict of Interests

The authors declare no conflict of interest related to this article.

Author statement (Disclaimer)

The contents and views expressed in this research paper/article are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

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