Objective Evaluation of Satellite Precipitation Datasets for Heavy Precipitation Events Caused by Typhoons in the Philippines

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Research article

Keywords: GSMaP, heavy precipitation, IMERG, PERSIANN, Philippines, typhoon

DOI: https://doi.org/10.21203/rs.3.rs-684518/v1

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Objective evaluation of satellite precipitation datasets for heavy precipitation events caused by typhoons in the Philippines

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Manuscript submitted to Progress in Earth and Planetary Science

3 July 2021

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Key Points/Highlights:

1. Satellite precipitation datasets during five typhoon-related heavy precipitation events in the Philippines were evaluated for the first time.

2. The 34-knot wind radii of the typhoons were used to select rain gauge measurements.

3. The satellite precipitation datasets were analyzed in terms of various rainfall intensities, the terrain, and wind velocity effects.

Running title: Satellite precipitation datasets for heavy precipitation events caused by typhoons in the Philippines
Abstract

Extreme weather events, such as typhoons, have occurred more frequently in the last few decades in the Philippines. The heavy precipitation caused by typhoons is difficult to measure with traditional instruments, such as rain gauges and ground-based radar, because these instruments have an uneven distribution in remote areas. Satellite precipitation datasets (SPDs) provide integrated spatial coverage of rainfall measurements, even for remote areas. This study performed subdaily (3-hour) assessments of SPDs (i.e., the Integrated Multi-satellitE Retrievals for Global Precipitation Measurement [IMERG], Global Satellite Mapping of Precipitation [GSMaP], and Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks datasets) during five typhoon-related heavy precipitation events in the Philippines between 2016 and 2018. The aforementioned assessments were performed through a point-to-grid comparison by using continuous and volumetric statistical validation indices for the 34-knot wind radii of the typhoons, rainfall intensity, the terrain, and wind velocity effects. The results revealed that the IMERG exhibited good agreement with rain gauge measurements and exhibited high performance in detecting rainfall during five typhoon events, whereas the GSMaP exhibited high agreement during peak rainfall. All the SPDs tended to overestimate rainfall during light to moderate rainfall events and underestimate rainfall during heavy
to extreme events. The IMERG exhibited a strong ability to detect moderate rainfall events (5–15 mm/3 hours), whereas the GSMaP exhibited superior performance in detecting heavy to extreme rainfall events (15–25, 25–50, and >50 mm/3 hours). The GSMaP exhibited the best performance for detecting heavy rainfall at high elevations, whereas the IMERG exhibited the best performance for rainfall detection at low elevations. The IMERG exhibited a strong ability to detect heavy rainfall under various wind speeds. A strong ability to detect heavy rainfall events for different wind speeds in the western and eastern parts of the mountainous region of Luzon were found for the GSMaP and IMERG, respectively. This study demonstrated that the IMERG and GSMaP datasets exhibit promising performance in detecting heavy precipitation caused by typhoon events.

**Keywords:**

GSMaP, heavy precipitation, IMERG, PERSIANN, Philippines, typhoon
1 Introduction

Heavy precipitation refers to a rainfall event that occurs in a certain area; exceeds a certain threshold; tends to be of short duration; can threaten human activity; and often causes natural disasters (such as floods and landslides) that result in social problems, environmental damage, and material losses (Bell et al. 2004; Hong et al. 2006; Wu et al. 2012; Stampoulis et al. 2013; Chen and Wu 2016). Heavy precipitation can be triggered by events such as tropical cyclones (typhoons) (Wang et al. 2016). Typhoons can cause heavy precipitation from the eye to the eyewall of the storm, a distance that can be tends to hundreds of kilometers across (Lonfat et al. 2007; Kimball 2008; Yokoyama and Takayabu 2008; Wang et al. 2009). Typhoons can also cause heavy rainfall in distant regions located thousands of kilometers from the center of a typhoon (Ross and Kurihara 1995; Wang et al. 2009; Chen and Wu 2016). The quantity of rainfall caused by typhoons is affected by several factors, such as the internal typhoon structure, track variations, large-scale moisture convergence, convection strength, cloud microphysics, typhoon interaction at midlatitude, and typhoon interaction with the topography (Jones et al. 2003; Wu et al. 2009; Zhang et al. 2010; Yang et al. 2011; Yu and Cheng 2013; Huang and Lin 2014; Chen and Wu 2016; Cheung et al. 2018; Hon, 2020). Because the diameters of typhoons range from 100 to 2000 km, monitoring the heavy rainfall caused by typhoons with conventional instruments is difficult (Huang
et al. 2019). Therefore, achieving an accurate quantitative estimation of heavy rainfall caused by typhoon events represents the largest challenge in hydrometeorological research and natural disaster modeling.

The analysis of heavy precipitation requires an accurate precipitation dataset with global coverage as well as high spatial and temporal resolutions (Setiawati et al. 2016; Liu et al. 2019; Liu et al. 2020a). Accurate rainfall data with high spatial and temporal resolution at regional and global scales are difficult to access in the fields of hydrology and weather forecasting. In situ measurements from rain gauge stations can supply reliable point-scale rainfall data (Duan et al. 2016). However, rain gauge stations are unevenly distributed, with few such stations being found in remote and mountainous areas, which limits the quantity of accurate spatial and temporal data that can be obtained for these areas (Javanmard et al. 2010; Ji et al. 2020). Weather radar can provide local precipitation data with sufficiently high spatial and temporal resolution. However, these data are affected by deviations from electromagnetic signals due to the effect of the terrain in mountainous areas (Li et al. 2013).

The rapid development of remote sensing techniques in the fields of hydrology and meteorology has resulted in the development of several satellite-based precipitation estimation methods with global coverage as well as high spatial and temporal resolution (Wu et al. 2019; Nashwan et al. 2020). Satellite precipitation datasets (SPDs) released
online to the public can overcome the problem caused by the unavailability of rain
gauge station and weather radar data. Rainfall estimation techniques using SPDs are
broadly based on the thermal infrared (TIR) radiation of geostationary satellites, the
passive microwave (PMW) radiations recorded by sensors in low Earth orbiting
satellites, or a combination of TIR and PMW radiations (Duan et al. 2016; Liu et al.
2019; Levizzani and Cattani 2019). These estimation techniques are not perfect in terms
of accurately predicting rainfall intensity. Therefore, calibration and validation are
necessary before SPDs can be used for hydrological modeling or meteorological
disaster observation. Global coverage can be achieved by several SPDs, such as the
Precipitation Estimation from Remotely Sensed Information Using Artificial Neural
Networks (PERSIANN; Hsu et al. 1997), the Climate Prediction Center Merged
Analysis of Precipitation (Xie and Arkin 1997), the Climate Prediction Center
Morphing Algorithm (CMORPH; Joyce et al. 2004), the Global Satellite Mapping of
Precipitation (GSMaP; Okamoto et al. 2005), the Integrated Multi-satellitE Retrievals
for Global Precipitation Measurement (IMERG; Hou et al. 2014), the Climate Hazards
Group InfraRed Precipitation with Station (CHIRPS; Funk et al. 2015), and the
Multisource Weighted-Ensemble Precipitation (Beck et al. 2017) datasets.

Revisions in the algorithms of SPDs had been made based on key studies which
improved the capability of SPDs in detecting heavy rainfall. Studies have evaluated the
performance of the Tropical Rainfall Measuring Mission (TRMM) 3B42 dataset during an extreme rainfall event (Pombo and de Oliveira 2015; Parida et al. 2017; Huang et al. 2018; Rashid et al. 2018; Liu et al. 2019; Palharini et al. 2020). Pombo and de Oliveira (2015) evaluated the performance of the TRMM 3B42 dataset in estimating the annual maximum daily rainfall in Angola. They discovered that the TRMM 3B42 dataset showed promise for the estimation of heavy precipitation events. The TRMM 3B42 dataset provided underestimated values compared with the rain gauge measurements. In a previous study, compared with rain gauge measurements for heavy precipitation events during June 2013 in the Western Himalayas, the TRMM 3B42 and CMORPH datasets underestimated the daily rainfall and peak rainfall intensity, whereas the GSMaP dataset both overestimated and underestimated rainfall values (Parida et al. 2017). The TRMM 3B42 dataset exhibited a promising ability to determine the monthly maximum 1-day precipitation, monthly maximum 2-day consecutive precipitation, monthly maximum 5-day consecutive precipitation, and total annual precipitation for wet days in China between 2009 and 2013 (Huang et al. 2018). For flooding caused by heavy rainfall from September 1 to September 7, 2014, in the Kashmir Valley in India, the TRMM 3B42 and GSMaP datasets underestimated rainfall, whereas the IMERG dataset demonstrated superior performance to that of the rain gauges in terms of daily estimation, with high correlation and Nash–Sutcliffe coefficients and the lowest bias
value (Rashid et al. 2018). TRMM 3B42 version 7 outperformed the PERSIANN and
CMORPH datasets in terms of accuracy of detecting monthly and annual heavy
precipitation events from 2009 to 2014 in the Wei River Basin in China (Liu et al. 2019).
The calibrated rain gauge of the TRMM, GSMaP, CMORPH, CHIRPS, and
PERSIANN datasets outperformed compare to the near-real-time of each datasets in
terms of estimating heavy rainfall in South America from 2012 to 2016 (Palharini et al.
2020). The accuracy of the CMORPH dataset was higher than that of the PERSIANN
dataset in terms of radar precipitation observations of heavy rainfall during seven major
flood events in regions of various terrains in northern Italy and southern France between
2003 and 2008 (Stampoulis et al. 2013). The GSMaP near-real-time dataset calibrated
by gauges outperformed the uncalibrated dataset in terms of estimating daily and
weekly heavy precipitation in East Asia and the Western Pacific from April 2000 to
March 2019 (Tashima et al. 2020). Studies have investigated the ability of SPDs to
measure heavy precipitation events on daily, monthly, seasonal, and annual scales.
Therefore, the ability of SPDs to measure heavy participation on a subdaily (3-hour)
scale must be investigated.

Several studies have compared the abilities of SPDs and rain gauges to measure
typhoon-related heavy precipitation events. Yu et al. (2009) performed 6-hourly and
daily evaluations of TRMM 3B42 version 6, the CMORPH dataset, and the
Geostationary Meteorological Satellite-5 infrared brightness temperature dataset in mainland China by using descriptive and categorical statistics. Chen et al. (2013) validated the TRMM, PERSIANN, and CMORPH datasets at various spatial and temporal resolutions for the extreme 2009 Typhoon Morakot in Taiwan by using descriptive and categorical statistics. Wang et al. (2016) evaluated the integrated rainfall data derived from the Climate Prediction Center morphing technique and gauge observations in terms of the estimation of heavy precipitation related to seven typhoon events by using rain gauge stations in areas within 400 km of the typhoon center. Huang et al. (2019) investigated the accuracy of the IMERG Early and Final Run datasets in terms of the probability distribution of precipitation rates, spatiotemporal variability, bias analysis, and contingency scores to detect heavy rainfall caused by six typhoons in the coastal area of the Pearl River Delta in southern China. Pham and Vu (2020) examined the horizontal and vertical precipitation structures of typhoons in the central coastal areas of Vietnam by using the TRMM and GSMaP datasets. Various studies that have compared the abilities of SPDs to detect heavy rainfall caused by landfalling typhoons have suggested performing a comparison in terms of rainfall distribution and spatiotemporal scale, analyzing rain gauges in areas within 400 km of the center of a typhoon in coastal regions, and using descriptive and categorical statistics to perform
an analysis. Therefore, the effects of terrain and wind velocity on the ability of SPDs to
detect heavy precipitation caused by typhoons must be investigated.

The Philippines is an archipelago with more than 7100 islands of complex
topography (Ramos et al. 2016; Bagtasa 2017). Two of its islands, namely Luzon in the
north and Mindanao in the south, have long chains of mountains, whereas the Visayas
region, which is located in the center of the country, consists of small islands (Ramos
et al. 2016; Bagtasa 2017). The Philippines frequently experiences typhoons that form
in the Northwestern Pacific Basin (Weinkle et al. 2012; Bagtasa, 2017). Every year,
approximately 19 typhoons cross the border of the Philippines, and half of these
typhoons make landfall (Cinco et al. 2016; Bagtasa 2017). Few studies have evaluated
the performance of SPDs for predicting precipitation in the Philippines. Jamandre and
Narisma (2013) investigated the error characteristics of the TRMM and CMORPH
datasets against the data of ground stations and the Asian Precipitation Highly-Resolved
Observational Data Integration Towards the Evaluation of Water Resources
(APHRODITE) gridded precipitation dataset from 2003 to 2005. Ramos et al. (2016)
evaluated the performance of the TRMM, CMORPH, GSMaP, and PERSIANN
datasets and compared their performance with that of measurements from 52 rain gauge
stations between 1998 and 2015. However, to the best of our knowledge, no study has
assessed the performance of SPDs during heavy precipitation events caused by
typhoons in the Philippines. Therefore, this study evaluated the performance of three SPDs, namely the IMERG, GSMaP, and PERSIANN datasets, during five typhoon-related heavy precipitation events in the Philippines between 2016 and 2018. The current study evaluated the performance of the aforementioned SPDs by comparing their data with those of ground rain gauges in terms of the 34-knot wind radius (R34) of a typhoon, rainfall intensity, and the effects of terrain and wind velocity. Section 2 describes the study area. Section 3 provides a detailed description of the dataset and methodology used in this study. Section 4 describes the performance of the three SPDs in terms of rainfall intensity, terrain, and wind velocity effects. Finally, Section 5 summarizes our findings.

2 Study Area

The study area was the Philippines, which is located between 4°40'N and 21°10'N and between 116°40'E and 126°34'E. This country has a total area of 300,055 km² (Figure 1a). The Philippines is located off the southeast coast of continental Asia across the South China Sea in the strategic zone between China, Taiwan, Borneo, and Indonesia. The Philippines is surrounded by the sea and is the only Southeast Asian country to not border neighboring countries (Bautista 2011). This country has a tropical maritime climate, and its seasonal changes are influenced by northeast and southwest
The Philippines experiences a cool dry season from December to February, a hot dry season from March to May, and a rainy season from June to November (The Philippine Atmospheric, Geophysical and Astronomical Services Administration [PAGASA]). Precipitation is the essential climatic factor of the Philippines. The distribution of precipitation in the country differs from one region to another and depends on the direction of moisture-bearing winds and the location of mountain systems (PAGASA). The mean annual precipitation of the Philippines ranges between 965 and 4064 mm per year (PAGASA). Precipitation in many areas of the Philippines is also influenced by typhoons (Ramos et al. 2016). Particular areas in the northern Philippines can receive approximately 50% to 60% of their annual precipitation from passing typhoons (Kubota and Wang 2009).

3 Datasets and Methods

3.1 Datasets

The multisource datasets used in this study can be categorized into four types: typhoon event data; traditional observational rainfall data obtained from surface rain gauges; precipitation information estimated from satellite measurements; and wind vector data, which constitute a reanalysis dataset. The following subsections provide a brief description of these four types of data.
3.1.1 Typhoon Events

Table 1 presents brief descriptions of five typhoon events that passed over the Philippines. The information regarding the typhoons was provided by the International Best Track Archive for Climate Stewardship (IBTrACS). IBTrACS maintains an archive of the typhoon best track data for specific locations to add to the knowledge on the distribution, frequency, and intensity of typhoons worldwide. The World Meteorological Organization Tropical Cyclone Programme has endorsed IBTrACS as an official recording and distribution resource for typhoon best track data (Knapp et al. 2010). The typhoon best track data contain 3-hour and long-term typhoon positioning records (from 1980 to the present). The typhoon track data are available online at [https://climatedataguide.ucar.edu/climate-data/ibtracs-tropical-cyclone-best-track-data](https://climatedataguide.ucar.edu/climate-data/ibtracs-tropical-cyclone-best-track-data).

The five typhoons analyzed in this study passed over Luzon island. Typhoons Mangkhut and Haima passed through the north, Typhoon Sarika passed through the middle, and typhoons Nock-ten and Doksoni passed through the south of the Luzon island. The five typhoons were classified into various categories according to PAGASA’s tropical cyclone intensity scale, namely typhoons (Mangkhut, Sarika, Haima, and Nock-ten), and tropical storms (Doksoni).
3.1.2 Data from Rain Gauge Measurements

The data from rain gauge measurements were used as a reference to evaluate the performance of the SPDs. Three-hour rainfall observation data for typhoons making landfall in the Philippines were obtained from PAGASA, the Department of Science and Technology, the Republic of the Philippines. PAGASA provides rainfall data from 222 automatic weather stations distributed across the Philippines. A total of 66 rain gauge stations were selected on the basis of whether the spatial distribution was affected by the R34 values of the typhoons and the completeness of the desired data. Table 1 lists the number of selected rain gauge stations within the R34 during the passing of the storm. PAGASA has made available high-quality rain gauge data for the five considered typhoon events.

3.1.3 IMERG Dataset

The high-resolution IMERG dataset is an improvement on the TRMM Multisatellite Precipitation Analysis dataset, whose global coverage data were made available from June 2000. The IMERG program was initiated by the National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA). Its algorithm intercalibrates, merges, and interpolates all available satellite microwave precipitation measurements, microwave-calibrated infrared measurements, surface rain gauge analyses, and other possible rainfall estimates on
The IMERG dataset provides half-hourly, daily, and monthly rainfall estimation at a spatial resolution of 0.1°. The IMERG dataset contains three types of data in terms of time release, namely early-, late-, and final-run data. The time-release delay is 4 hours for the early-run data, 12 hours for the late-run data, and 3.5 months for the final-run data (Huffman et al. 2019). This study used the latest Level-3 IMERG half-hourly data from version 06B of the final-run dataset. The final-run dataset exhibits superior performance to that of the early- and late-run datasets. The final-run dataset is also more appropriate for use in climate and hydrological studies than the other two datasets are (Tang et al. 2016). The IMERG dataset is available online at https://gpm.nasa.gov/data/directory.

3.1.4 GSMaP Dataset

The GSMaP dataset is a satellite-based precipitation dataset constructed by the Core Research for Evoloutional Science and Technology program under the authority of the Japan Science and Technology Agency between 2002 and 2007, and the aforementioned program was extended by the JAXA (Ushio et al. 2009; Liu et al. 2020a). The GSMaP algorithm merges information from various passive microwave sensors of low Earth orbit satellites and infrared sensors on geostationary satellites to create a high-precision precipitation dataset (Kubota et al. 2007). The GSMaP dataset is available in near-real-time, post-real-time, and reanalysis versions.
time versions consists of two datasets: the GSMaP Near Real Time (GSMaP_NRT) and
GSMaP Gauge Near Real Time (GSMaP_Gauge_NRT) datasets. The post-real-time
versions are the GSMaP Moving Vector with Kalman filter (GSMaP_MVK) and
GSMaP_Gauge datasets. Finally, the reanalysis versions are the GSMaP_NRT and
GSMaP_Gauge_NRT datasets. This study used the GSMaP_MVK version 7 dataset,
which has a temporal resolution of 1 hour, spatial resolution of 0.1° × 0.1°, worldwide
coverage (60°N to 60°S), and contains data from 2014 to the present. A previous
assessment of daily rainfall by using 52 rain gauges in the Philippines from 1998 to
2015 revealed that the GSMaP_MVK dataset had a lower level of bias than the TRMM
and CMORPH datasets did (Ramos et al. 2016). The hourly GSMaP_MVK version 7
dataset can be downloaded from the website of the JAXA
(ftp://rainmap:Niskur+1404@hokusai.eorc.jaxa.jp/standard/v7/hourly/).

3.1.5 PERSIANN Dataset

The PERSIANN dataset was established by the Center for Hydrometeorology and
Remote Sensing at the University of California, Irvine, in association with NASA and
the Global Network on Water and Development Information for Arid Lands of the
United Nations Educational, Scientific and Cultural Organization. The PERSIANN
retrieval algorithm is primarily based on integrated infrared imagery from
geosynchronous satellites, with forecasts generated by an artificial neural network to
transform infrared imagery into global rainfall data (Sorooshian et al. 2000). PERSIANN includes four precipitation datasets, namely the PERSIANN, the PERSIANN-Cloud Classification System (PERSIANN-CCS), the PERSIANN-Climate Data Record (PERSIANN-CDR), and PERSIANN Dynamic Infrared Rain Rate near-real-time (PDIR-Now) datasets. PERSIANN contains hourly rainfall estimates from March 2000 to the present with a spatial resolution of 0.25° and global coverage (60°N–60°S). PERSIANN-CCS contains hourly rainfall data from January 2003 to the present with worldwide coverage and a spatial resolution of 0.04°. PERSIANN-CDR contains daily global rainfall data from January 1983 to the present at a spatial resolution of 0.25°. PDIR-Now contains real-time global precipitation estimates from March 2000 to the present at a spatial resolution of 0.04°. All the PERSIANN datasets are accessible and have been widely used for various studies by researchers and professionals in the fields of climate, hydrology, water resource management, and disaster modeling. This study used the PERSIANN-CCS precipitation dataset, which is available online at https://chrsdata.eng.uci.edu/. The spatial resolution of PERSIANN-CCS is higher than that of all the other aforementioned SPDs; thus, the PERSIANN-CCS dataset can be used to examine variations in rainfall in small areas (Rivera et al. 2018).
3.1.6 Wind Data

The wind data used in this study was ERA5, which is a grid reanalysis dataset obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 contains the latest ECMWF atmosphere, land surface, and ocean reanalysis data for global climate monitoring (Hersbach et al. 2020). Through reanalysis, model data containing observations from around the world can be integrated into a complete and worldwide consistent dataset (Olauson, 2018; Ramon et al. 2019; Hersbach et al. 2020). ERA5 is frequently used in various applications and outperforms previous reanalysis methods. It provides long-term (1979 to present) hourly estimates of variables on pressure levels at a spatial resolution of 0.25°. This study used the components $u$ and $v$ of the wind dataset at a pressure level of 925–850 hPa. The aforementioned dataset can be downloaded from https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels?tab=form.

3.2 Methods

A point-to-grid comparison was performed to compare the point-based rain gauge measurement data with the grid satellite precipitation dataset and grid reanalysis wind data (Fenta et al. 2018; Liu et al. 2020a). The performance of the SPDs was assessed in terms of the 3-hour temporal scale, rainfall intensity, the terrain, and wind velocity.
effect by comparing the precipitation estimates with the rain gauge measurements. The comparison between SPDs estimates and rain gauge measurements was carried out when the rain gauge is within R34 during the passing of the storm. The half-hourly IMERG estimation and hourly GSMaP and PERSIANN estimation data were converted into 3-hour rainfall data so that their temporal resolution matched that of the rain gauge measurements. Only a few data points were missing from both the rain gauge stations and SPDs, and they were excluded from the analysis. The 3-hour rainfall estimates obtained by the SPDs were assessed as functions of rainfall intensity. The 3-hour rainfall intensities for all precipitation datasets were categorized into the following five groups: 0–5 mm/3 hours (light rain events), 5–15 mm/3 hours (moderate rain events), 15–25 mm/3 hours (heavy rain events), 25–50 mm/3 hours (very heavy rain events), and >50 mm/3 hours (extreme rain events). The performance of the SPDs in terms of the terrain effect was evaluated by dividing the rain gauge stations into two elevation categories: ≤1000 m (low altitude) and >1000 m (high altitude). The evaluation of the SPD performance in terms of wind velocity was conducted by dividing wind speed into the following five categories: 0–5, 5–10, 10–15, 15–20, 20–25, and ≥25 m/s. The distribution of the SPD performance in terms of wind direction was modeled as a wind rose, in which wind direction was divided into eight categories: north (N), northeast
(NE), east (E), southeast (SE), south (S), southwest (SW), west (W), and northwest (NW).

The performance of the SPDs was evaluated by conducting a quantitative analysis of two categories of validation statistics. The first statistical category was continuous statistics, which describe the differences between satellite rainfall magnitude and ground rainfall station measurements and include bias ratio (BR), correlation coefficient ($R$), mean error (ME), and root mean square error (RMSE). BR refers to the tendency of SPDs to underestimate or overestimate rainfall compared with the rain gauge station measurements. The perfect score for BR is 1. A BR below 1 indicates that the satellite datasets tend to underestimate rainfall compared with the ground rainfall measurements, and a BR above 1 indicates that the satellite datasets tend to overestimate rainfall. The parameter $R$ measures the strength of the linear association between the satellite rainfall estimates and the ground-based observations. A value of 1 is the ideal score for $R$. ME indicates the average error in rainfall measurements between the SPDs and the ground-based observations. RMSE reflects the average deviation in absolute magnitude between the SPD data and the ground-based observations. The ideal value of ME and RSME is 0. RB, $R$, ME, and RMSE were computed using the following equations (Ebert 2007; Tang et al. 2016; Liu et al. 2020a):

$$BR = \frac{S_i}{G_i}$$
\[
R = \frac{\sum_{i=1}^{N} (S_i - \bar{S})(G_i - \bar{G})}{\sqrt{\sum_{i=1}^{N} (S_i - \bar{S})^2 \sum_{i=1}^{N} (G_i - \bar{G})^2}}
\]

(2)

\[
ME = \frac{1}{N} \sum_{i=1}^{N} (S_i \cdot G_i),
\]

(3)

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (S_i \cdot G_i)^2},
\]

(4)

where \( S_i \) represents a satellite rainfall estimate, \( G_i \) represents the corresponding ground-based rainfall measurement, \( \bar{S} \) indicates the average of the satellite rainfall estimates, \( \bar{G} \) represents the average of the ground-based rainfall measurements, \( N \) represents the total number of data points, and \( i \) represents the number of the sample.

The second statistical category was volumetric indices, which represent the ability of SPDs to detect an accurately/inaccurately amount of rainfall. This category includes volumetric hit index (VHI), volumetric false alarm ratio (VFAR), and volumetric critical success index (VCSI). VHI provides information regarding the volume of rainfall accurately detected by the SPDs relative to the volume of rainfall accurately detected by the satellites and the missing observations. VFAR represents the volume of false rainfall detected by the SPDs relative to the sum of rainfall detected by the SPDs. VCSI represents the overall measure of volumetric performance. VHI, VFAR, and VCSI range from 0 to 1, with the ideal score for VHI and VCSI being 1 and the ideal score for VFAR being 0. The equations for the volumetric indices are as follows (Aghakouchak and Mehran 2013; Ayehu et al. 2018; Liu et al. 2020a):
VHI = \frac{\sum_{i=1}^{N} (S_i | (S_i > t \& G_i > t))}{\sum_{i=1}^{N} (S_i | (S_i > t \& G_i > t)) + \sum_{i=1}^{N} (G_i | (S_i < t \& G_i > t))}, \tag{5}

VFAR = \frac{\sum_{i=1}^{N} (S_i | (S_i > t \& G_i \leq t))}{\sum_{i=1}^{N} (S_i | (S_i > t \& G_i > t)) + \sum_{i=1}^{N} (S_i | (S_i > t \& G_i \leq t))}, \tag{6}

VCSI = \frac{\sum_{i=1}^{N} (S_i | (S_i < t \& G_i > t))}{\sum_{i=1}^{N} (S_i | (S_i > t \& G_i > t)) + \sum_{i=1}^{N} (G_i | (S_i \leq t \& G_i > t)) + \sum_{i=1}^{N} (S_i | (S_i > t \& G_i \leq t))}, \tag{7}

where \( t \) represents the threshold value of 15 mm/3 hours.

4 Results and Discussion

The ability of the SPDs to estimate rainfall during heavy precipitation events caused by typhoons was evaluated in terms of rain rate intensity, elevation, and wind velocity by using continuous statistics (i.e., BR, \( R \), ME, and RMSE) and volumetric indices (i.e., VHI, VFAR, and VCSI). High \( R \), VHI, and VCSI values; low ME, RMSE, and VFAR values; and BR values close to 1 indicated a high performance level.

4.1 Performance of SPDs During Typhoon Events

The agreement between the rain gauge observations and the satellite rainfall datasets for each typhoon event was determined by using the scatter plots in Figure 2. In general, in all typhoon events, the satellite rainfall dataset exhibited strong agreement with the rain gauge observations at low rainfall rates, and this agreement decreased with increasing rainfall rates. According to the \( R \) values, the IMERG dataset exhibited
stronger agreement with the rain gauge observations (0.64–0.83) than did the GSMaP (0.39–0.63) and PERSIANN (0.38–0.73) datasets for almost all the typhoons (Sarika, Nock-ten, Doksur, and Mangkhut). However, the PERSIANN dataset exhibited a stronger agreement with the rain gauge observations \( R = 0.73 \) than did the other satellite rainfall datasets during Typhoon Haima. Huang et al. (2019) revealed that the \( R \) value for IMERG Final Run version 5 dataset was approximately 0.4–0.63 for six typhoon events in southern China. The current study confirmed that the latest version of the IMERG dataset exhibits increased agreement with the rain gauge observations for higher \( R \) values.

Table 2 presents a summary of the overall quantitative evaluation of the SPDs and rain gauge measurements during the five typhoon events. The statistic metric summary indicates that three satellite rainfall datasets exhibited different behaviors. This result might have been caused by the complex typhoon structures, different tracks of the typhoons, the structure of the atmosphere, the diverse topographic conditions, and heterogeneous rainfall conditions on the spatiotemporal scale (Huang et al. 2019). The GSMaP dataset substantially overestimated rainfall for all typhoon events compared with the rain gauge data, yielding positive ME (1.75–7.68 mm/3 hours) and BR values (1.22–1.73). ME and BR values greater than 1 were obtained for the aforementioned dataset. A previous study found that GSMaP overestimated the daily extreme
precipitation over the Western Himalayas (Parida et al. 2017). Both the IMERG and PERSIANN datasets underestimated rainfall compared with the rain gauge data, yielding negative ME and BR values for all typhoon events. The underestimation of the IMERG dataset in this study is in agreement with the findings of other studies that have applied this dataset to evaluate rainfall in southern China during typhoons Mawar, Pakhar, Hato, and Merbok on a cumulative scale (Huang et al. 2019). In this study, the IMERG dataset outperformed the GSMaP and PERSIANN datasets in terms of ME, BR, and RMSE for all typhoon events except the Dokuri typhoon, for which the ME and BR of the IMERG dataset were marginally higher than those of the PERSIANN dataset.

In terms of the ability of the SPDs to detect heavy precipitation events, the GSMaP dataset achieved the highest scores for VHI but the lowest scores for VFAR. The IMERG dataset achieved the highest scores for VFAR (Sarika, Haima, Dokuri, and Mangkhut) and VCSI (Sarika, Haima, Nock-ten, Dokuri, and Mangkhut). The PERSIANN dataset achieved the highest scores for VFAR during the Nock-ten typhoon. To demonstrate the performance of three SPDs more comprehensively, Figure 3 presents a performance diagram that displays an overview of the statistics that indicate how well the three SPDs detected heavy precipitation events caused by typhoons in terms of VHI, VFAR, VCSI, and BR. Such a performance diagram was proposed by
Roebber to create a visual framework of the association among multiple aspects of model performance (Roebber 2009). VHI is represented on the y-axis; success ratio (1 − VFAR) is represented on the x-axis; BR is represented by the dotted lines beginning at the origin, where the diagonal dotted line represents no bias; and VCSI is represented by the dashed contour lines. The best performance is in the top right corner of the diagram and along the diagonal dotted line, where BR is 1. The IMERG dataset achieved the best performance among the SPDs during typhoons Sarika, Haima, Nock-ten, Doksurī, and Mangkhut. This result can probably be attributed to the high temporal resolution of the IMERG dataset when determining the frequency of precipitation events, which allows this dataset to detect the regional variance in subdaily precipitation more effectively (Dezfuli et al. 2017; Liu et al. 2020a).

The temporal variation in rainfall is a critical factor in the assessment of extreme weather phenomena and the hydrological cycle (Liu et al. 2016a; Liu et al. 2016b; Huang et al. 2019). Heavy rainfall in a short period can cause natural disasters, such as floods and landslides. Figure 4 presents plots of the average 3-hour rainfall in the Philippines during the five typhoon events. The highest values for average 3-hour rainfall were different for each typhoon event probably due to the differences in atmospheric conditions and the complexity of the typhoon structure. In general, the patterns of temporal variations of precipitation found using the three SPDs were in good
agreement with that of rain gauge measurements. The GSMaP dataset exhibited superior agreement with the rainfall station observations during peak rainfall. The IMERG and PERSIANN datasets considerably underestimated rainfall during rainfall peaks in the typhoon events.

4.2 Performance of SPDs Under Different Rainfall Intensities

The BR values between the rain gauge station measurements and the data of the IMERG, GSMaP, and PERSIANN datasets for different rainfall rate intervals were derived. Figure 5 presents a boxplot of the BRs for the IMERG, GSMaP, and PERSIANN datasets during the five typhoon events under different rainfall intensities. The bottom and top of the boxplot represent the first and the third quartiles of the data, respectively. The line inside the boxplot represents the second quartile and median. The maximum and minimum values of the data are represented by the lines at the top and bottom of the whisker, respectively. Outliers are any line not within the whisker. The datasets tended to overestimate rainfall during light to moderate rain (0–5 and 5–15 mm/3 hours) and tended to underestimate rainfall during heavy to extreme rain (15–25, 25–50, and >50 mm/3 hours). This result is consistent with those of other studies, one of which confirmed that the IMERG and GSMaP datasets overestimate the frequency of light to moderate rainfall events (1–10 mm) and underestimate the frequency of extreme rainfall events (> 0 mm) (Liu et al. 2020a). Another study revealed that the
GSMaP and PERSIANN datasets underestimate the frequency of extreme rainfall (75–100 mm/day) (Palharini et al. 2020). Fang et al. (2019) discovered that the IMERG dataset underestimates extreme precipitation. The underestimation of the SPDs during heavy to extreme rainfall might be caused by the interpolation process of classifying heavy rainfall (Fang et al. 2019). The IMERG dataset exhibited a satisfactory ability to detect moderate rainfall events (5–15 mm/3 hours), whereas the GSMaP dataset exhibited superior performance to the other two datasets in detecting heavy to extreme rainfall (15–25, 25–50, and >50 mm/3 hours) during the five typhoon events in the Philippines.

The performance of the SPDs was also assessed at various rainfall thresholds: 5, 15, 25, and 50 mm/3 hours. Figure 6 presents the performance diagram for the IMERG, GSMaP, and PERSIANN datasets in terms of the volumetric indices (VHI, VCSI, and BR) for 3-hour precipitation under various rainfall thresholds. The ability of these three SPDs to detect precipitation decreased with an increase in rainfall. VHI and VCSI decreased and VFAR increased with increasing rainfall intensity. These results indicated that the satellite sensors performed poorly in terms of detecting precipitation in extreme rainfall events (Sun et al. 2016; Huang et al. 2019). The IMERG dataset exhibited a stronger rainfall detection ability than did the other two datasets when the rainfall was 5, 15, and 25 mm/3 hours. However, the GSMaP dataset exhibited the
The strongest ability to detect rainfall when the rainfall was 50 mm/3 hours. The PERSIANN dataset exhibited the weakest ability to detect rainfall at all rainfall rates. Research demonstrated that the PERSIANN dataset did not perform well in the detection of daily moderate rainfall events (10 mm) and daily heavy rainfall events (25 mm) in the Wei River Basin in China (Liu et al. 2019). The poor performance of PERSIANN dataset may due to the fact that the precipitation estimation algorithm of PERSIANN is not calibrated with the rain gauge observations. The IMERG dataset is calibrated using the monthly rainfall dataset from the Deutscher Wetterdienst Global Precipitation Climatology Centre (Nguyen et al. 2018; Huffman et al. 2019).

4.3 Performance of the SPDs at Different Elevations

The variation in rainfall in the island area is caused by orographic uplift and the complexity of topography (Lee et al. 2014). Topography has a prominent effect on precipitation (Chen et al. 2020). The altitudes of the rain gauge stations used in this study were divided into two categories: ≤1000 m (low altitude) and >1000 m (high altitude). Table 3 presents an assessment of statistical metrics for the IMERG, GSMaP, and PERSIANN datasets for 3-hour precipitation estimates at different elevations. According to the BR and ME values, the SPDs tended to overestimate rainfall at low elevation and underestimate rainfall at high elevations. The IMERG dataset had the highest $R$ and lowest RMSE values at both high and low altitudes. The IMERG dataset
exhibited superior performance at low altitudes because it had the best scores in the continuous statistical analysis (BR, R, ME, and RMSE). The BR of the GSMaP dataset was 0.96 at high altitudes, which indicates that this dataset had 4% bias compared with the rain gauge measurements. The high BR of the GSMaP dataset at high elevations was possibly caused by the inclusion of a topographic dataset from the Shuttle Radar Topography Mission 30 Arc Second to classify orographic and nonorographic rainfall (Yamamoto and Shige 2015).

Satellite rainfall estimates performed better in detecting heavy precipitation at high altitudes than at low altitudes. This result might have been caused by orographic uplift (Tang et al. 2018). In terms of the ability of SPDs to detect heavy rainfall at different elevations, the PERSIANN dataset exhibited the lowest VHI and VCSI values at low altitudes, whereas the GSMaP dataset exhibited the worse VFAR values at low elevations (Table 3). The GSMaP dataset exhibited the highest VHI at both altitudes; the IMERG dataset exhibited the best VFAR values at low altitudes; and the PERSIANN dataset had a perfect VFAR value at high altitudes. The performance diagram summarizes the three SPDs’ ability to detect heavy rainfall accurately at different altitudes (Figure 7). The GSMaP dataset outperformed the other datasets in terms of the ability to detect heavy rainfall at high elevations, whereas the IMERG dataset outperformed the other datasets at low elevations. The PERSIANN dataset
performed poorly at both elevations probably because its rainfall estimation algorithm does not contain a terrain component (Nguyen et al. 2018).

4.4 Performance of the SPDs Under Different Wind Velocities

The levels of infrastructural and environmental damage caused by typhoon events are influenced by wind intensity. High wind intensity is also associated with heavy rainfall, which is another hazard of typhoon events (Bloemendaal et al. 2020). In a previous study, the rainfall caused by typhoon events was forecasted using satellite estimates of rainfall data, typhoon intensity, and wind vectors (Kidder et al. 2005). The effect of wind velocity on the ability of SPDs to detect heavy precipitation caused by typhoon events should be investigated. In this study, the averages of the wind vector components $u$ and $v$ from the ECMWF at a pressure level of 925–850 hPa, which is observed at the considered rain gauge stations, were processed into wind speed and direction, respectively. The frequency distribution indicates the relationship between wind speed and the continuous performance statistics (Figure 8). The IMERG and PERSIANN datasets underestimated rainfall compared with the gauge station measurements, yielding a high-frequency concentration of negative MEs ($\sim$$-20$–$0$ mm/3 hours) and a BR below 1 for the distribution of wind speed. The GSMaP dataset tended to overestimate rainfall, with a distribution of frequency concentrated on positive MEs ($0$–$20$ mm/3 hours) and a BR above 1. The IMERG dataset exhibited superior
agreement with the rain gauge observations at different wind speeds, with the distribution frequency of $R$ ranging from 0.4 to 1. For the PERSIANN and GSMaP datasets, the distribution frequency of $R$ ranged from 0.1 to 1 and from 0 to 0.9, respectively. The frequency distributions of RMSE at each wind speed for the IMERG and PERSIANN datasets ranged from 0 to 30 mm/3 hours, whereas those for the GSMaP dataset ranged from 0 to 40 mm/3 hours. Among the three SPDs, the IMERG dataset was the most consistent with the rain gauge measurements in terms of having the most continuous statistical parameters at the different wind speeds. The distribution frequencies of ME, RMSE, $R$, and BR for the IMERG dataset were concentrated around the near-perfect value for the continuous statistics.

The distribution percentage of each volumetric index presented in Figure 9 was used to describe the association between wind speed and the ability of the SPDs to detect heavy rainfall events caused by typhoons. In terms of the VHI distribution, the GSMaP dataset exhibited the best performance, followed by the IMERG and PERSIANN dataset. The GSMaP dataset yielded high frequency distribution for a VHI range of 0.9–1.0 in the wind speed range of 7.5–12.5 m/s. The IMERG dataset exhibited high frequency distribution for a VHI range of 0.9–1.0 in the wind speed range of 10–12.5 m/s, and the PERSIANN dataset exhibited high frequency distribution for a VHI range of 0.5–0.6 in the wind speed range of 7.5–10 m/s. In terms of false rainfall
estimates, the IMERG dataset outperformed the GSMaP and PERSIANN datasets. The IMERG dataset had a high-frequency distribution at a lower VFAR than did the other SPDs. The comprehensive evaluation of the volumetric index performance indicates that compared with the other SPDs, the IMERG dataset exhibited a stronger ability to detect heavy rainfall at various wind speeds.

Complex topography and mountainous regions with orographic convection and low-troposphere winds represent a challenge in rainfall estimation by satellites (Shige et al. 2013). Luzon, which is located in the northern part of the Philippines, has a complex and mountainous topography and often experiences typhoons. Therefore, the influence of wind in mountainous areas on the performance of satellite rainfall estimations must be studied. Wind direction and speed data were collected from a selected rainfall measurement station on Luzon island (Figure 1b) and analyzed in the form of wind roses. A wind rose is a graph that represents the distribution of wind speed and direction for an area over a certain period. Figure 10a presents a wind rose for the eastern part of the mountainous region, and Figure 10k presents a wind rose for the western part of the region. A total of 75% of the winds are in the NW direction in the eastern part of the mountainous region, and the most frequent wind speed interval is 10–15 m/s, which accounts for 50% of the wind speeds. In the eastern part of the mountainous region, wind speed is primarily in the intervals of 10–15, 0–5, 5–10, and
A total of 41% of the winds in the western part of the mountainous region are in the north direction, and the predominant wind speed is >25 m/s, which accounts for 23% of the wind speeds. In the western part of the mountainous region, wind speed is predominantly in the intervals of >25, 20–25, and 15–20 m/s. This finding indicates that wind speeds are higher in the western part of the mountainous region than in its eastern part.

Figure 10(b–j) depicts the distribution of volumetric statistical values for the different wind direction and wind speed ranges in the eastern part of the mountainous region of Luzon. Figure 10(l–t) illustrates the distribution of volumetric statistical values for the western part of the mountainous region. The IMERG dataset outperformed the other SPDs in detecting heavy rainfall events in the eastern part of the mountainous region, as indicated by the distributions of VHI, VFAR, and VCSI. Compared with the other SPDs, the IMERG dataset exhibited superior distributions of VHI, VFAR, and VCSI under almost all ranges of wind speed and wind direction. The GSMaP dataset yielded high VHI and VCSI values for most wind speed ranges and wind directions in the western part of the mountainous region. This result indicated that the GSMaP dataset exhibited a strong performance in detecting heavy rainfall events under high wind speeds. However, the VFAR values of the GSMaP dataset were higher than those of the other SPDs, which were approximately 0.5–1 for the western part of
the mountainous area. This result indicates that the GSMaP algorithm generates a large quantity of false rainfall data under high wind speeds. Among the three SPDs, the GSMaP and IMERG datasets demonstrated a stronger ability to detect heavy rainfall events in terms of the effect of wind velocity in the western and eastern parts of the mountainous region, respectively.

5. Conclusion

Assessing the performance of SPDs during heavy precipitation caused by typhoons is crucial for utilizing them and evaluating their algorithms. Studies have analyzed the ability of SPDs to detect heavy precipitation caused by typhoon events on daily, monthly, seasonal, annual, and cumulative scales. This study performed a subdaily (3-hour) assessment of the performance of three SPDs, namely the IMERG, GSMaP, and PERSIANN datasets, during five typhoon-related heavy precipitation events in the Philippines between 2016 and 2018. This assessment was performed through a point-to-pixel comparison by using continuous and volumetric statistical validation indices to assess the R34 values of the typhoons, rainfall intensity, the terrain, and wind velocity effects. This study yielded the following results:

1. The IMERG dataset exhibited good agreement with the rain gauge observations and performed considerably well in detecting rainfall during the
five typhoon events over the Philippines. The GSMaP dataset exhibited superior agreement with the rainfall station observations during peak rainfall.

2. The precipitation datasets tended to overestimate rainfall in light to moderate rainfall events and underestimate rainfall in heavy to extreme rainfall events. The IMERG dataset exhibited a strong ability to detect rainfall in moderate rainfall events (5–15 mm/3 hours), whereas the GSMaP dataset exhibited superior performance in detecting rainfall during heavy to extreme rain events (15–25, 25–50, and >50 mm/3 hours) during the five typhoon events in the Philippines.

3. The GSMaP dataset outperformed the other SPDs in terms of ability to detect heavy rainfall at high elevations, whereas the IMERG dataset outperformed the other SPDs in terms of ability to detect rainfall at low elevations.

4. Wind direction and wind speed influence the ability of SPDs to detect rainfall. The IMERG dataset exhibited a strong ability to detect heavy rainfall under various wind speeds. The GSMaP dataset exhibited a stronger ability to detect heavy rainfall events in terms of wind velocity in the western part of the mountainous region than in its eastern part. By contrast, the IMERG dataset exhibited better performance in the eastern part of the mountainous region than in its western part.
The accurate detection and estimation of heavy precipitation with SPDs remains a challenge in archipelagos with complex terrain or mountainous areas. In this study, the IMERG and GSMaP datasets demonstrated a promising ability to detect heavy precipitation caused by typhoon events. An in-depth investigation is required before the IMERG and GSMaP datasets are applied to tropical-cyclone-related studies. Developments in SPD algorithms are expected to focus on improving the detection of extreme rainfall and the use of hourly rain gauge observations for calibration. In the most recent study, the cloud microphysical and optical properties, such as cloud-top altitude, cloud optical thickness and effective cloud droplet radius could be retrieved accurately from the observation of geostationary satellite (e.g., Liu et al., 2020b), and all the cloud properties are associated with the precipitation as already known before. Additional studies might be including the analysis of cloud properties and other typhoon event samples to investigate the precipitation processes and quantify the source of error in SPDs.

Declarations

- Availability of data and materials: Please contact author for data requests.
- Funding: This work was supported by the Ministry of Science and Technology of Taiwan (grants MOST 109-2625-M-008-013, MOST 109-2111-M-008-025,
Competing interests: The authors declare that they have no competing interests.

Author’s Contributions: CYL conceived and designed this study. PA performed the data analysis and wrote the original draft. All the authors discussed the results and reviewed, edited, and commented on the manuscript. All the authors read and approved the final version of this manuscript for publication.

Acknowledgments: We credit the providers of the IMERG, GSMaP, and PERSIANN datasets. We also acknowledge PAGASA, Department of Science and Technology, Republic of the Philippines, for its support in obtaining gauge station rainfall data across the Philippines. PA was supported by the International Ph.D. Program in Environmental Science and Technology (University System of Taiwan) at National Central University, Taiwan. This work was supported by the Ministry of Science and Technology of Taiwan (grants MOST 109-2625-M-008-013, MOST 109-2111-M-008-025, MOST 110-2625-M-008-002, and MOST 110-2111-M-008-033) and Academia Sinica (grants AS-TP-107-M10-3 and AS-GC-110-01).
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### Table 1. Information regarding five typhoon events in the Philippines.

| Name of Typhoon | Start Time (UTC) | End time (UTC) | Duration (hours) | Maximum Wind Speed (knots) | Number of stations | Maximum Actual Rainfall Rate (mm/3 hours) | Maximum Cumulative Actual Rainfall (mm) |
|-----------------|------------------|----------------|------------------|-----------------------------|--------------------|------------------------------------------|----------------------------------------|
| Sarika          | 2016-10-14 15:00| 2016-10-16 12:00| 45               | 95                          | 31                 | 167.0                                    | 629.5                                  |
| Haima           | 2016-10-18 21:00| 2016-10-20 12:00| 39               | 115                         | 15                 | 247.0                                    | 836.5                                  |
| Nock-ten        | 2016-12-24 12:00| 2016-12-26 9:00 | 45               | 105                         | 16                 | 183.0                                    | 284.0                                  |
| Doksurri        | 2017-09-11 6:00 | 2017-09-12 15:00| 33               | 40                          | 21                 | 151.5                                    | 436.0                                  |
| Mangkhut        | 2018-09-13 18:00| 2018-09-15 21:00| 51               | 148                         | 40                 | 93.5                                     | 344.0                                  |
Table 2. Statistical metric summary of the Integrated Merged Multisatellite Retrievals for Global Precipitation Measurement (IMERG), Global Satellite Mapping of Precipitation (GSMaP), and Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN) datasets for the five typhoon events. Unit of the mean error (ME) and root mean square error (RMSE): mm/3 hours.

| Name of Typhoon | SPD    | BR   | R    | ME   | RMSE  | VHI  | VFAR | VCSI |
|-----------------|--------|------|------|------|-------|------|------|------|
| Sarika          | IMERG  | 0.95 | 0.72 | -2.06| 12.51 | 0.67 | 0.29 | 0.52 |
|                 | GSMaP  | 1.73 | 0.62 | 2.08 | 16.31 | 0.77 | 0.52 | 0.41 |
|                 | PERSIANN| 0.91 | 0.55 | -2.69| 14.89 | 0.48 | 0.48 | 0.33 |
| Haima           | IMERG  | 0.88 | 0.71 | -4.95| 21.35 | 0.59 | 0.34 | 0.46 |
|                 | GSMaP  | 1.22 | 0.63 | 5.49 | 27.07 | 0.68 | 0.44 | 0.45 |
|                 | PERSIANN| 0.81 | 0.73 | -7.99| 22.41 | 0.51 | 0.38 | 0.39 |
| Nock-ten        | IMERG  | 0.97 | 0.83 | -0.93| 15.65 | 0.70 | 0.28 | 0.55 |
|                 | GSMaP  | 1.35 | 0.56 | 2.91 | 24.23 | 0.69 | 0.48 | 0.42 |
|                 | PERSIANN| 0.73 | 0.68 | -4.02| 17.36 | 0.60 | 0.18 | 0.53 |
| Doksurui        | IMERG  | 0.89 | 0.64 | -3.60| 14.60 | 0.55 | 0.38 | 0.42 |
|                 | GSMaP  | 1.42 | 0.39 | 7.68 | 28.00 | 0.56 | 0.60 | 0.30 |
|                 | PERSIANN| 0.99 | 0.38 | -1.35| 19.22 | 0.45 | 0.54 | 0.29 |
| Mangkhut        | IMERG  | 0.97 | 0.68 | -0.40| 12.44 | 0.57 | 0.41 | 0.41 |
|                 | GSMaP  | 1.29 | 0.57 | 1.75 | 14.37 | 0.67 | 0.48 | 0.41 |
|                 | PERSIANN| 0.84 | 0.51 | -1.11| 13.94 | 0.48 | 0.43 | 0.35 |
| All Typhoon     | IMERG  | 0.93 | 0.72 | -2.39| 15.31 | 0.62 | 0.34 | 0.47 |
|                 | GSMaP  | 1.40 | 0.55 | 3.98 | 22.00 | 0.67 | 0.50 | 0.40 |
|                 | PERSIANN| 0.86 | 0.57 | -3.43| 17.56 | 0.50 | 0.40 | 0.38 |
Table 3. Statistical metric summary of the IMERG, GSMaP, and PERSIANN datasets at different elevations. Unit of ME and RMSE: mm/3 hours.

| Elevation | SPD  | BR   | R     | ME    | RMSE | VHI  | VFAR | VCSI |
|-----------|------|------|-------|-------|------|------|------|------|
| Low       | IMERG| 1.08 | 0.70  | 1.70  | 13.25| 0.64 | 0.38 | 0.45 |
|           | GSMaP| 1.43 | 0.55  | 3.57  | 19.12| 0.66 | 0.54 | 0.38 |
|           | PERSIANN| 1.09| 0.52  | 1.94  | 15.59| 0.52 | 0.50 | 0.34 |
| High      | IMERG| 0.71 | 0.81  | -6.78 | 17.79| 0.54 | 0.23 | 0.47 |
|           | GSMaP| 0.94 | 0.76  | -5.16 | 18.91| 0.74 | 0.22 | 0.62 |
|           | PERSIANN| 0.50| 0.74  | -9.72 | 20.51| 0.50 | 0.00 | 0.50 |
Figure 1. (a) Map of the Philippines, including distribution of the rain gauge stations (black dots), terrain, and tracks of the five typhoons (colored dots). (b) Map of Luzon island, including the selected rain gauge stations (colored stars) and terrain.
Figure 2. Scatter plot of rain gauge measurements for different satellite precipitation datasets (IMERG, GSMaP, and PERSIANN) during the five typhoon events: Sarika (a–m), Haimagot (d–j), Nock τen (g–l), Doksuir (j–r), and Manghung (n–o).
c), Haima (d–f), Nock-ten (g–i), Doksu-r (j–l), and Mangkhut (m–o). The parameter $R$ represents the correlation coefficient.
Figure 3. Performance diagram for the SPDs that represents their ability to detect rainfall during typhoon events. Different colors represent different typhoon events (red: Sarika; yellow: Haima; magenta: Nock-ten; green: Doksuri; blue: Mangkhut; and black: all typhoons).
Figure 4. Average 3-hour rainfall during the five typhoon events: (a) Sarika, (b) Haima, (c) Nock-ten, (d) Doksuri, and (e) Mangkhut.
Figure 5. Boxplot of the bias ratios (BRs) for different rainfall intensities for the IMERG, GSMaP, and PERSIANN datasets during the typhoon events: (a) Sarika, (b) Haima, (c) Nock-ten, (d) Doksuri, (e) Mangkhut, and (f) all typhoons.
Figure 4. Performance diagram of the SPDs at different threshold values. Different colors represent different threshold values (red: 5 mm/3 hours; yellow: 15 mm/3 hours; green: 25 mm/3 hours; and blue: 50 mm/3 hours).
Figure 5. Performance diagram of the SPDs at different altitudes. Different colors represent different altitudes (green: low altitude and red: high altitude).
Figure 6. Distribution percentage of each continuous statistic for the IMERG, GSMaP, and PERSIANN datasets at different wind speeds: (a–c) ME, (d–f) RMSE, (g–i) $R$, and (j–l) BR. The ME and RMSE value are presented in mm/3 hours.
Figure 9. Distribution percentage of each volumetric index for the IMERG, GSMaP, and PERSIANN datasets at different wind speeds: (a–c) volumetric hit index (VHI), (d–f) volumetric false alarm ratio (VFAR), and (g–i) volumetric critical success index (VCSI).
Figure 10. Three-hour, eight-sector wind rose and distribution of volumetric indices for the IMERG, GSMaP, and PERSIANN datasets for different wind directions and wind speed ranges on Luzon island: (a) wind rose for the eastern part of the mountainous region, (b–d) VHI for the eastern part of the mountainous region, (e–g) VFAR for the eastern part of the mountainous region, (h–j) VHI for the eastern part of the mountainous region, (k) wind rose for the western part of the mountainous region, (l–n) VHI for the western part of the mountainous region, (o–q) VFAR for the western part.
of the mountainous region, and (r–t) VHI for the western part of the mountainous region.