

Comparative analysis of gridded precipitation products and the development of a blended product in the Andes and surrounding regions

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Abstract

Accurate precipitation estimates are essential for land surface models and the management of water resources. However, traditional gauge-based precipitation measurements are limited by spatial and temporal coverage and are prone to errors and uncertainties. Gridded precipitation products derived from reanalysis data and satellite observations offer a more continuous and comprehensive alternative, though their performance varies regionally and is often uncertain. This study evaluates the performance of five widely available gridded precipitation products (MERRA-2, ERA5, CHIRPS, MSWEP, and IMERG) across the Andes and surrounding regions. Using gauges and the Extended Triple Collocation (ETC) method, we assess the accuracy and reliability of these products at daily, seasonal, and annual scales over the period 2001-2023. Our results indicate that MERRA-2 has the lowest errors when compared with gauges, followed by MSWEP and ERA5. CHIRPS shows a high probability of detecting precipitation events but tends to overestimate, resulting in higher errors. IMERG outperforms others in the ETC analysis, with the lowest errors and highest correlation coefficient. Recognizing the lack of a single best-performing product, we developed MIMERG, a new gridded product that combines MERRA-2 and IMERG through advanced interpolation techniques based on the Braseth algorithm. MIMERG demonstrates improved performance over MERRA-2 in ETC analysis and enhances IMERG's alignment with gauges. This study highlights the importance of tailored precipitation product selection and the potential for innovative combinations like MIMERG to improve precipitation estimates, ultimately supporting more accurate environmental modeling and water resource management.

1. Introduction

Accurate, reliable, and high-resolution precipitation data are crucial for various applications, including the study of extreme events, hydrological modeling, water resource management, and hydroclimatic research. Precipitation is the primary driver of hydrological processes, yet its precise estimation remains highly uncertain and challenging in many regions worldwide. Mountainous areas, in particular, face significant challenges due to the scarcity of reliable precipitation data, as gauges, essential for accurate precipitation estimates, are difficult to obtain. Moreover, gauge-based estimates, often sparse in both time and space, struggle to capture the strong spatial heterogeneity of precipitation and are prone to errors and uncertainties. As a result, gridded precipitation products are widely used. These products, derived from reanalysis and satellite observations, offer continuous long-term estimates of precipitation across both time and space (Gelaro et al., 2017; Hersbach et al., 2020; Molteni et al., 1996; Rienecker et al., 2011; Yatagai et al., 2012), making them the most practical option for modeling efforts, especially in remote regions. They provide precipitation estimates at various spatiotemporal resolutions and generally cover the period from 1980 to the present (Funk et al., 2015; Hersbach et al., 2020; Huffman et al., 2015; Rienecker et al., 2011; Yatagai et al., 2012). However, the performance of these gridded products varies depending on the region and its physical characteristics. Many of these products show mixed performance, particularly over complex mountainous terrains (Derin et al., 2016; Duan et al., 2016; Ebert, 2001; Maggioni et al., 2016; Zandler et al., 2019) such as High Mountain Asia (Dollan et al., 2024; Maina et al., 2022) and the Andes (Xu et al., 2017).

Our study area encompasses the entire Andes Mountain range, the world's longest mountain range, extending over 7,000 km along the western edge of South America from Venezuela in the north to Chile and Argentina in the south, and includes low-elevation regions such as portions of the Amazon River basin. In the Andes, altitudes exceed 6,000 m. The meteorology of the Andes and surrounding regions is highly complex and varied due to the range's extensive latitudinal span, high altitudes, and the diverse topographical features (Garreaud, 2009).

The Andes create a sharp division between the climates of the Pacific coast and the interior regions of South America, playing a crucial role in shaping the weather and climate patterns of the continent (Garreaud et al., 2009; Vuille et al., 2008). These climatological complexities, combined with the scarcity of gauges, make reliable precipitation estimates over the Andes challenging.

Consequently, previous studies have evaluated the performance of gridded precipitation products across the Andes and South America more broadly. For example, Manz et al., (2017) evaluated the Integrated Multi-satellite Retrievals for Global Precipitation Measurement (GPM) (IMERG, Huffman et al., 2015) and the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA, Huffman et al., 2007)) over the tropical Andes by comparing them with gauges. Their results show that IMERG provides better estimates of gauge-based rainfall probability distributions particularly across the high Andes. Similarly, Mantas et al., (2015); Ochoa et al., (2014a, 2014b); and Scheel et al., (2011) assessed IMERG, TMPA, and the TRMM product 3B42V7 across the South American continent, finding that while these datasets capture seasonal precipitation patterns, they often underestimate precipitation intensities, resulting in significant daily biases. Juárez et al., (2009) also evaluated six datasets, including the Global Precipitation Climatology Project (GPCP, (Huffman et al., 1997)), and the TRMM product in the South American region and demonstrated consistent annual precipitation patterns but substantial quantitative differences among datasets. Additionally, Silva et al., (2011) and Albuquerque de Almeida et al., (2018) evaluated NCEP and ERA-Interim reanalyses in South America by comparing them to observations, highlighting their underestimation of the South American monsoon.

While the GPM mission products are among the most widely evaluated gridded precipitation datasets for the South American continent, the performance of other precipitation products such as the Climate Hazards Group Infrared Precipitation with Station data (CHIRPS, Funk et al., 2015), the Multi-Source Weighted-Ensemble Precipitation (MSWEP, Beck et al., 2019)), the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN, (Nguyen et al., 2018)), the Climate Prediction Center morphing method (CMORPH, (Joyce et al., 2004)), the Global Satellite Mapping of Precipitation (GSMaP, (Okamoto et al., 2005)) has also been studied over the South American continent (de Goncalves et al., 2006; Dinku et al., 2010a, 2010b; Falck et al., 2015; Rivera et al., 2018; Salio et al., 2015; Zambrano-Bigiarini et al., 2017). These studies found that PERSIANN tends to underestimate no-rain areas and heavily overestimate regions with light rainfall, while GSMaP severely underestimates precipitation. CMORPH generally underestimates both the occurrence and amount of rainfall, with its best performance observed at lower elevations. CHIRPS data effectively

reproduce seasonal and interannual variability and capture the spatial patterns of precipitation but perform poorly over high-elevation areas.

These studies have found that each product has both strengths and limitations with different performances in orographic regions and low-elevations zones, and the optimal gridded precipitation product performing well at different elevation ranges for the entire South American region has yet to be identified. Furthermore, the scarcity of high-quality gauges in the region hampers the evaluation of these gridded precipitation products. Additionally, to the best of our knowledge, the performance of other widely used precipitation datasets, such as the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2, (Gelaro et al., 2017)) and the European Centre for Medium-Range Weather Forecasts (ECMWF)'s fifth generation of atmospheric reanalysis of the global climate (ERA5; (Hersbach et al., 2020)) have not been extensively studied or evaluated over the entire Andes and surrounding regions.

In this study, we assess five gridded precipitation products over the Andes and surrounding regions. These products represent a mix of modern reanalysis, satellite-, and ground observation-based precipitation products: ERA5 (Hersbach et al., 2020), the final product of IMERG version 7; (Huffman et al., 2015), CHIRPS; (Funk et al., 2015), MERRA-2; (Gelaro et al., 2017), and MSWEP, (Beck et al., 2019). These products were selected based on their temporal coverage and availability. Previous studies have demonstrated that IMERG outperforms TRMM and TMPA—which are included in MSWEP—while GsMAP, CMORPH (also included in MSWEP), and PERSIANN exhibit lower performance; therefore, we excluded these products from our analysis. We evaluate these products by comparing them against 1178 gauges. Given the limited spatial coverage and temporal sparsity of our gauges, we also utilize the Extended Triple Collocation (ETC, McColl et al., 2014) method, which allows evaluating different products without relying solely on the sparse gauges. ETC is an advanced statistical technique that builds on the traditional Triple Collocation (TC, Stoffelen, 1998) method by accounting for biases and allowing more flexible error structures. ETC assesses the accuracy and error characteristics of three independent datasets by comparing them against each other.

Since establishing a universally accurate precipitation dataset is challenging, we also present the development of a merged product that combines the two datasets with the best performances based on the comparative analysis. This merged product was created using an optimal interpolation technique based on the Bratseth algorithm (Bratseth, 1986) as outlined by

Fortin et al., (2015) and Kemp et al., (2022). Merging different precipitation products is a common approach to address the inconsistencies and differences between individual datasets. It also helps filter out features that individual gridded precipitation products may not agree on. Furthermore, previous studies have shown that merged precipitation estimates are generally more accurate than any of the individual gridded precipitation products (Clark, 2017; Maina et al., 2022; Weusthoff et al., 2011). The performance of this precipitation analysis has been thoroughly evaluated by comparing it to the selected five gridded precipitation datasets, using both gauges and the ETC method.

2. Study area: the Andes and its surrounding

Our study area in South America spans from 41.2° South to 9° North latitude and from 82.6° West to 59° West longitude (Figure 1). This region features a wide range of elevations, from sea level to over 6,000 meters, and includes the entire Andes Mountain range as well as low-lying areas such as parts of the Amazon River basin. The selected domain covers eight countries: Venezuela, Colombia, Ecuador, Peru, Brazil, Bolivia, Argentina, and Chile. The Andes Cordillera, which runs along the west coast of South America, acts as a barrier to tropospheric flow, facilitating interactions between tropical and extra-tropical air masses. This mountain range creates a climatic divide, with dry conditions to the west and moist conditions to the east at tropical and subtropical latitudes (Garreaud, 2009; Garreaud et al., 2009). As a result, the unique geographical location and complex orographic patterns of the Andes contribute to a diverse climate system with extreme hydroclimatic gradients, leading to highly variable water availability. The biannual migration of the Intertropical Convergence Zone (ITCZ), the El Niño-Southern Oscillation (ENSO), and the cold Humboldt Current in the Pacific Ocean, along with the influence of the Andes Mountains and the Amazon Basin, govern the spatiotemporal variations of precipitation (Boers et al., 2015; Rollenbeck and Bendix, 2011; Vuille et al., 2000). ENSO plays a significant role in shaping the climate of the Andes, with El Niño events typically causing drier conditions in the northern and central Andes, while La Niña brings wetter conditions. Precipitation within our study area can exceed 6,000 mm per year (according to precipitation datasets over the past two decades) in certain regions of Colombia, Brazil (e.g., the Amazon), and the eastern slopes of the Andes. The northern Andes experience a tropical climate at lower elevations, characterized by high temperatures and substantial rainfall, especially on the eastern slopes where moist air from

the Amazon Basin rises and cools, resulting in orographic precipitation (Buytaert and De Bièvre, 2012). In contrast, semi-arid and arid climates prevail on the Pacific slopes, the highlands of Bolivia and Peru, and the inter-Andean valleys, due to the influence of the cool and dry air masses brought by the Pacific Humboldt Current (Vuille et al., 2000).

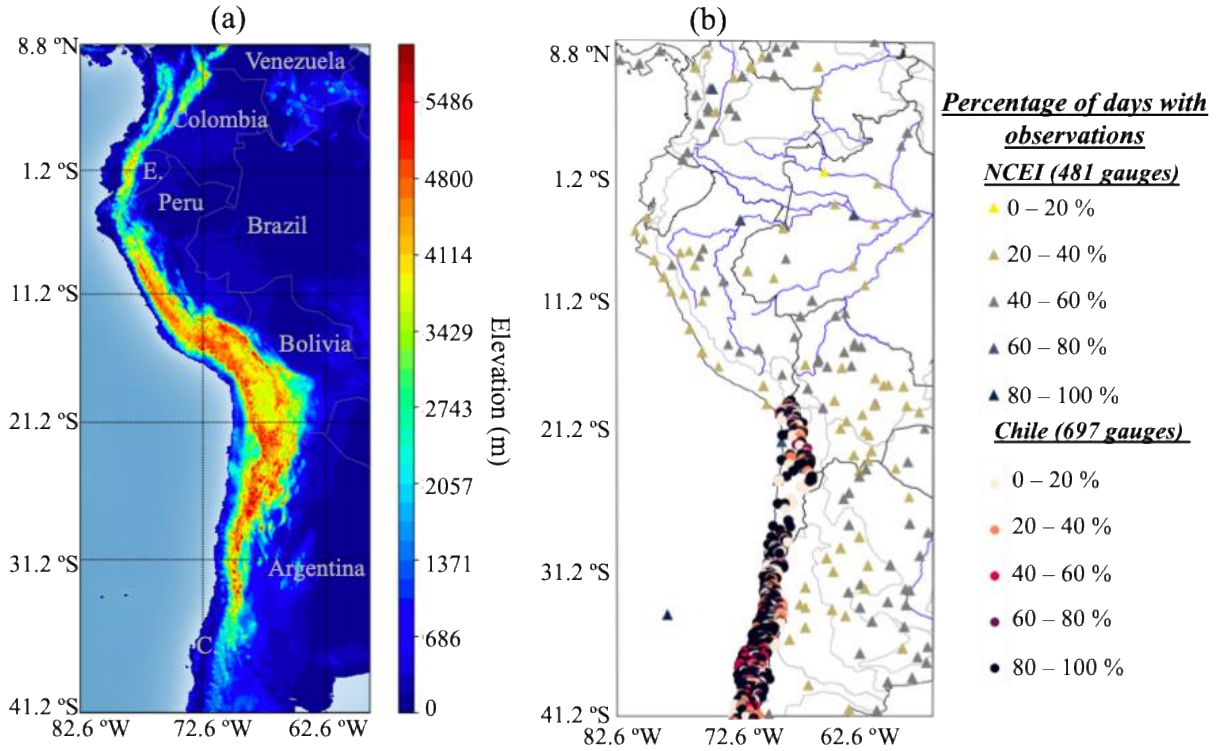


Figure 1: Spatial extent of the South American domain (a) elevation and (b) the location of the gauges used in this study. The gray areas represent the country boundaries, the black lines delineate the major hydrological basin, and the blue lines represent the rivers. Two gauges datasets are utilized: the National Centers for Environmental Information (NCEI) dataset (481 gauges) and a Chilean dataset (697 gauges). Gauges are color-coded based on the percentage of days with valid observations over their respective records.

The Andean region hosts a diverse ecosystem comprising five major landscapes: páramo, jalca, puna, montane forests, and cloud forests (Ochoa-Tocachi et al., 2016). Páramo, jalca, and puna are high-altitude tropical ecosystems typically found above the tree line (3,000 to 3,500 m) and below the permanent snow line (4,500 to 5,000 m). The páramo, located in the northern areas of Colombia, Venezuela, and Peru, serves as a crucial water source for the Andean highlands (Buytaert et al., 2006). The jalca is found in central and northern Peru, while the puna

stretches from central Peru to northern Argentina and Chile (Ochoa-Tocachi et al., 2016). The tropical Andes are rich in clean freshwater, with water supply primarily dependent on surface water. Groundwater, however, is not easily accessible due to the geological setting, making extraction complex and costly (Buytaert and De Bièvre, 2012).

3. Data and Methodology

3.1. Selected Gridded Products

We selected five gridded precipitation datasets: ERA5, CHIRPS, IMERG, MERRA-2, and MSWEP.

ERA5 is the fifth generation of ECMWF atmospheric reanalysis. It provides a comprehensive, high-resolution dataset of global climate and weather conditions (Hersbach et al., 2020). The product is widely used for climate monitoring, research, and operational applications. ERA5 provides estimates of precipitation by combining satellite and in-situ data into global estimates using advanced modeling and data assimilation systems at a horizontal resolution of approximately 31 kilometers ($0.25^\circ \times 0.25^\circ$), making it much finer than previous reanalysis products and a temporal resolution of an hour, which enables detailed analysis of precipitation events, including the timing and intensity of rainfall (Hersbach et al., 2020).

IMERG combines data from multiple satellites, including microwave and infrared sensors, to provide high-resolution global precipitation estimates and provides near-real-time and retrospective precipitation data at a spatial resolution of $0.1^\circ \times 0.1^\circ$ (approximately 10 km) and at half-hourly intervals (Huffman et al., 2015). IMERG is widely used for studying precipitation patterns, weather forecasting, hydrology, and climate research, providing detailed insights into rainfall distribution and intensity across the globe. We used the final run product, which incorporates multi-satellite and gauge data. We bias corrected version 7 of IMERG using the monthly GPCP version 2.2 (Huffman et al., 2023). IMERG Version 7 has been shown to underestimate precipitation over snow-covered regions. To address this, we multiplied the IMERG precipitation by the ratio of the monthly climatologies of GPCP and IMERG. These monthly climatologies were computed using 20 years of data.

CHIRPS is a high-resolution precipitation dataset developed to monitor and analyze rainfall patterns, particularly in regions prone to drought (Funk et al., 2015). CHIRPS combines satellite infrared data with in-situ rainfall measurements from weather stations, providing global

precipitation estimates at a spatial resolution of $0.05^\circ \times 0.05^\circ$ (approximately 5 km) and daily, pentadal, and monthly timescales. Covering data from 1981 to the present, CHIRPS is widely used in climate monitoring, agricultural planning, drought prediction, and water resource management, offering critical insights into rainfall variability and trends (Funk et al., 2015).

MSWEP is a global precipitation dataset that integrates data from multiple sources, including satellite observations (e.g. CMORPH, GSMaP, TRMM, and TMPA), gauges (e.g., WorldClim and Global Historical Climatology Network-Daily (GHCN-D)), and reanalysis outputs (e.g. ERA) (Beck et al., 2019). MSWEP provides high-resolution precipitation estimates at a $0.1^\circ \times 0.1^\circ$ (approximately 10 km) spatial resolution and at sub-daily, daily, and monthly timescales, covering the period from 1979 to the present. It is designed to offer accurate and consistent global precipitation data, making it valuable for hydrological modeling, climate studies, flood forecasting, and water resource management. MSWEP is particularly noted for its ability to capture precipitation patterns in both well-observed and data-sparse regions (Beck et al., 2019).

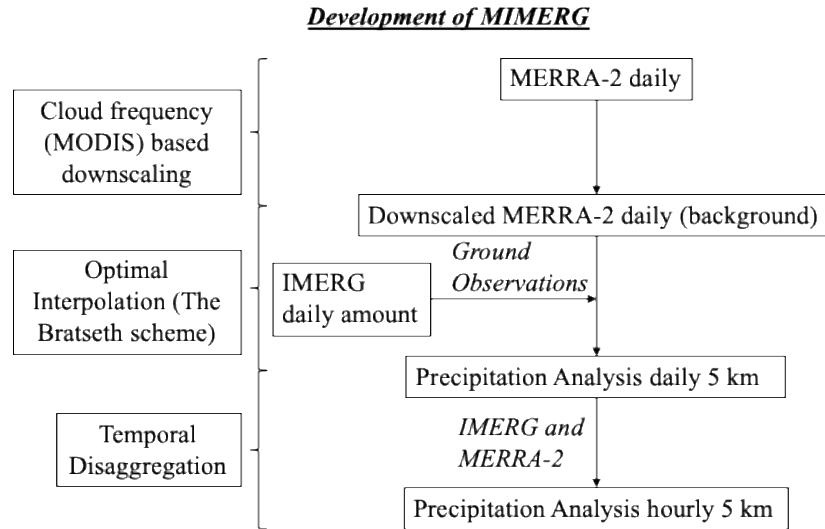
MERRA-2 is a global atmospheric reanalysis product developed by NASA (Gelaro et al., 2017), which provides comprehensive climate and weather data, including precipitation at a spatial resolution of $0.5^\circ \times 0.625^\circ$ and at hourly intervals, covering the modern satellite era from 1980 to the present. It generates precipitation estimates primarily through the Goddard Earth Observing System (GEOS) atmospheric model, constrained by the assimilation of ground-based observations such as surface pressure, temperature, humidity, and winds from meteorological stations and radiosondes. Satellite data, including microwave and infrared radiances and cloud motion vectors, are also assimilated to refine the atmospheric state. MERRA-2 is widely used in climate research, weather analysis, and environmental studies, offering detailed insights into atmospheric processes and long-term climate trends (Gelaro et al., 2017).

	Product	Spatial resolution	Temporal resolution	Temporal coverage
1	CHIRPS	$0.05^\circ \times 0.05^\circ$	Daily	1981 - present
2	IMERG	$0.1^\circ \times 0.1^\circ$	30 min	2000 - present
3	ERA5	$0.25^\circ \times 0.25^\circ$	1 hour	1979 - present
4	MERRA-2	$0.5^\circ \times 0.625^\circ$	1 hour	1980 - present
5	MSWEP	$0.1^\circ \times 0.1^\circ$	12-hour	1979 - present

Table 1: Selected precipitation products

3.2.MIMERG: an assimilation of IMERG into MERRA-2

The developed precipitation analysis called MIMERG blends the daily precipitation amounts of IMERG with the daily precipitation of MERRA-2 using the optimal interpolation technique based on the Bratseth algorithm (Kemp et al., 2022). The Bratseth algorithm is an iterative form of optimal interpolation that progressively refines estimates by minimizing the difference between observations and the background field. Figure 2 describes the different steps employed to generate MIMERG at a spatial resolution of 5 km and a temporal resolution of one hour. Because MERRA-2 has a resolution coarser than MIMERG, we downscale it to 5 km using a cloud frequency based algorithm following (Karger et al., 2021).



Optimal Interpolation: The Bratseth scheme

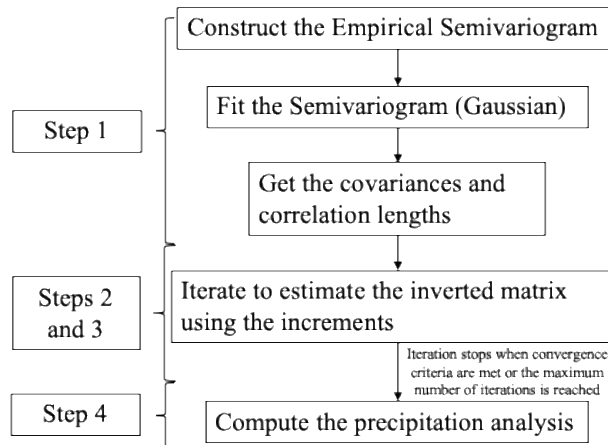


Figure 2: Schematic representation of the development of an hourly 5 km precipitation analysis merging IMERG and MERRA-2 using the Braseth scheme

3.2.1. A cloud-cover informed downscaling

Because MERRA-2 has a very coarse resolution, we downscale it to 5 km using the MODIS monthly cloud cover frequency following (Petitcolin and Vermote, 2002) as described in Karger et al., (2021). The MOD09 cloud detection algorithm provides a binary classification (cloudy/not cloudy) without offering an estimate of confidence in the cloud state (i.e., the probability that a pixel is actually cloudy based on the tests). The algorithm minimizes confusion between clouds and snow or ice by incorporating surface air temperature. We extracted daily cloud flags from both the Terra (MOD09GA, collected around 10:30 AM local time) and Aqua (MYD09GA, collected around 1:30 PM) satellites and computed their monthly cloud frequency time series (i.e., the proportion of days with a positive cloud flag) separately. We then incorporated these monthly cloud frequencies into the daily precipitation estimates, assuming that cloud occurrence frequency is related to precipitation events, and their geographic distribution reflects a spatial pattern of precipitation (Arkin and Meisner, 1987; Richards and Arkin, 1981). Specifically, it is assumed that where no clouds are present, no precipitation occurs, and where clouds occur more frequently, precipitation is more likely following (Betts et al., 2017). First a cloud cover-corrected daily precipitation P_c is estimated using the following equation:

$$P_c = P_{merra2} * cf_m \quad (1)$$

Where cf_m is the monthly cloud frequency, and P_{merra2} the MERRA-2 precipitation at the 5 km grid derived from the coarse resolution MERRA-2 precipitation by using a budget-bilinear interpolation.

The daily precipitation at each grid cell $P_{d,i}$ is then computed using:

$$P_{d,i} = \frac{P_c}{\frac{1}{n} \sum_{i=1}^n P_{c,i}} P_m \quad (2)$$

where n equals the number of 5 km contains in the MERRA-2 $0.5^\circ \times 0.625^\circ$ grid cell, P_c the cloud cover-corrected precipitation, and P_m the average cloud cover-corrected precipitation over the MERRA-2 $0.5^\circ \times 0.625^\circ$ grid cell.

3.2.2. Optimal Interpolation

Due to the vast size of our study domain and the large number of grid cells ($\sim 482,933$), and because the classic optimal interpolation technique demands substantial memory and is computationally intensive (Fortin et al., 2015), we utilize a parallelized Bratseth algorithm.

The optimal interpolation consists of correcting the analysis values with observation increments ($\mathbf{y}_o - \mathbf{y}_b$) defined as the differences between the observed values and the analysis. The optimal interpolation analysis equation is given by:

$$\mathbf{p}_a = \mathbf{p}_b + \tilde{\mathbf{B}}(\mathbf{B} + \mathbf{R})^{-1}(\mathbf{y}_o - \mathbf{y}_b) \quad (3)$$

where $\mathbf{p}$ is a n -length vector of precipitation values at analysis points (total number of grid cells); $\mathbf{y}$ is a p -length vector of values at the observation points; and subscripts a, b, and o indicate analysis, background, and observed values, respectively.

The observation increments are multiplied by observations and background error covariances. $\tilde{\mathbf{B}}$ is a background error covariance matrix with covariances between observation and analysis points; $\mathbf{B}$ is a background error covariance matrix, and $\mathbf{R}$ is an observation error covariance matrix; both are symmetric, positive-definite, and contain error covariances between observation points.

The solution of equation (3) is computationally expensive because it requires the inversion of the matrix $(\mathbf{B} + \mathbf{R})^{-1}$. Direct inversion is cumbersome for problems with a large number of observations. To reduce the computing time, previous studies have limited the number of observations (Fortin et al., 2015). To avoid the reduction of the observed values to be included in the analysis while reducing the computation time, Kemp et al., (2022) uses the Bratseth algorithm (Bratseth, 1986) which avoids the matrix inversion in the optimal interpolation. Following the Bratseth algorithm, the inverse of a matrix $\mathbf{A} = (\mathbf{B} + \mathbf{R})$ which is symmetric and positive-definite with eigenvalues μ in the range $0 \leq \mu \leq 1$ can be approximated by iterations:

$$\mathbf{A}^{-1} \approx \sum_{k=0}^v (\mathbf{I} - \mathbf{A})^k \quad (4)$$

where $\mathbf{I}$ is the identity matrix with the same dimensions as $\mathbf{A}$.

Likewise, a matrix-vector product $(\mathbf{B} + \mathbf{R})^{-1}(\mathbf{y}_o - \mathbf{y}_b)$ can be approximated as:

$$\mathbf{A}^{-1}(\mathbf{y}_o - \mathbf{y}_b) \approx \sum_{k=0}^v (\mathbf{I} - \mathbf{A})^k (\mathbf{y}_o - \mathbf{y}_b) \quad (5)$$

This transformation allows rewriting equation (3) into:

$$\mathbf{p}_a = \mathbf{p}_b + \tilde{\mathbf{B}}\mathbf{M}^{-1}\mathbf{d} \quad (6)$$

where $\mathbf{d}$ is given by:

$$\mathbf{d} = \mathbf{M}(\mathbf{B} + \mathbf{R})^{-1}(\mathbf{y}_o - \mathbf{y}_b) \quad (7)$$

and $\mathbf{M}$ is a diagonal matrix selected to shrink the eigenvalues of the product $\mathbf{M}(\mathbf{B}+\mathbf{R})^{-1}$ and is defined by:

$$(\mathbf{M})_{j,k} = \sum_{k=1}^p |(\mathbf{B})_{j,k} + (\mathbf{R})_{j,k}| \quad (8)$$

where the subscripts are row and column indices, then the eigenvalues of $\mathbf{M}(\mathbf{B}+\mathbf{R})^{-1}$ will lie within the range $0 < \mu \leq 1$. Thus, equation (7) can be approximated by iterating the series:

$$\mathbf{d} = \sum_{k=0}^v [\mathbf{I} - (\mathbf{B}+\mathbf{R})\mathbf{M}^{-1}]^k (\mathbf{y}_o - \mathbf{y}_b) \quad (9)$$

Therefore, using the Bratseth algorithm, the optimal interpolation is approximated by using four steps (also illustrated in Figure 2):

- **Step 1: Covariances and correlation lengths**

This step allows calculating the diagonal matrix $\mathbf{M}$ using equation (8) with the values of $\mathbf{B}$ (i.e., the MERRA-2 error covariance matrix) and $\mathbf{R}$ (i.e., IMERG error covariance matrix).

The computation of $\mathbf{B}$ and $\mathbf{R}$ requires the covariances and correlation lengths. Here, to save memory and to reduce the computation time, we assume that the background errors are uncorrelated with the observations (i.e., the IMERG values to be assimilated). The background error is assumed to be Gaussian and is given by:

$$(\tilde{\mathbf{B}})_{i,j} = \sigma_b^2 \exp(-D_{i,j}^2/L_b^2) \quad (10)$$

$$(\mathbf{B})_{i,j} = \sigma_b^2 \exp(-D_{i,j}^2/L_b^2) \quad (11)$$

where σ_b^2 is the background error variance, and L_b is the background error correlation length. $D_{i,j}^2$ is the great circle distance between points i and j is calculated using the following equation:

$$D_{i,j}^2 = r_{earth}^2 \cos^{-1} \left(\cos(lat_i) \cos(lat_j) \cos(lon_i - lon_j) + \sin(lat_i) \sin(lat_j) \right) \quad (12)$$

where r_{earth} is the earth radius, lat_i and lat_j are the latitudes of points i and j , and lon_i and lon_j are the longitudes of points i and j .

Likewise, the observation (IMERG) error covariances are parameterized as:

$$(\mathbf{R})_{i,j} = \sigma_o^2 \exp(-D_{i,j}^2/L_o^2) \quad (13)$$

where σ_o^2 is the observation error variance, and L_o is the observation error correlation length.

More details about the computation of the error variance and correlation length can be obtained in Kemp et al., (2022).

- **Step 2: First estimation of the inverted matrix**

After the calculation of the matrix $\mathbf{M}$, the inverted diagonal $\mathbf{M}^{-1}$ is estimated.

- **Step 3: Iterations to correct the estimation of the inverted matrix**

Since the Bratseth algorithm relies on iteration to approximate the values of the inverted matrix $\mathbf{M}^{-1}$, iterations of equation (9) are then performed until either $\mathbf{d}$ converges or an iteration limit is reached. Here we plan to set the convergence criteria to a threshold equal to 0.01, therefore, iterations are stopped when the maximum (over all the grid points) differences of $\mathbf{d}$ between two consecutive iterations are lower than the threshold. If the convergence criteria are not met and iteration exceeds 5, they are also stopped.

- **Step 4: Computation of the analysis (i.e., precipitation analysis)**

After the convergence criteria have been met or the maximum number of iterations is reached, the final values of $\mathbf{d}$ are used in equation (3) to compute the precipitation analysis vector $\mathbf{p}_a$.

3.2.3. Temporal disaggregation

The temporal resolution of the resulting precipitation analysis MIMERG is daily. We use a temporal disaggregation based on IMERG and MERRA-2 to convert these daily amounts of precipitation to the hourly following:

$$P_{a,h} = P_{a,d} * inter_h \quad (14)$$

$P_{a,h}$ is the precipitation analysis associated with hour h of day d , $P_{a,d}$ the precipitation analysis of day d and $inter_h$ is given by:

$$inter_h = \frac{(P_{Sat,h})}{\sum_{k=1}^{24} (P_{Sat,k})} \quad (15)$$

where P_{Sat} is equal to the mean of $P_{imerg,h}$ and $P_{merra2,h}$.

3.3. Statistical Analyses

3.3.1. Averages and trends

We compute the annual average precipitation of the five gridded precipitation products and the precipitation analysis MIMERG. We also compute the trends using the Mann-Kendall test which determines whether a time series has a monotonic upward or downward trend (Kendall, 1948; Mann, 1945; Yue et al., 2002). The Mann-Kendall trend test is computing using the following formula:

$$S = \sum_{i=1}^{n-1} \sum_{j=k+1}^n \text{sign}(x_j - x_i) \quad (16)$$

where x is the time series variable. The subscript j and k are the observation time. $\text{sign}(x_j - x_i)$ is equal to +1, 0, or -1, which means increasing trend, no trend, and decreasing trend, respectively.

We estimate the magnitude of the trend using Sen's slope estimator, which calculates the median of all pairwise slopes using:

$$\text{Slope} = \text{median} \left(\frac{x_j - x_i}{j - i} \right) \text{ for all } 1 \leq i \leq j \leq n \quad (17)$$

where each slope represents the change in x between two-time steps normalized by the time interval.

In this study, we use a confidence level of 95% which means that we only consider trends with a significance level of 5%.

3.3.2. RMSE, Bias, Correlation Coefficient

To evaluate the five gridded precipitation products and the precipitation analysis MIMERG against ground measurements, we compute statistical metrics which includes the root mean square error (RMSE, equation 18), the correlation coefficient (CC, equation 19), and bias ratio (BR, equation 20) widely used in the evaluation of precipitation (e.g., Dinku et al., 2007; Golian et al., 2015; Hénin et al., 2018; Liu, 2015; Qin et al., 2014). The statistical metrics are computed using daily precipitation and are defined as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (P_{gi} - P_{oi})^2} \quad (18)$$

$$CC = \frac{\sum_{i=1}^N (P_{gi} - \bar{P}_g)(P_{oi} - \bar{P}_o)}{\sqrt{\sum_{i=1}^N (P_{gi} - \bar{P}_g)^2} \sqrt{\sum_{i=1}^N (P_{oi} - \bar{P}_o)^2}} \quad (19)$$

$$BR = \frac{\frac{1}{N} \sum_{i=1}^N P_{gi}}{\frac{1}{N} \sum_{i=1}^N P_{oi}} \quad (20)$$

where P_{gi} is the precipitation estimation at each station, N is the total number of samples at each station, and P_{oi} is the observation at each station. $\bar{P}_g$ and $\bar{P}_o$ are the average of the gridded products and observations, respectively.

3.3.3. Probability of detection and false alarm ratio

We also evaluate the probability of detection (i.e., the fraction of days with precipitation greater than 10 mm correctly captured by the products, equation 21) and the false alarm ratio (i.e., days where the products indicated precipitation while gauges recorded less than 1 mm, equation 22) for the gridded precipitation products relative to the NCEI and Chilean gauge datasets, using the following equations:

$$\text{Probability of detection} = \frac{Hits_{POD}}{Hits_{POD} + Misses} \quad (21)$$

$$\text{False alarm ratio} = \frac{False\ alarms}{Hits_{FAR} + False\ alarms} \quad (22)$$

Where $Hits_{POD}$ is the number of days where both the product and the gauge have precipitation above 10 mm, $Misses$ is the number of days where the gauge recorded precipitation above 10 mm but the product did not, $False\ alarms$ is the number of days where the product indicated precipitation greater than 1 mm while the gauge recorded less than 1 mm, and $Hits_{FAR}$ is the number of days where both the product and the gauge have precipitation less than 1mm.

3.3.4. Extended triple collocation

Since gauges are sparse and often insufficient for comprehensive comparisons, we use the ETC method. This approach enables the estimation of unknown errors associated with three datasets without needing a reference dataset (McColl et al., 2014; Roebeling et al., 2012). The ETC method has been effective for evaluating precipitation products in data-scarce regions (Maina et al., 2022; Yoon et al., 2019). It allows for the quantification of accuracy measures such as RMSE and CC. A precipitation estimates, P_i , can be written as:

$$P_i = P'_i + \epsilon_i = \alpha_i + \beta_i t + \epsilon_i \quad (23)$$

where $X_i (i \in \{1, 2, 3\})$ are collocated measurements that are linearly related to the unknown true value t , ϵ_i represents additive random errors, and α_i and β_i are offset and gain terms. Assuming that the errors are uncorrelated with each other $cov((\epsilon_i, \epsilon_j) = 0, i \neq j)$ and with the unknown truth $cov((\epsilon_i, t) = 0)$, the $RMSE$ (equation 24) and CC (equation 25), can be estimated as:

$$RMSE = \left[\begin{array}{c} \sqrt{Q_{11} - \frac{Q_{12}Q_{13}}{Q_{23}}} \\ \sqrt{Q_{22} - \frac{Q_{12}Q_{23}}{Q_{13}}} \\ \sqrt{Q_{33} - \frac{Q_{13}Q_{23}}{Q_{12}}} \end{array} \right] \quad (24)$$

$$CC = \pm \left[\begin{array}{c} \sqrt{\frac{Q_{12}Q_{13}}{Q_{11}Q_{23}}} \\ sign(Q_{13}Q_{23})\sqrt{\frac{Q_{12}Q_{13}}{Q_{22}Q_{13}}} \\ sign(Q_{12}Q_{23})\sqrt{\frac{Q_{13}Q_{23}}{Q_{33}Q_{12}}} \end{array} \right] \quad (25)$$

Where Q_{ij} is the covariance of X_i and X_j . The signs $\pm$ refer to positive or negative linear correlation although r is expected to be positively correlated to the unknown truth.

Because the ETC can only compare three independent datasets at a time, and we have six datasets to evaluate, we perform multiple ETC analyses by grouping the datasets into sets of three and then averaging the results.

4. Results

4.1.Averages and trends

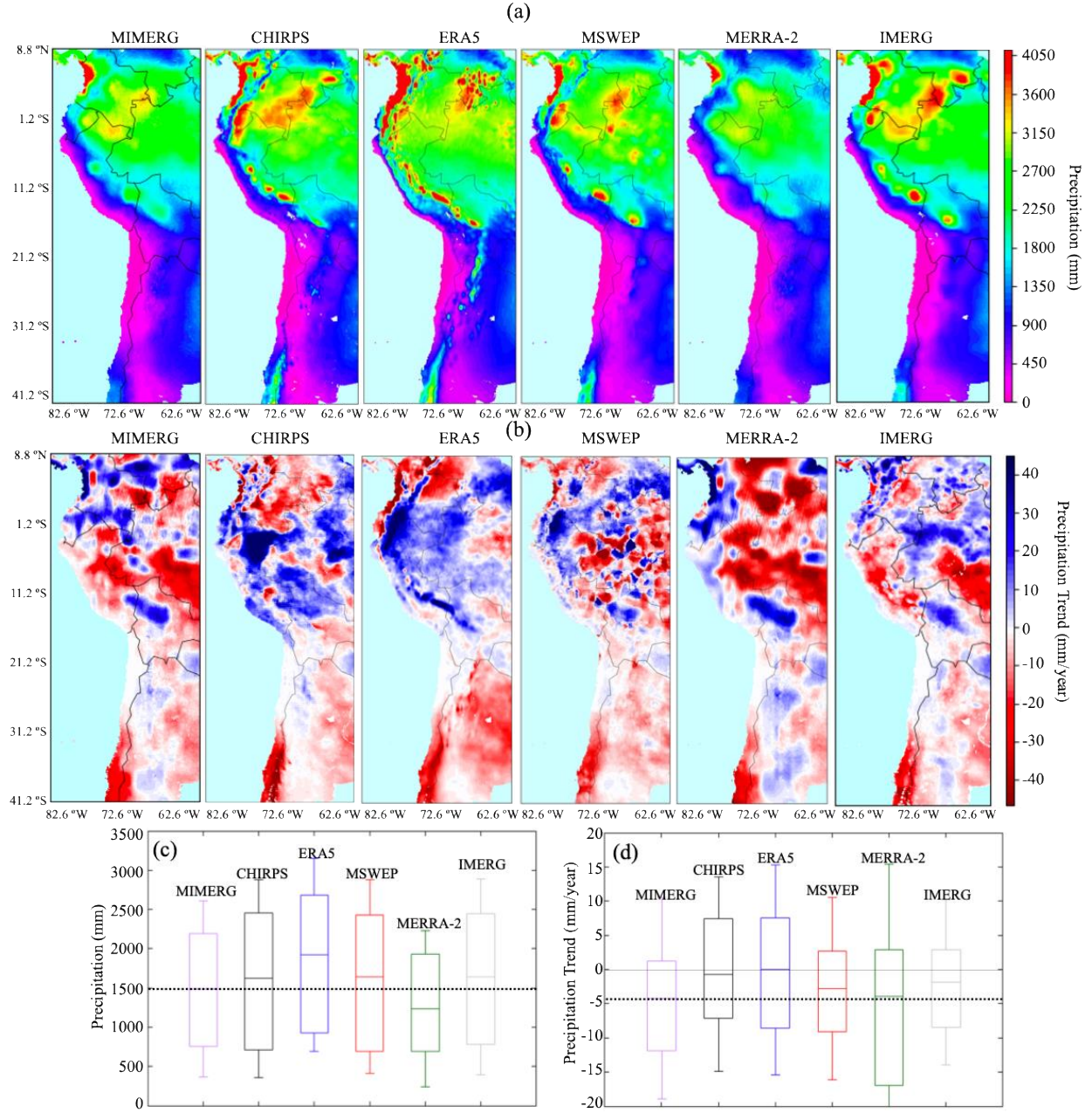


Figure 3: Spatial distributions of (a) annual average precipitation and (b) annual trends in precipitation. The boxplots of the annual average precipitation and its trends over the entire domain are shown in (c) and (d) respectively. The averages and trends are computed from 2001 to 2023.

Figure 3a presents the annual average precipitation across the six gridded precipitation products (MIMERG, CHIRPS, ERA5, MSWEP, MERRA-2, and IMERG). While these products share similar spatial resolutions, the magnitude of precipitation varies between them. In the high-

altitude regions of the Andes, annual precipitation is less than 1,000 mm, which is less than half of the precipitation values in the northern part of the study area, corresponding to the Amazon basin. In this region, precipitation can exceed 5,000 mm per year, particularly along the western edge of the basin. The boxplot in Figure 3c indicates that ERA5 records the highest median precipitation values, followed by CHIRPS and MSWEP. IMERG's spatial distribution of precipitation closely resembles that of CHIRPS, with similar precipitation values. MERRA2 registers the lowest precipitation values, generally producing lower precipitation estimates than the other products across most of the domain. Precipitation trends in the region show a bidirectional pattern: the southwestern area exhibits decreasing trends in precipitation (up to -40 mm/year in some areas) across all products, while the northern area shows a mix of increasing and decreasing trends. ERA5 demonstrates an overall positive precipitation trend in the northern region (from 20 mm/year to 50 mm/year), whereas MERRA-2 shows a predominantly decreasing trend with approximately same magnitude. A similar pattern is observed in IMERG and MSWEP, though these products display more areas with increasing trends than MERRA-2. The spatial distribution of CHIRPS trends is mixed, with both positive and negative trends in the northern region. As illustrated in the boxplot, ERA5 and CHIRPS generally show predominantly negative precipitation trends, while MERRA-2, MSWEP, and IMERG display more positive than negative trends.

Although these products exhibit similar spatial distributions of precipitation, the magnitude varies between them. Additionally, the precipitation trends differ among the products analyzed. The developed product, which combines IMERG and MERRA-2, reflects characteristics from both, with trends and averages falling between the two.

To further analyze spatial and seasonal averages and trends, we divided the domain into five zones based on differences in elevation and land cover. Zone 1 corresponds to the Southern Andes; Zone 2 includes the grasslands and lower elevations in the southern part of the domain; Zone 3 covers the Central Andes; Zone 4 encompasses the Amazon Basin; and Zone 5 represents the Northern Andes (Figure A1 in the appendix). As shown in Figures A1 and A2 in the appendix, the results are consistent with the spatial patterns of precipitation trends and averages discussed above. Zones 1 and 2, located in the southern region, exhibit relatively low average rainfall, which is decreasing over time. In contrast, Zones 3, 4, and 5 receive higher average precipitation, especially Zone 4, and show increasing trends in several areas. Across all zones, ERA5 generally shows the highest annual precipitation and the most positive trends. In zones 1 and 2, MIMERG

reports higher average annual precipitation than most other products, except ERA5, while CHIRPS, MSWEP, MERRA-2, and IMERG report lower values. In zones 3, 4, and 5, the annual precipitation patterns are consistent with those shown in Figure 3c, which illustrates the domain-wide annual precipitation. With respect to trends, zones 1 and 2 mostly exhibit negative values, with only ERA5 and CHIRPS showing some areas with positive trends. In contrast, zones 3, 4, and 5 display trend patterns similar to the domain average. Regarding seasonality, precipitation peaks during DJF (December-January-February) and reaches its lowest during JJA (June-July-August). DJF precipitation is decreasing over time, whereas JJA precipitation shows an increasing trend (Figure A2).

To better evaluate the performance of each product, we compare them against ground measurements.

4.2. Comparisons to observations

Figure 4 depicts the RMSE, bias, and correlation coefficient obtained by comparing the six products to gauges. Because of the availability of the datasets, we performed the comparison from 2001 to 2013 for the NCEI observations and from 2001 to 2019 for the Chilean gauges. We use daily precipitation data to compute these metrics, evaluating them whenever an observation is available. Figure 1c illustrates the data availability throughout the study period, expressed as the percentage of days with available observations. Because we used two different gauge datasets, we calculated these metrics separately for each dataset.

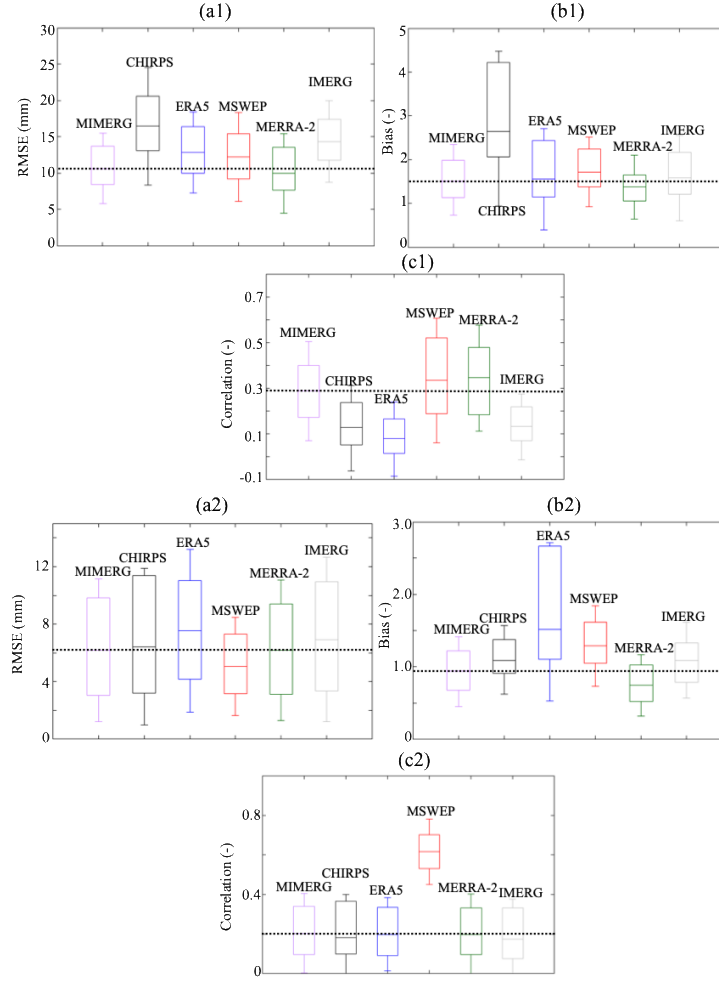


Figure 4: Boxplots of the (a1) RMSE, (b1) Bias, and (c1) Correlation Coefficient of the comparisons between the gridded precipitation products and NCEI gauges. (a2), (b2), and (c2) illustrates the results of the comparisons between the gridded precipitation products and the gauges over Chile.

MERRA-2 consistently shows the best performance, with one of the lowest RMSE (a median of around 10 mm for NCEI and 6 mm for the Chilean gauges) and bias (a median equal to ~1.3 for NCEI and ~0.7 for the Chilean gauges), as well as one of the highest correlation coefficient (a median equal to ~0.35 for NCEI and 0.18 for the Chilean gauges) across both datasets. In contrast, CHIRPS has one of the highest RMSE (with the median of ~16 mm for NCEI and 6.3 mm for the Chilean dataset) and bias (with a median of ~2.6 for NCEI and ~1.05 for the Chilean dataset), and the lowest correlation coefficient (with a median of ~0.1 NCEI and 0.18 for the Chilean dataset) for both gauge datasets. ERA5 and MSWEP outperform IMERG, while only

MERRA-2 outperforms MIMERG with a median RMSE of 10.5 mm and 6 mm, compared to the NCEI and the Chilean datasets, respectively. The MIMERG performance relative to gauges has slightly declined due to the inclusion of IMERG. MSWEP performs very well against the Chilean dataset, showing the lowest median RMSE and the highest correlation coefficient. In contrast, ERA5 exhibits relatively lower performance when compared to both datasets.

Figure A3 in the appendix presents the RMSE values for the NCEI dataset across the five previously defined zones. We did not compute RMSE for the Chilean dataset by zone, as it only covers the Southern Andes. Overall, across all zones, CHIRPS exhibits the lowest performance, while MERRA-2 shows the highest, followed by MIMERG. MSWEP also performs well, particularly in Zone 2. Interestingly, CHIRPS performs relatively well in Zone 3 (the Central Andes), along with the other products. Similar patterns are observed in the seasonal RMSE analysis shown in Figure A4 in the appendix. In contrast to the NCEI-based evaluation, where MERRA-2 outperforms the other datasets, MSWEP emerges as the best-performing product when evaluated against the Chilean dataset, closely followed by MIMERG.

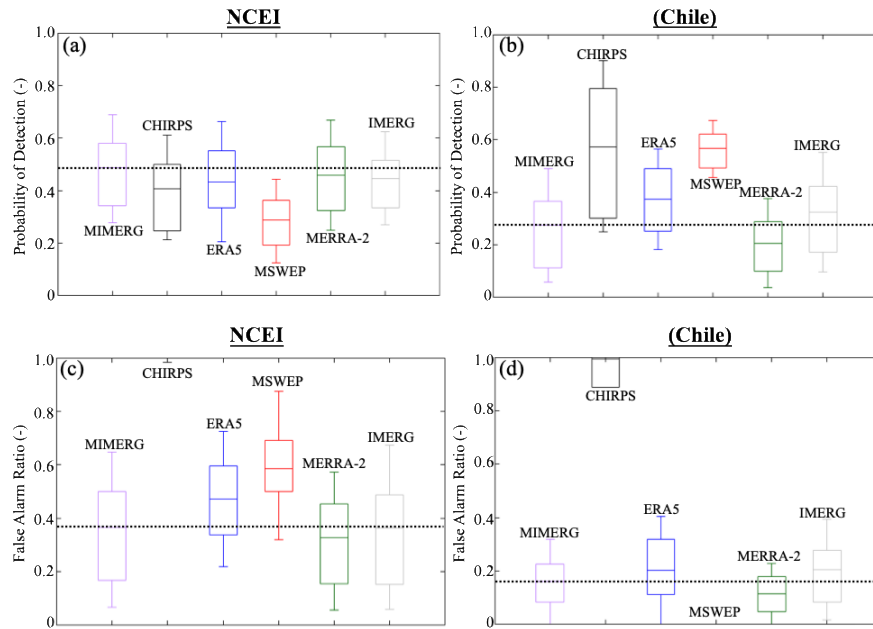


Figure 5: Boxplots of the probability of detection of (a) NCEI gauges and (b) Chilean gauges and false alarm ratio of (c) NCEI gauges and (d) Chilean gauges. Note that in panel (c), the false alarm ratio for CHIRPS is 1, causing its boxplot to be hidden as it overlaps with the upper limit of the figure.

Figure 5 illustrates the probability of detecting precipitation greater than 10 mm across different products, as well as the corresponding false alarm ratio (i.e., when products indicate noticeable precipitation in cases where gauges report less than 1 mm). MIMERG has the highest probability of detection of the NCEI dataset while CHIRPS exhibits the highest probability of detection (i.e., a median greater than 0.59) for the Chilean gauges. While CHIRPS effectively captures most of the precipitation events in the region, its RMSE and bias are high due to overestimation of precipitation, as shown in Figure A5 in the appendix. This tendency of CHIRPS to consistently overestimate precipitation compared to the gauges adversely affects its performance, leading to higher RMSE and a higher false alarm ratio.

MSWEP, despite having low RMSE and bias when compared to observations, shows a lower probability of detection, particularly for the NCEI gauges (with a median of ~ 0.3), but performs better for the Chilean gauges (with a median of > 0.45), ranking second after CHIRPS. Because MSWEP tends to underestimate measured precipitation, its false alarm ratio (with a median of 0.6 for NCEI) is higher than that of MERRA-2 (with a median of ~ 0.36 for NCEI) and IMERG (with a median of ~ 0.38 for NCEI). MERRA-2 and IMERG have relatively high detection rates for the NCEI datasets (with median values of approximately 0.47), but lower detection for the Chilean gauges (with a median of 0.18 for MERRA-2 and 0.27 for IMERG), where their false alarm ratios are lower compared to the other products.

IMERG stands out as one of the products with one of the lowest false alarm ratios, with a median of 0.38 for the NCEI and 0.22 for the Chilean gauge. While CHIRPS also exhibits a low probability of detection, it performs poorly for the false alarm ratio, with a median close to 1, because of its high precipitation estimates. ERA5 and MSWEP have the highest false alarm ratios for the NCEI dataset. In addition, ERA5, with a median exceeding 0.25, performs particularly poorly for the Chilean gauge, while MSWEP has the lowest false alarm ratio, with a median of 0. MERRA-2 shows similar performance to IMERG for the NCEI but has a slightly lower false alarm ratio (a median of ~ 0.1) for the Chilean gauges. MIMERG, with a median false alarm ratio of 0.39 for the NCEI and 0.18 for the Chilean gauges, outperforms most other products, except for its individual components, MERRA-2 and IMERG.

Additional boxplots for different detection thresholds (1 mm, 5 mm, and 25 mm) are presented in Figure A6 in the appendix. The overall results are consistent with those discussed above: IMERG consistently shows the highest probability of detection for both NCEI and

CHIRPS, while MSWEP achieves the highest probability of detection for the Chilean dataset. Similar conclusions are observed when analyzing the results by season (Figure A7 in the appendix) and by zones (Figure A8 in the appendix).

The probability of detection for MIMERG is higher than that of its individual components (i.e., MERRA-2 and IMERG), particularly when compared to the NCEI. This is because MIMERG leverages the strengths of both products, adding precipitation when one dataset reports nonnegligible precipitation while the other indicates none. Consequently, this approach increases the probability of detection but also leads to a higher false alarm ratio compared to its individual constituents.

Although the RMSE, bias, and correlation coefficients indicate that MERRA-2 and MIMERG are among the best products, in terms of probability of detection and false alarm ratios, ERA5, and MSWEP may outperform them. However, a high probability of detection or low false alarm ratio does not necessarily mean these products accurately capture measured precipitation, as they may overestimate it, as seen with CHIRPS and ERA5.

In Figures 6a and 6b, the average daily precipitation of the various products is compared with values obtained from measurements. Generally, the precipitation values align well across the products. CHIRPS shows the highest average values, while MIMERG falls between the other products (i.e., MERRA-2 and IMERG) for the NCEI gauges. For the Chilean gauges, MERRA-2 and IMERG have notably low precipitation values, as discussed earlier, resulting in MIMERG having lower values than CHIRPS, ERA5, and MSWEP.

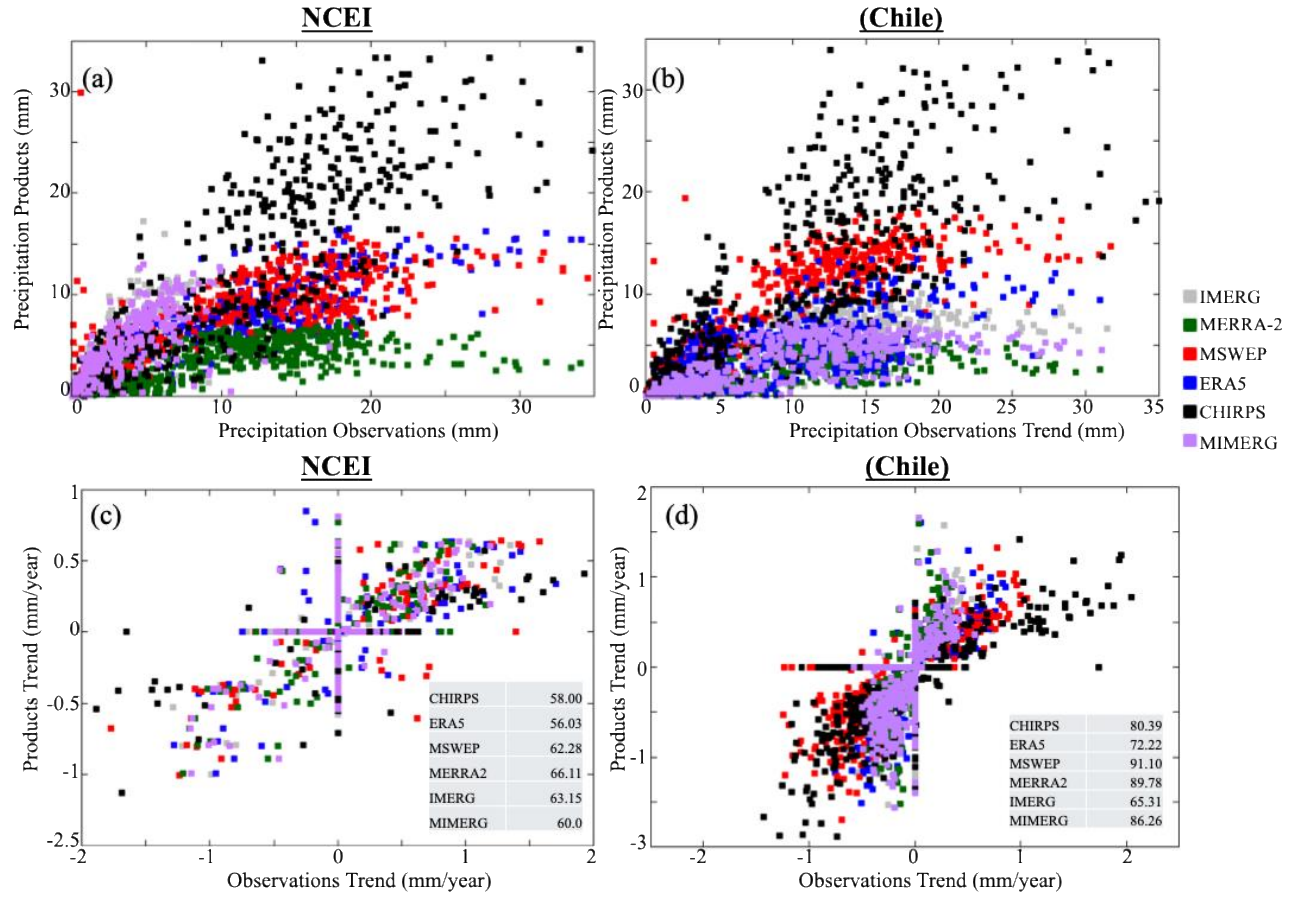


Figure 6: Daily average precipitation of the gridded products with respect to the daily average precipitation of (a) NCEI gauges and (b) Chilean gauges. Similar plots for trends are depicted in (c) for NCEI gauges and (d) for Chilean gauges.

Figure 6c and d illustrate comparisons between precipitation trends derived from gridded products and gauges. Overall, most products capture more than 50% of the observed trends in precipitation for the NCEI and more than 65% for the Chilean gauges. CHIRPS and ERA5, which showed predominantly positive trends in the northern areas, have the lowest percentage of captured trends for the NCEI dataset. In contrast, MERRA-2, which shows positive trends in the north and negative trends in the south, captures the highest percentage of correct trends, followed by IMERG and MSWEP, with IMERG slightly outperforming MSWEP.

For the NCEI dataset, MIMERG's performance in capturing precipitation trends is lower than that of IMERG and MERRA-2, but still better than ERA5 and CHIRPS. The Chilean dataset mainly covers the southern region of the study area, where all products indicate negative

precipitation trends. Consequently, most products show a high percentage of trend capture, exceeding 65%, with IMERG having the lowest percentage and MSWEP the highest. For the Chilean dataset, MIMERG performs better than both MERRA-2 and IMERG, with only MSWEP surpassing MIMERG's capture percentage of 86.26%.

4.3.The extended triple collocation (ETC)

As previously explained, because the ETC can only be performed using three products at a time, we conducted multiple ETC analyses for each product (see Table 2 for the different combinations) and calculated the average results. For ERA5, CHIRPS, MERRA-2, IMERG, and MSWEP, a total of six ETCs were conducted, representing all possible combinations of these products in groups of three. Because the ETC assumes product independence, only three ETCs were performed for MIMERG, which combined ERA5, CHIRPS, and MSWEP, as MIMERG itself is a combination of IMERG and MERRA-2, making it inappropriate to include those two in its ETC analysis. The ETC analysis was based on data from 2001 to 2023.

Product	ETCs performed
ERA5	6 (ERA5-CHIRPS-MSWEP, ERA5-IMERG-CHIRPS, ERA5-IMERG-MSWEP, ERA5-MERRA2-MSWEP, ERA5-MSWEP-IMERG, ERA5-MERRA2-MSWEP)
MERRA-2	6 (MERRA2-CHIRPS-MSWEP, MERRA2-ERA5-CHIRPS, MERRA2-ERA5-IMERG, MERRA2-ERA5-MSWEP, MERRA2-IMERG-CHIRPS, MERRA2-IMERG-MSWEP)
IMERG	6 (IMERG-CHIRPS-MSWEP, IMERG-ERA5-CHIRPS, IMERG-MERRA2-ERA5, IMERG-ERA5-MSWEP, IMERG-MERRA2-CHIRPS, IMERG-MERRA2-MSWEP)
CHIRPS	6 (CHIRPS-ERA5-IMERG, CHIRPS-ERA5-MSWEP, CHIRPS-IMERG-MSWEP, CHIRPS-MERRA2-ERA5, CHIRPS-MERRA2-IMERG, CHIRPS-MERRA2-MSWEP)
MSWEP	6 (MSWEP-CHIRPS-ERA5, MSWEP-CHIRPS-IMERG, MSWEP-CHIRPS-MERRA2, MSWEP-IMERG-ERA5, MSWEP-MERRA2-ERA5, MSWEP-IMERG-MERRA2)

MIMERG	3 (MIMERG-CHIRPS-ERA5, MIMERG-ERA5-MSWEP, MIMERG-MSWEP-CHIRPS)
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Table 2: Extended triple collocation analyses performed for each gridded precipitation products

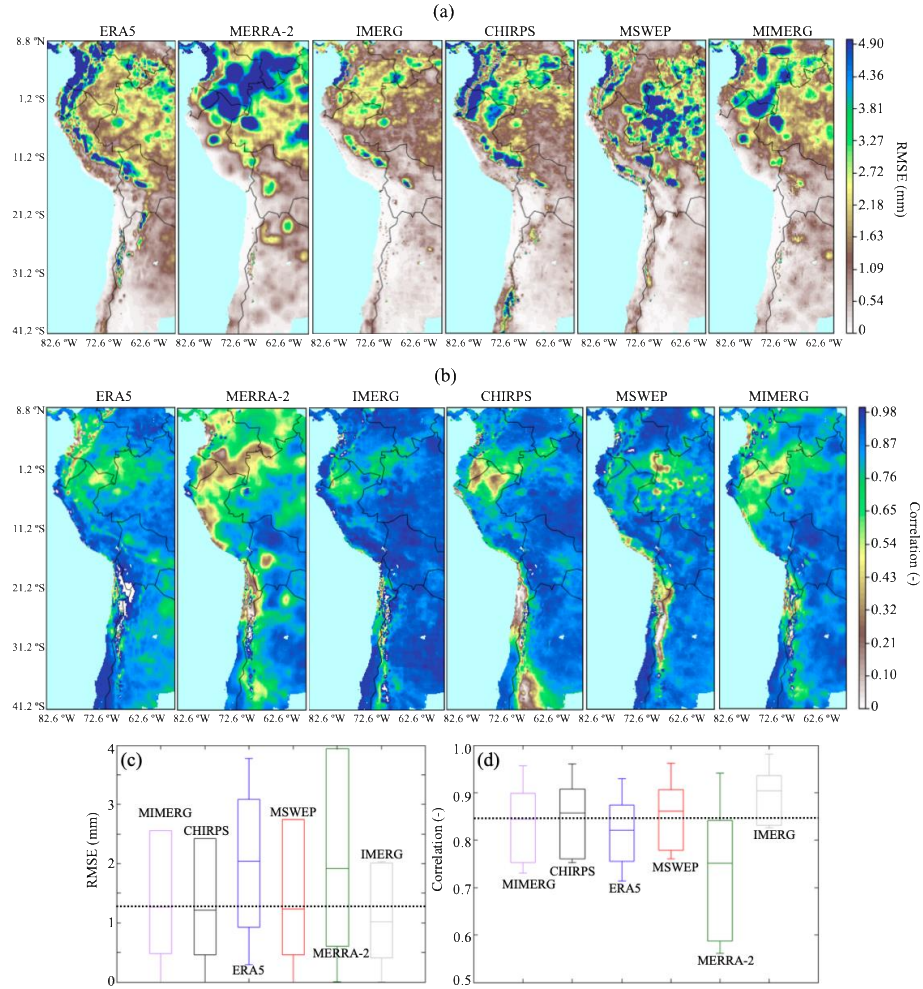


Figure 7: Spatial distributions of the extended triple collocation (a) RMSE and (b) correlation coefficient. The boxplots of the extended triple collocation RMSE and correlation coefficient are shown in (c) and (d) respectively.

Figure 7 presents the RMSEs, and correlation coefficients derived from the ETC analysis. These values were obtained by averaging the individual RMSEs and correlation coefficients calculated for each product across the six ETC combinations (or three combinations for MIMERG). The spatial distributions of RMSE are consistent across the six products, with lower

RMSE (< 1 mm) in the southern region due to lower precipitation values and higher RMSE (> 4 mm) in the northern region, where precipitation is greater. IMERG displays the lowest RMSE (with a median < 1 mm), as illustrated in Figure 7c, with a median RMSE that is half that of ERA5 and MERRA-2, the products with the highest RMSE (with a median of ~ 2 mm). MERRA-2's RMSE is particularly high over the Amazon basin. For ERA5 and CHIRPS, the RMSEs are primarily elevated in the high-altitude areas of the southern part of the study area. Only IMERG has a lower RMSE than MSWEP (with a median of ~ 1.22 mm). MIMERG's RMSE (with a median of ~ 1.25 mm) falls between those of MERRA-2 and IMERG, but it remains higher than the RMSEs of CHIRPS and MSWEP.

The correlation coefficients obtained from the ETC analysis are presented in Figure 7b, with the corresponding boxplot in Figure 7d. MERRA-2 has the lowest correlation coefficient (with a median of ~ 0.75), indicating it as one of the poorest performers in terms of ETC, while IMERG exhibits the best performance (with a median higher than 0.9). The correlation coefficient results align with the RMSE analysis, where areas and products with high RMSE correspond to areas with low correlation coefficients.

The results of the ETC analysis differ somewhat from conclusions drawn by direct comparisons with gauges, highlighting the distinctions between the two approaches. While ETC primarily evaluates random and systematic errors and biases, ground-based validation provides a direct performance assessment. For instance, IMERG exhibits relatively low errors in the ETC analysis, yet performs poorly when compared to gauges. Conversely, MERRA-2 demonstrates better performance in ground-based comparisons than in the ETC evaluation. This highlights the importance of using both approaches to comprehensively assess product performance. Additionally, it is important to acknowledge that gauges themselves are subject to various sources of uncertainty and error, including instrument inaccuracies, measurement biases, and data recording or transmission errors.

5. Summary and conclusions

Precipitation is arguably the most critical input for land surface models, driving the dynamics of ecosystems and the evolution of water resources over both short and long periods. Typically, precipitation estimates are derived from gauge observations, radars, and satellite remote sensing. However, gauge-based estimates face significant limitations: they are sparse, unable to

capture the strong spatial variability of precipitation, and prone to errors and uncertainties. Gridded precipitation products, derived from reanalysis data and satellite observations including radar, offer continuous long-term estimates across time and space, making them widely used. However, these gridded products come with inherent uncertainties, and their performance varies depending on the characteristics of the region they cover.

In this study, we evaluated the performance of five gridded precipitation products (MERRA-2, ERA5, CHIRPS, MSWEP, and IMERG) over a South American domain, including the Andes and surrounding regions. We compared these products against gauges and against each other using the ETC method. Our results show that MERRA-2 has the lowest errors when compared to gauges, followed by MSWEP and ERA5. CHIRPS stands out for its high probability of detection and though its false alarm ratio is high, indicating its ability to capture most precipitation events. However, a high probability of detection does not equate to low errors, as CHIRPS tends to overestimate ground precipitation, leading to a high RMSE.

When comparing the products using the ETC method, IMERG emerged with the lowest errors and highest correlation coefficient, followed by MSWEP. This highlights a critical finding: there is no single “best” product with consistently low RMSE when compared to both gauges and other gridded precipitation products.

To address this, we developed MIMERG, a new precipitation product that combines the strengths of the two top-performing products: MERRA-2, which excelled in ground measurement comparisons, and IMERG, which performed best in the ETC method. MIMERG integrates IMERG into MERRA-2 using advanced interpolation techniques. Our comparisons show that MIMERG improves the MERRA-2’s performance in the ETC analysis and enhances IMERG’s performance in gauges.

This study highlights the importance of selecting and combining precipitation products tailored to specific regional characteristics and analysis needs. The development of MIMERG demonstrates a significant step forward in enhancing the accuracy and reliability of precipitation estimates, which are crucial for effective water resource management and environmental modeling.

Acknowledgements

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Data availability

Datasets used in this study can be found in the following websites:

- ERA5: <https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5>
- MERRA-2: https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/data_access/
- MSWEP: <https://www.gloh2o.org/mswep/>
- IMERG: <https://gpm.nasa.gov/taxonomy/term/1372>
- CHIRPS: <https://www.chc.ucsb.edu/data>

Conflict of interest

The authors declare no conflict of interest.

Appendix A

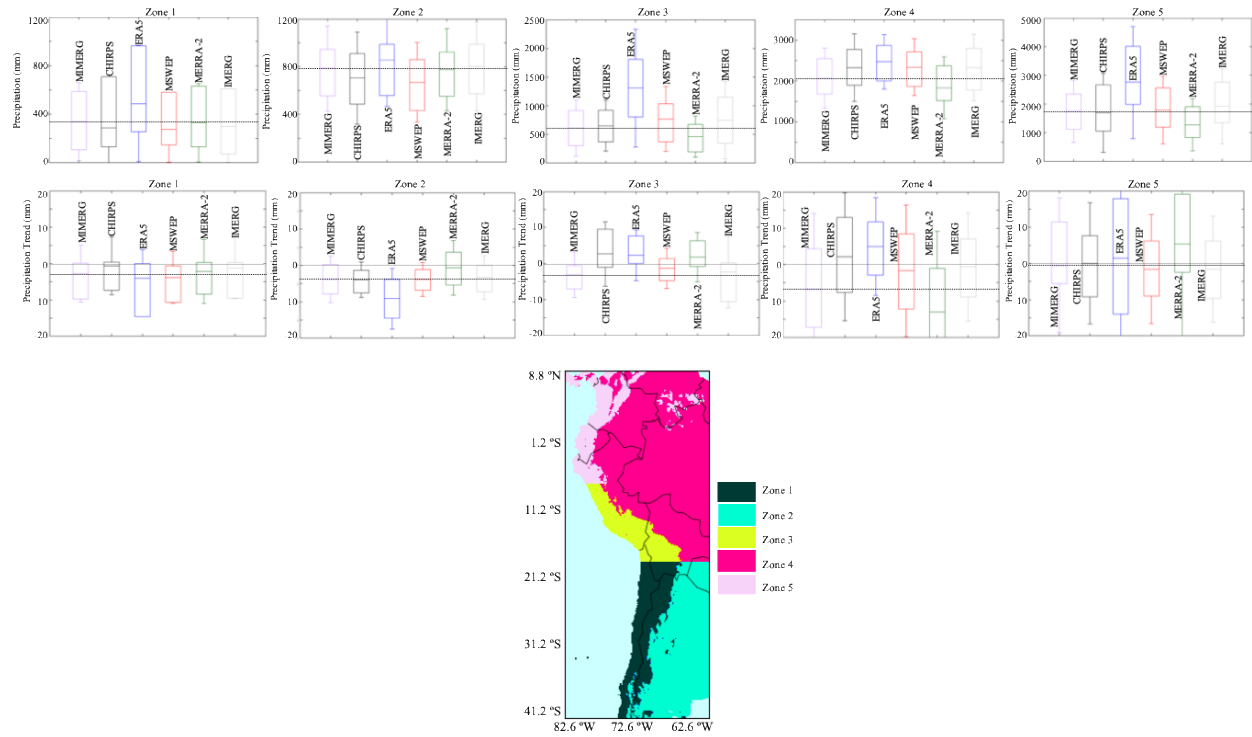


Figure A1: Boxplots of the annual average precipitation and its trends for 5 zones depicted in the bottom figure. The averages and trends are computed from 2001 to 2023.

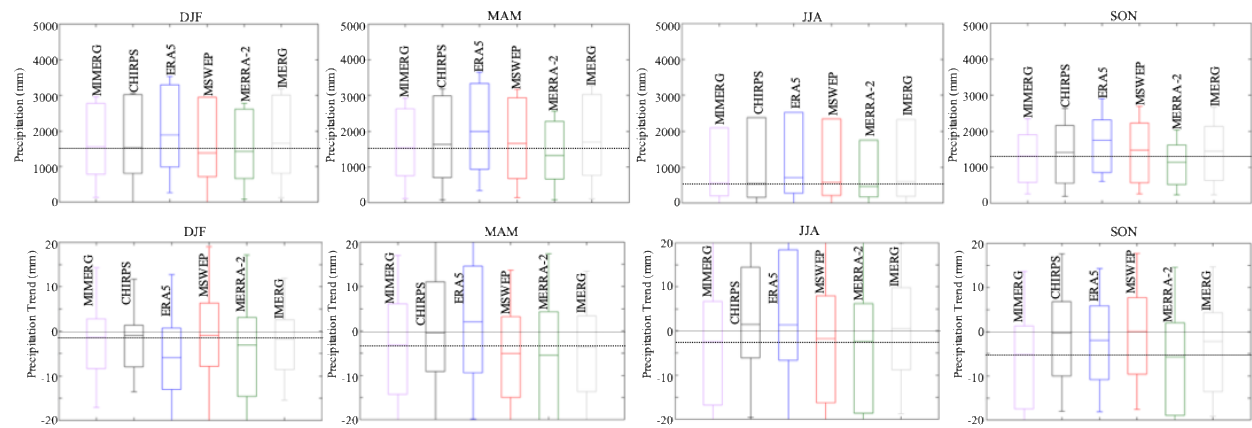


Figure A2: Boxplots of the annual average precipitation and its trends for 4 seasons. The averages and trends are computed from 2001 to 2023. DJF for December-January-February, MAM for March-April-May, JJA for June-July-August, and SON for September-October-November.

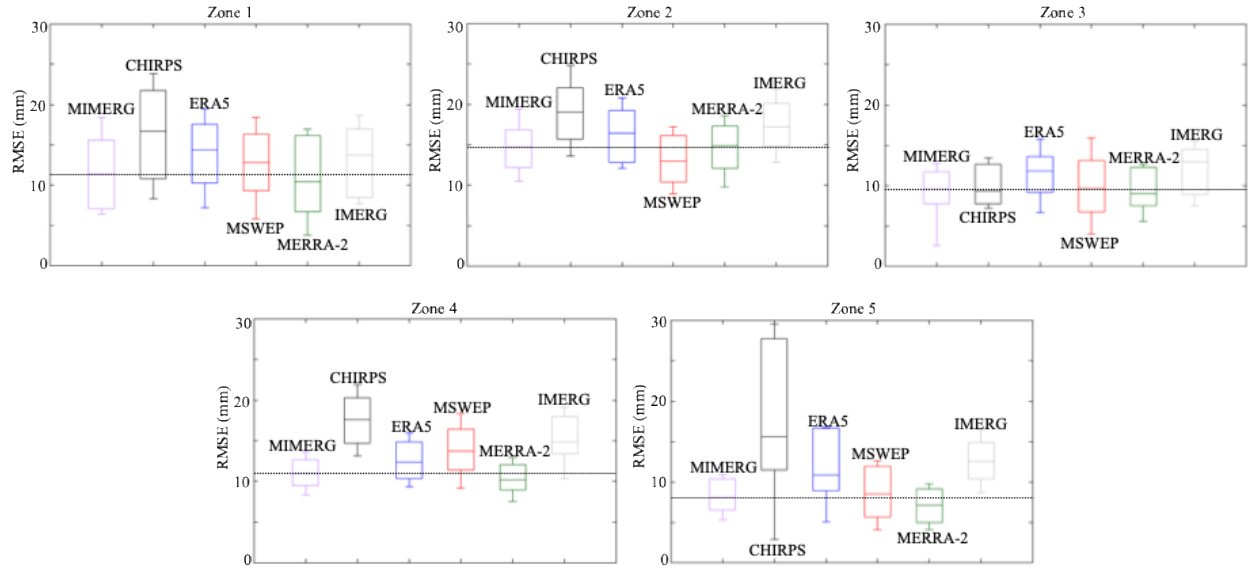


Figure A3: Boxplots of the RMSE of the comparisons between the gridded precipitation products and NCEI gauges for the 5 zones previously defined.

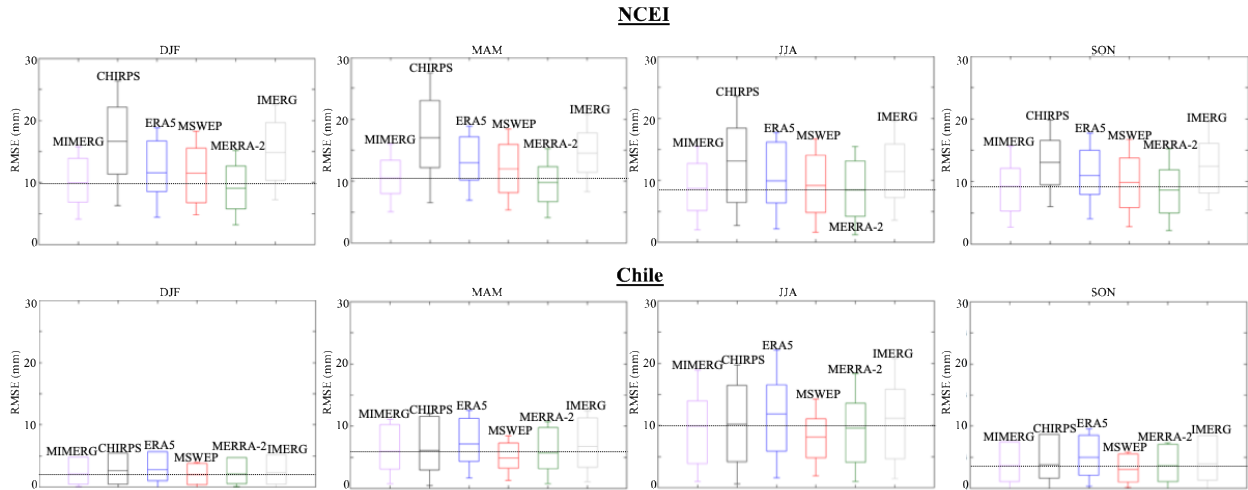


Figure A4: Boxplots of the RMSE of the comparisons between the gridded precipitation products and NCEI and the Chilean gauges for 4 seasons DJF (December-January-February), MAM (March-April-May), JJA (June-July-August), and SON (September-October-November).

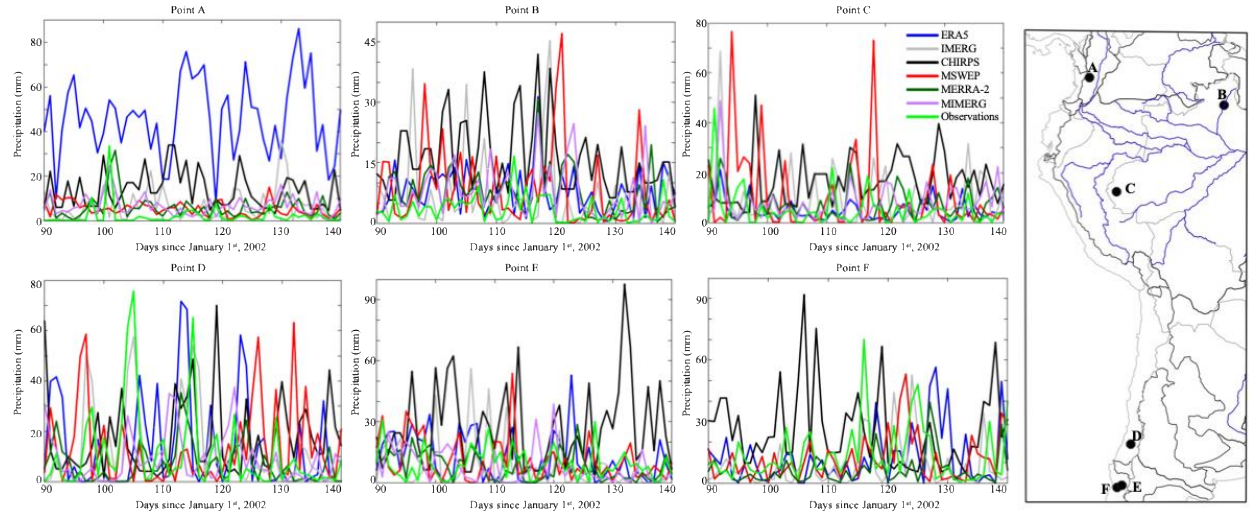


Figure A5: Time series of daily precipitation from the five studied products, MIMERG, and gauges at six selected points whose locations are shown on the right.

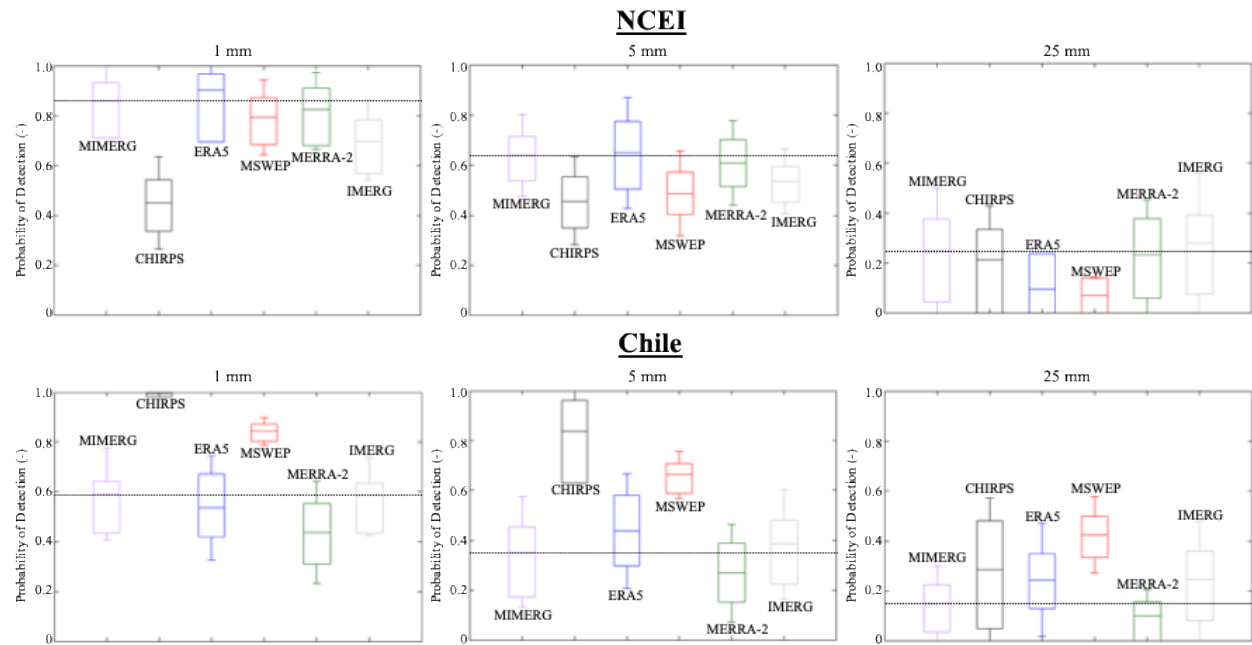


Figure A6: Boxplots of the probability of detection for different thresholds (1mm, 5mm, and 25mm) for the NCEI and Chilean gauges.

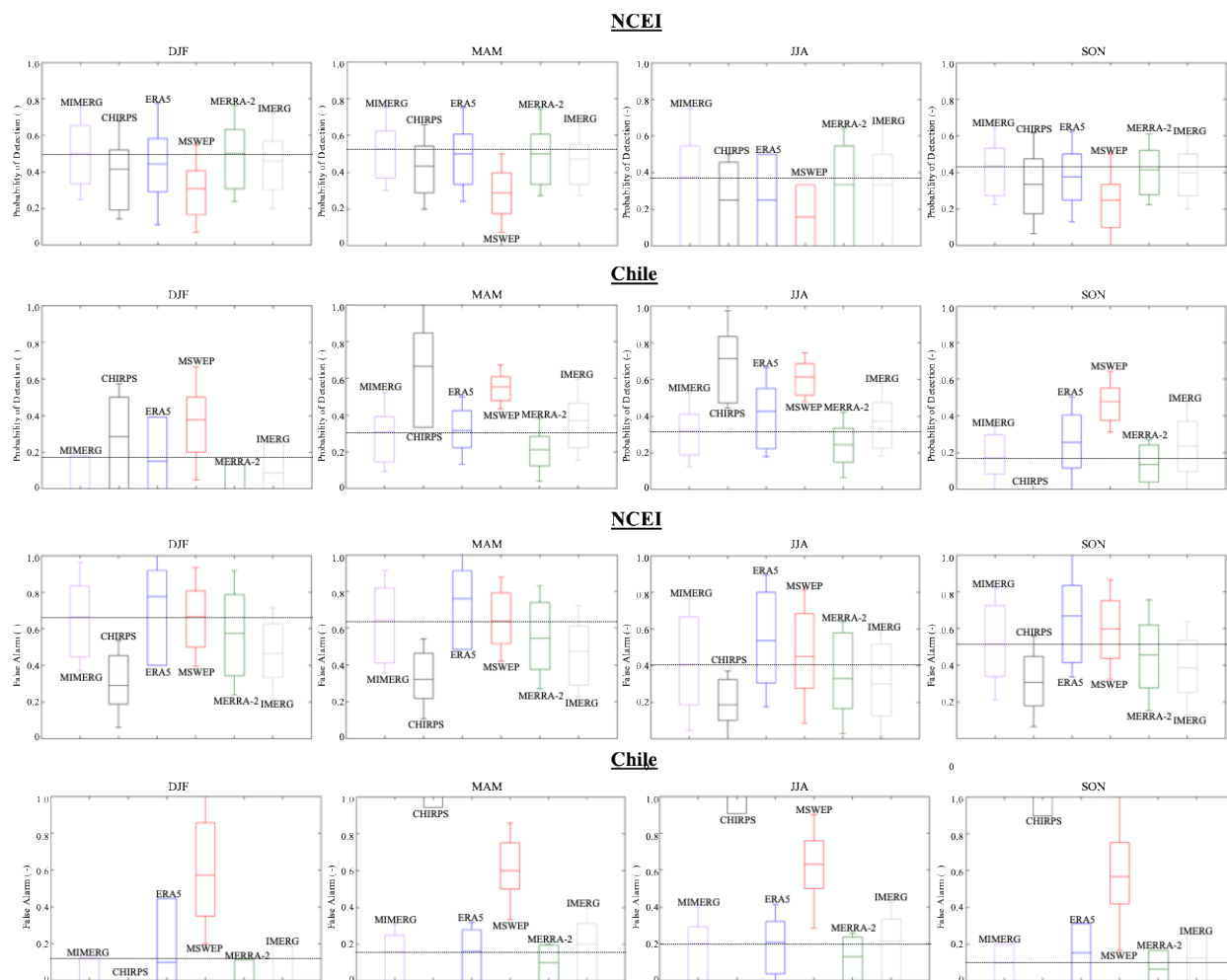


Figure A7: Boxplots of the probability of detection and false alarm of NCEI gauges and Chilean gauges for 4 seasons DJF (December-January-February), MAM (March-April-May), JJA (June-July-August), and SON (September-October-November).

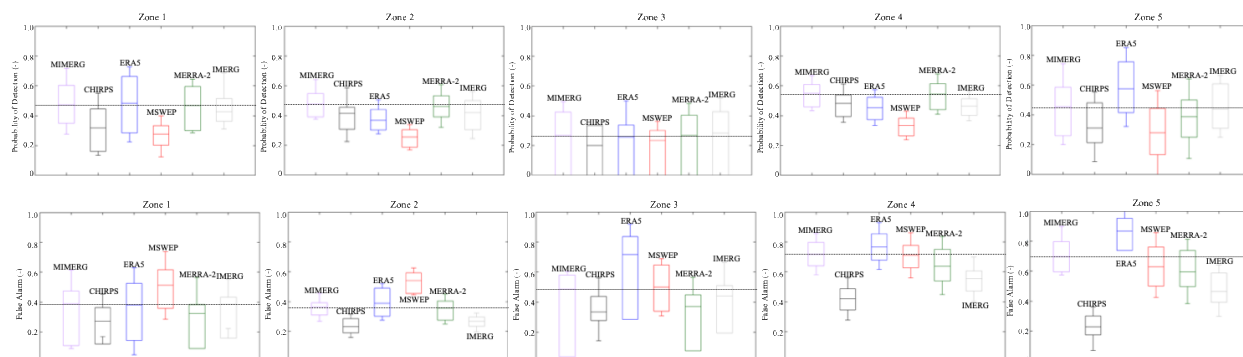


Figure A8: Boxplots of the probability of detection and false alarm of NCEI gauges for the 5 zones previously defined.

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