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The Quantitative Comparison of Grid Re-analysis Rainfall Products, Satellite Rainfall Products, and Hourly Rainfall Gauge Observation over Bali Province

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Abstract. Grid re-analysis and satellite-based rainfall products offers a means of estimating rainfall information at both regional and worldwide level. Numerous rainfall estimates are accessible, each varying in terms of the retrieval algorithm, sensor instrumentation, spatial-temporal resolution, and geographical coverage. The objective of this research was to assess the accuracy of grid re-analysis precipitation dataset (ERA-5) and the satellite-derived rainfall dataset (IMERG) when compared to hourly rain gauge observations in Bali Province during the period spanning 2017 to 2020. To assess grid-based datasets, conventional point-to-pixel comparison methods, along with statistical metrics in the forms of continuous, categorical, and volumetric measurements. The comparative findings illustrate that IMERG exhibits superior performance at sub-daily scales in accurately detecting volume, whereas ERA-5 demonstrates greater capability in identifying rainfall events. Both products display a tendency to overestimate the capture of low to moderate rainfall occurrences and for underestimating intense to exceptionally heavy rainfall occurrences. The IMERG product excels across various elevations.

1 INTRODUCTION

Rainfall, being an essential element of the hydrological cycle, exerts profound effects on water storage, human endeavors, industries, agriculture, the ecosystem, economic development, and the intricate climate system [1–3]. Historically, rainfall information has been primarily obtained through direct measurements at specific locations using rain gauge stations [4,5]. The scarcity of rain gauge stations, coupled with their uneven dispersion, is most pronounced in remote and mountainous terrains, as well as oceanic regions. Overcoming this limitation is pivotal to achieving effective spatial coverage [4,6,7]. A

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complementary alternative lies in ground radar, capable of furnishing localized rainfall data over a continuous temporal spectrum and with comprehensive spatial coverage. The radar calculates rainfall intensity by translating reflectivity values[4] .However, the precision of radar-based rainfall estimates remains subject to atmospheric conditions, distance range, and elevation, particularly in mountainous landscapes [8,9]. It's worth noting that both rain gauge stations and ground radar possess constraints pertaining to spatial coverage, especially in mountainous regions and over open waters [4].

Advancements in recent times have led to the emergence of gridded rainfall products (GRPs), which can be broadly categorized into three distinct groups delineated by variations in data sources and retrieval methodologies. These classifications encompass interpolated precipitation datasets generated from ground-based networks [10], precipitation datasets dependent on satellite technology obtained through visible/infrared/microwave precipitation estimations on a near-global scale [11], and reanalysis-derived precipitation datasets featuring predictive modeling and data assimilation processes. These processes establish connections between models and observations from diverse origins, including satellite and in-situ data sources [12].

Diverse research endeavors have showcased the efficacy of gridded rainfall datasets across global and regional scales [13,14], as well as temporal [15], seasonal [16], and climatological contexts [17]. These datasets have been assessed in intricate terrains [18,19] and varying levels of rainfall intensities [20,21]. Findings from earlier investigations have yielded disparate outcomes concerning the effectiveness of GRPs. To enhance their efficiency, endeavors are ongoing to incorporate diverse input data categories and refine estimation methodologies within algorithmic advancements, informed by these assessment outcomes. As a consequence, the appraisal of GRPs ' performance necessitates an ongoing alignment with algorithmic developments to ensure consistent enhancement.

Exploration into the performance evaluation of GRPs in the context of Bali remains exceedingly limited. GRP assessment within Bali's domain has been undertaken for a subset of products, including Tropical Rainfall Measuring Mission (TRMM), Climate Prediction Center Morphing Algorithm (CMOPRH), Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN), Integrated Merged MultisatellitE Retrievals for Global Precipitation Measurement/GPM (IMERG), Global Satellite Mapping of Precipitation (GSMaP), and Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) [15,17,22]. As far as we are aware, there are no existing studies that have conducted an evaluation of the performance of the IMERG and European Centre for Medium-Range Weather Forecasts Reanalysis v5 (ERA-5) products specifically for the geographical area of Bali.

By and large, the precipitation patterns experienced in Bali are influenced by the climate system of the maritime continent, coupled with localized dynamics arising from interactions between land and sea. Moreover, the intricate terrain of Bali, characterized by complex features, substantially contributes to the fluctuations in rainfall. This terrain-related aspect holds the potential to exert a noteworthy impact on the performance of GRPs [23]. Consequently, it becomes imperative to comprehensively evaluate the efficacy of GRPs across varying elevations before their application in diverse domains such as water resources management, climatology, flood monitoring, and landslide forecasting. This study's primary goal was to undertake a performance assessment of two specific rainfall products: the grid re-analysis rainfall product (ERA-5) and the satellite rainfall product (IMERG). This assessment was conducted by comparing their outcomes against the data collected from hourly rain gauge observations spanning the period from 2017 to 2020 in Bali Province.

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2 Methods

The study was conducted within the geographical boundaries of Bali Province, Indonesia, encompassing coordinates ranging from 8.06°S to 8.85°S in latitude and 114.43°E to 115.71°E in longitude [15]. The entire land square footage under investigation spanned 5636.66 km², as illustrated in Figure 1. Bali boasts a tropical climate, characterized by biannual shifts brought about by the alternating monsoon winds [24].

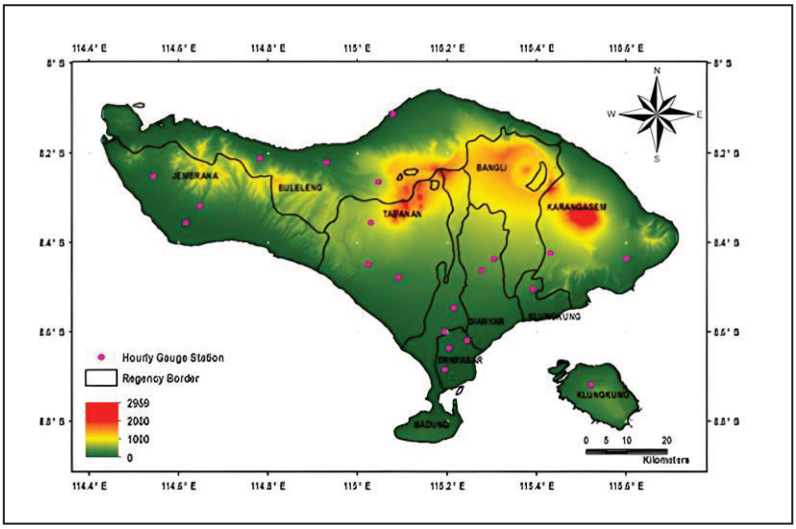

Fig. 1. A map of Bali Province is provided, indicating the positions of rain gauge stations (depicted as purple dots), along with the names of the regencies and corresponding elevations.

Hourly precipitation data spanning the timeframe from 2017 to 2020, sourced from Balai Wilayah Sungai Bali-Penida (BWS-BP), have been employed for the purpose of this study. The selected GRPs encompass IMERG and ERA-5, spanning the period of 2017 to 2020. The current investigation utilized the most recent thirty minutes and third level of IMERG dataset, retrieved through brand-06B of the early run product [25]. Notably, this data file is accessible found at https://gpm.nasa.gov/data. The ERA-5 product employed in this research is characterized by a geospatial acuity approximately 25 km x 25 km and a time clarity of an hour. It is accessible online: https://cds.climate.copernicus.eu/cdsapp#!/search?type=dataset.

To evaluate the suitability of gauge rainfall data for use with GRPs, we conducted a point-to-grid assessment, following the methodologies described in prior research [15,26,27]. The efficacy of the GRPs was evaluated across a spectrum of temporal scales, encompassing one hour, three hours, six hours, daytime, nighttime, and daily intervals. This evaluation was extended to include diverse elevations and varying rainfall intensities. For the evaluation process, we divided the hourly rainfall intensity into six separate categories: Less than 0.1 mm (indicating no rain), 0.1-1 mm (reflecting very minimal intensity), 1-5 mm (representing low intensity), 5-10 mm (indicating moderate intensity), 10-20 mm (corresponding to heavy intensity), and greater than 20 mm (signifying very heavy intensity). Furthermore, considering the distribution of rain gauge stations across different elevation levels, the performance of the GRPs was assessed with respect to terrain-induced effects. The elevation categorization employed for this assessment comprised two classes: > 1000 m (high elevation) and ≤1000 m (low elevation) [27].

The evaluation of differences between satellite estimations and real observations involved a variety of continuous statistical measures, such as deviation ratio (DR), mean square root deviation (MSRD), average error (AE), and correlation coefficient (C) [7,18,28], as frequently employed in previous studies. Additionally, categorical statistics were utilized to determine the satellite datasets' capability to differentiate rainfall events. Three metrics emerged: chances of detection (COD), ratio of incorrect alarms (RIA), and index of critical success (ICS) [28]. Furthermore, volumetric measures were established, including the volumetric success ratio (VSR), volumetric incorrect alarm ratio (VIAR), and index of volumetric critical success (IVCS) [15,27,29,30]. These indices were established to account for the volume of rainfall. Notably, a rainfall threshold (t) of 0.1 mm/hour was adopted to ascertain VSR, VIAR, and IVCS outcomes.

3 Result and Analysis

3.1 Performance Assessment on Various Time-Scales

The alignment between the GRPs and the gauge investigations is assessed using the correlation coefficient (C), as depicted in Figure 2a. Both GRPs exhibit a limited level of concordance with the rain gauge stations at hourly, 3-hourly, and 6-hourly intervals but demonstrate a moderate level of agreement on a daily scale. In general, IMERG exhibits significantly superior performance, boasting higher correlation coefficients across nearly all time scales when compared to ERA-5. Furthermore, IMERG outperforms ERA-5 products based on the mean square root deviation (MSRD) value, as depicted in Figure 2b. Both IMERG and ERA-5 products consistently underestimate rainfall when compared to rain gauge data, resulting in a deviation ratio (DR) of less than one and negative average error (AE) values. In the recent study, IMERG's superiority over ERA-5 products is affirmed through assessments involving C, MSRD, and AE values.

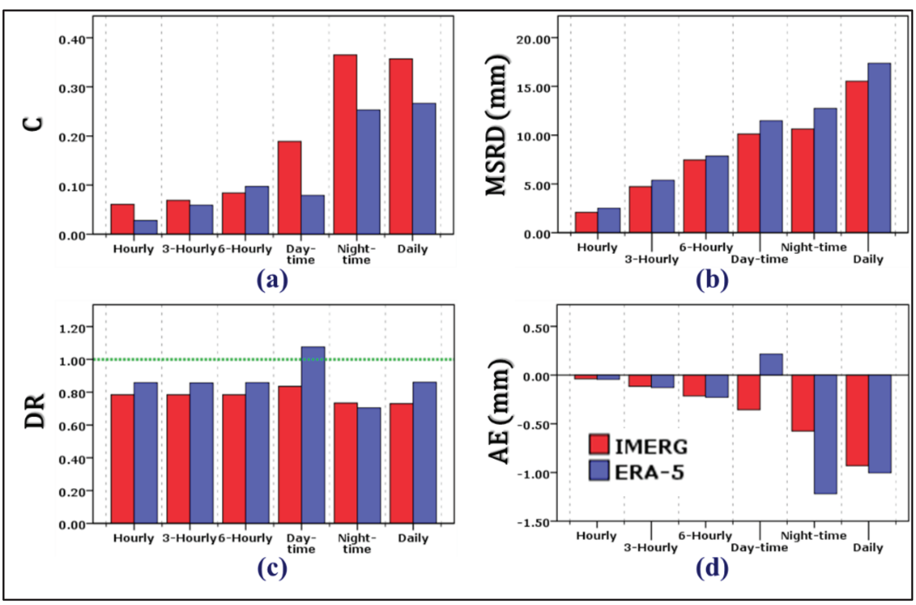

Fig. 2. Particular inferential statistical measurements across various temporal intervals encompass: (a) C, (b) MSRD, (c) DR, and (d) AE.

Contingency analysis typically employs the chances of detection (COD), ratio of incorrect alarms (RIA), and index of critical success (ICS) to quantitatively assess the achievement of GRPs. As depicted in Figures 3a, 3b, and 3c, overall contingency scores are presented for the detection of rainy events using a 0.1 mm/hour threshold to distinguish between rainy and non-rainy occurrences. Figures 3a, 3b and 3c reveal that ERA-5 exhibits superior achievement in expressions of COD (varying between 0.22 and 0.68) and ICS (ranging from 0.10 to 0.48), while IMERG outperforms ERA-5 in terms of FAR (ranging from 0.36 to 0.78). This performance distinction holds across various time scales, including one hour, three hours, six hours, daytime, nighttime, and one day. Notably, an ability of GRPs to detect rainfall events increases as the time scale increases. Statistical analysis supports the conclusion that satellite-derived products exhibit sufficient accuracy when compared to ground-based data in terms of accumulation [28]. The majority of classification metrics assessments indicate that ERA-5 exhibits superior performance in detecting rainfall occurrences when compared to IMERG products.

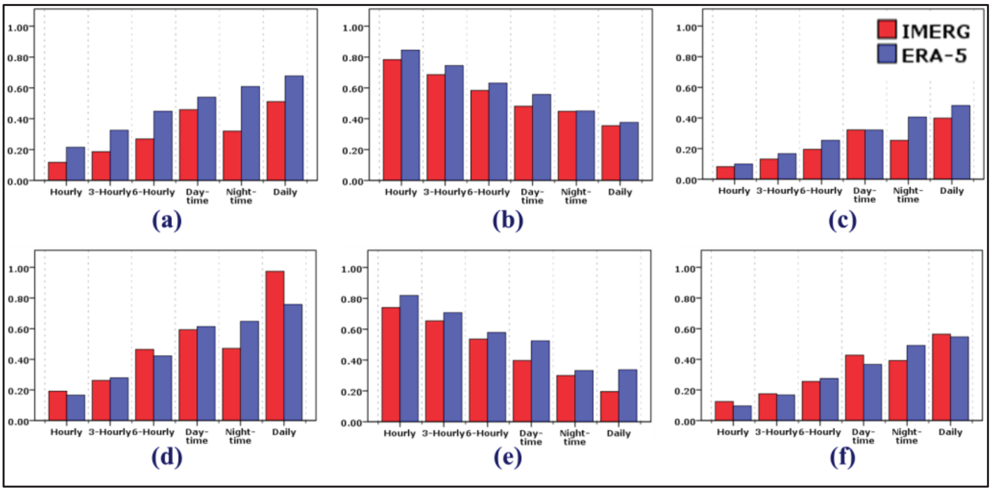

Fig. 3. The categorical performance metrics and volumetric indicators across various temporal intervals consist of: (a) COD, (b) RIA, (c) ICS, (d) VSR, (e) VIAR, and (f) IVCS.

Figures 3d, 3e, and 3f present the VSR, VIAR, and IVCS grades, respectively, for both the IMERG and ERA-5 products. The figures illustrate that both products exhibit their highest VSR and IVCS scores at the one day intensity, but their lowest grades at the one hour intensity. The IMERG product outperforms ERA-5 in terms of VSR, VIAR, and IVCS grades across one hour, three hours, six hours, and one day intensity. The IMERG product achieves VHI, VFAR, and VCSI scores ranging from 0.19 to 0.97, 0.2 to 0.74, and 0.12 to 0.56, respectively. This superiority can likely be attributed to IMERG's high temporal resolution, which enables it to more effectively capture regional variations in sub-daily precipitation frequency [15].

3.2 Performance Assessment on Rainfall Intensity

The probability distribution function (PDF) has been employed in numerous research studies to evaluate the effectiveness of GRPs [31]. The figure 4 illustrates PDF for our research area, where we calculated the PDF for hourly rainfall events spanning between January 2017 and December 2020. When contrasted with rain gauge data, all GRPs displayed a pattern of underestimating the presence of intense rainfall issues (10-20 mm/hour and >20 mm/hour), while overestimating the occurrence of light (1-5 mm/hour) and moderate (5-10 mm/hour) rainfall issues (refer to Figure 4b and 4c). The overestimation of IMERG in detecting light and moderate rainfall may be attributed to the inclusion of two more advanced instruments, namely the two frequency rainfall radar and microwave imager on the GPM were engineered to deliver more accurate momentary precipitation assessments, with a particular focus on light rainfall. [32]. Furthermore, as illustrated in Figure 4a, IMERG exhibited a tendency to overstate the occurrence of non-rain issues (>0.1 mm/hour), whereas ERA-5 tended to underestimate them. Moreover, ERA-5 datasets demonstrated a propensity to overstate the occurrence of extremely light rainfall issues (0.1-1 mm/hour), while IMERG had a tendency to provide lower estimates for these events.

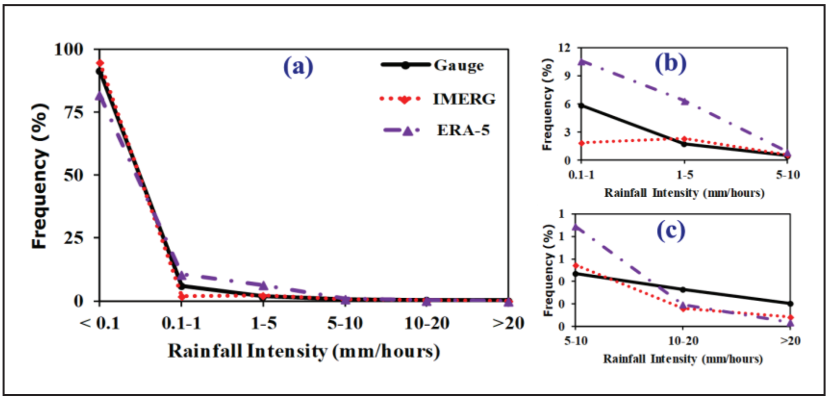

Fig. 4. The probability distribution functions (PDFs) for rainfall occurrences as observed by rain gauges are as follows: (a) for all levels of rainfall intensities, (b) for low to moderate intensities, and (c) for moderate to very heavy intensities.

3.3 Performance Assessment on Elevation

The terrain's impact may play a significant capacity in influencing the effectiveness of GRPs [23]. Figure 5 presents a performance chart that offers a preview of the statistics demonstrating the accuracy of the two GRPs in detecting intense rainfall issues in expressions of DR, ICS, RIA, and COD.

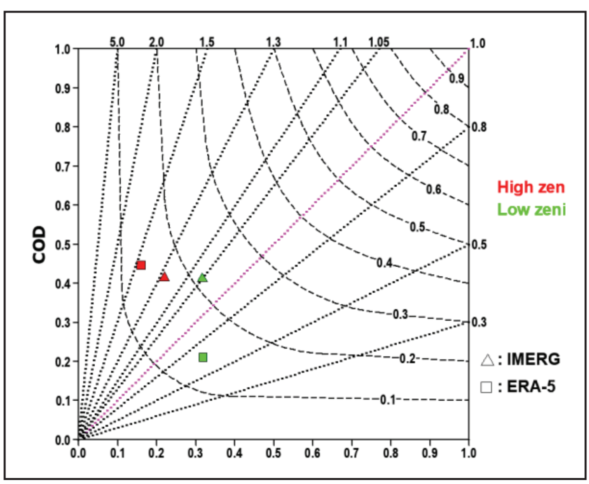

Fig. 5. The capability chart depicts the GRPs at different zenith, with unique colors assigned to each zenith (green indicating low zenith and red representing high zenith).

This graph effectively showcases the capabilities of the GRPs. This capability chart was initially introduced by Roebber to visually depict the relationship between various aspects of model performance [33]. Generally, the IMERG dataset performs well at various zenith. It tends to overestimate rainfall at most zenith, while ERA-5 underestimates rainfall at lower zenith. Conversely, ERA-5 tends to overestimate rainfall at higher zenith.

4 CONCLUSION

The results of this comparative analysis reveal that IMERG demonstrates superior performance when it comes to accurately estimating rainfall volume at sub-daily time scales. On the other hand, ERA-5 exhibits greater proficiency in identifying rainfall events. It's worth mentioning that both products have a tendency to provide higher estimates for the occurrence of light to moderate rainfall issues and lower estimates for intense to extremely heavy rainfall events. Additionally, IMERG performs exceptionally well across diverse elevations. Obtaining precise rainfall data through satellite-based estimates remains a daunting task, particularly in regions characterized by intricate topography, severe weather occurrences, and high susceptibility to natural disasters. To delve deeper into this subject, it is advisable to assess the performance of GRPs over an extended duration under varying environmental conditions, such as different land cover types, slopes, evapotranspiration rates, and soil moisture levels.

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