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Satellite-based precipitation estimates using a dense rain gauge network over the Southwestern Brazilian Amazon: Implication for identifying trends in dry season rainfall

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ABSTRACT

Accurate long-term estimates of rainfall at fine spatial and temporal resolution are vital for hydrometeorology and climatology studies, but such data are often unavailable in remote regions. We assessed the accuracy of three satellite-based precipitation products that have data from 1981 to 2019 over the state of Rondônia in the Brazilian Amazon: (a) satellite-only, using the Climate Hazards Group Infrared Precipitation (CHIRP) product, (b) CHIRP with sparse gauge data (CHIRPS), and (c) CHIRPS calibrated with data from a dense rain gauge network ($N = 73$) (dnCHIRPS). We evaluated the rainfall products using additional validation gauges ($N = 55$) at the monthly and seasonal time scales and compared their drought events and temporal trends. Both CHIRP (10.0 mm/month mean error (ME), 23.6% percent bias (PB)) and CHIRPS (−0.08ME, 7.4% PB) underestimate high monthly rainfall in the wet season and overestimate low monthly rainfall during the dry season. dnCHIRPS had a lower error in monthly rainfall (−0.01ME, 1.1%PB) compared with CHIRP and CHIRPS, with the largest percentage difference between dnCHIRPS and the other two datasets in the dry season. dnCHIRPS captured decreasing trends in dry season rainfall over agricultural parts of the state, trends that were missed by the other two products. We conclude that a high density of rain gauges is essential for documenting the spatial pattern and trends in rainfall during the dry season and droughts in this important agricultural region of the Amazon basin.

1. Introduction

Rainfall in the Amazon Basin exhibits high spatial and temporal variability. Rainfall patterns over the Amazon have changed over 1981–2017 (Paca et al., 2020); some of these changes in rainfall may be due to deforestation, which reduces evapotranspiration (Rizzo et al., 2020; Stickler et al., 2013), and others may be due to ocean forcing and/or global climate change (Staal et al., 2020). Reliable datasets on rainfall variability and change in the Amazon, especially associated with flood and drought events, are critically important for agriculture, water management, and understanding the consequences of land cover and climate change. Consistent long-term rainfall time series are required for analyses of spatial and temporal climate variability (Dinku et al., 2018), and for understanding how drought magnitude and severity have changed during periods of the combined forcing from land-use change and greenhouse gases.

Improvements in the spatial resolution of rainfall datasets are essential for documenting trends, validating high-resolution climate models, and attributing changes in precipitation to forcing factors, such as land use. Deforestation can impact rainfall on several spatial scales. On local scales, deforestation induces convection over newly cleared areas (Davidson et al., 2012; De Sales et al., 2020; Mu et al., 2021). Land-use changes in the Amazon occur on private properties in large agricultural zones but clearing within those zones can be heterogeneous in ways that could impact rainfall with high spatial variability. Clearings are spatially autocorrelated with a range of ∼150 km (Biggs et al., 2008). Therefore, rainfall datasets with a high spatial resolution are required to quantify the impacts of land-use changes, ocean forcing, and global climate change.

Conventional rain gauge networks are the primary sources for accurate point measurements of rainfall (Katsanos et al., 2016). However, ground-based rain gauges are inadequate for regions with sparse gauge networks and complex topography, and frequent gaps in rain gauge data complicate the mapping of spatial patterns and trends. In recent

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decades, several satellite-based rainfall products have been developed to estimate rainfall, each with different spatial coverage, data sources, spatial resolutions, and temporal spans and latencies (Sun et al., 2018). A few commonly used satellite-based rainfall products include the Climate Prediction Centre Merged Analysis (CMAP) (Xie and Arkin, 1997), the Global Precipitation Climatology Project (GPCP) (Adler et al., 2003), African Rainfall Climatology version 2 (Novella and Thiaw, 2013), and the Tropical Applications of Meteorology using SATellite data and ground-based observations (TAMSAT) (Tarnavsky et al., 2014; Maidment et al., 2017). CMAP and GPCP have global coverage, but they are available in very coarse spatial (2.5°) and temporal resolutions.

The Climate Hazards Group Infrared Precipitation (CHIRP) and CHIRP combined with gauge data (CHIRPS) are satellite-based rainfall products with a fine spatial (0.05°) and temporal (daily) resolution, spanning 50°S - 50°N from 1981 to present (Funk et al., 2015a). Validations of CHIRPS have been conducted in several regions, including Nepal (Shrestha et al., 2017) and the Central Andes of Argentina (Rivera et al., 2018). Hessels (2015) compared several satellite rainfall products in the Nile basin and concluded that CHIRPS was one of the best products for hydro-meteorological studies. In the Brazilian Amazon, Cavalcante et al. (2020) concluded that monthly CHIRPS rainfall was similar to that from rain gauges, but CHIRPS underestimated extreme rainfall. Paca et al. (2020) used CHIRPS to document trends in annual precipitation over the Amazon basin and cross-validated their results with ground gauge data. They found that the spatial average precipitation of the Amazon basin had increased only slightly over 1981–2017, but the trend had a large spatial variation, with some areas showing increases and others decreases. Trends in intra-annual values like monthly or seasonal precipitation, which are critical for soil moisture stress in both natural and agricultural ecosystems, are less well documented.

Previous analyses of CHIRPS and other rainfall products over the Amazon (e.g. Cavalcante et al. (2020); Paca et al. (2020)) used readily available rain gauge networks over the entire Amazon basin, which have significant spatial and temporal gaps. Cavalcante et al. (2020) used relatively few gauges ($N = 45$) for the whole Amazon, and no gauges were located in some important agricultural regions, such as the state of Rondônia. Paca et al. (2020) had a more complete dataset, but mostly limited their comparison to the gauges with 20 or more years of data, in order to ensure accurate trend tests. This method may miss spatial patterns of extreme events like droughts. Paca et al. (2020) considered monthly trends and had a thorough analysis of the annual trends over the entire Amazon. The Brazilian National Water Agency (ANA) extended its rain gauge network to include more gauges, some equipped with telemetry (Fig. S1). We will use this relatively dense network of 128 gauges to document errors and trends in satellite-based rainfall by season for agriculturally significant regions in the Brazilian Amazon.

The aim of this study is to assess the accuracy of the CHIRPS product for monthly precipitation estimates and to develop and evaluate a new dataset (dnCHIRPS) by combining CHIRPS with a dense network of rain gauges in the state of Rondônia of the Brazilian Amazon. We carried out point-to-pixel comparisons for CHIRP, CHIRPS, and dnCHIRPS on the monthly and seasonal scales. We aimed to answer the following questions: (i) What is the spatiotemporal structure of differences between satellite rainfall estimates and rain gauges? (ii) What is the impact of calibrating the satellite rainfall estimates with rain gauge data on observed spatial patterns and trends in monthly and seasonal rainfall?

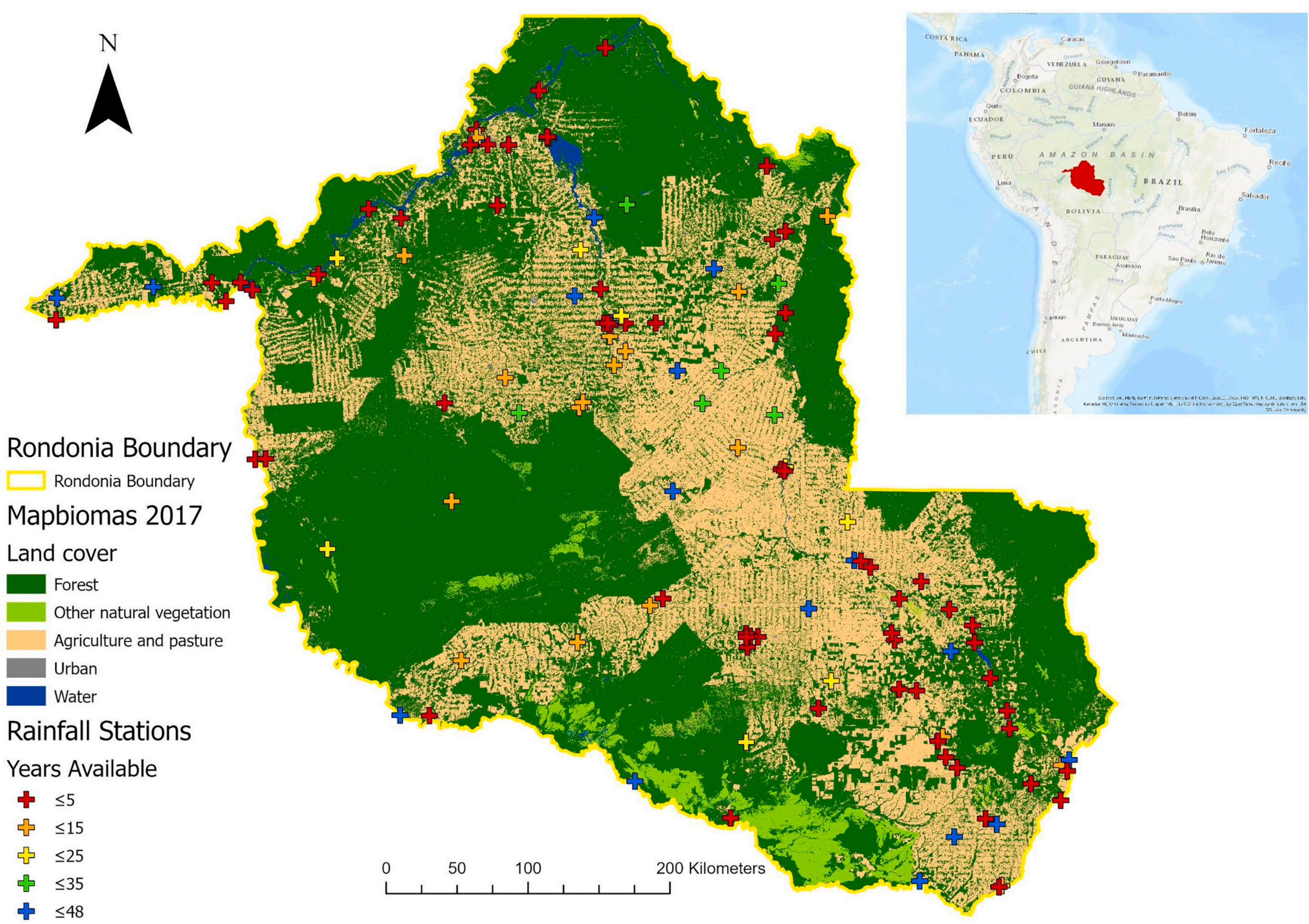

Fig. 1. The study region, locations of rain gauges, and the number of years of data for each gauge. The land cover data are from Mapbiomas Project (2019).

The distinguishing features of the study, compared to previous studies of the region (Cavalcante et al., 2020; Paca et al., 2020), are that (i) we use a large number of gauge observations over a long period (1981 to 2019), and (ii) we focus on intra-annual (monthly and seasonal) precipitation. The study is significant for examining the number of rain gauges needed to calibrate satellite estimates for the purpose of detecting monthly patterns and trends in rainfall, and for documenting monthly and seasonal changes and trends in rainfall over the period of deforestation in the Brazilian Amazon, which can only be achieved with a comparison of satellite rainfall estimates with rain gauges at high spatial resolution.

Section 2 introduces the study region and climatic setting. Section 3 describes the datasets, their quality control and blending methods, and statistical metrics. Section 4 evaluates the results and discusses the main findings, while Section 5 has conclusions and recommendations.

2. The study region

The study region is the state of Rondônia in Brazil (10.60° S, 62.31° W) (Fig. 1), which covers 243,000 km^2 of the Brazilian Legal Amazon's 5,000,000 km^2 (Guild et al., 2004) and has experienced high deforestation rates starting in the 1980s (INPE 2020). The region has gently undulating topography with elevations between about 14 and 1100 m above sea level. The climate is humid tropical, with a dry season from June to August, a dry-to-wet season transition from September to October, and a peak wet season from December to March (Butt et al., 2011).

3. Methodology and data

3.1. Satellite-based rainfall data

Each of the methods and processing steps is described below (Fig. 2). Two satellite-based rainfall products (CHIRP and CHIRPS v2.0) from the Climate Hazard Group were used in this study (available online at https://data.chc.ucsb.edu/products/CHIRPS-2.0/). CHIRP includes only satellite data and mean climatology grids, while CHIRPS incorporates gauge data to calibrate the satellite-based data. CHIRP integrates several sources: (a) pentadal (six pentads per month) precipitation from long-term climatology; (b) Climate Prediction Centre (CPC) Infrared (IR) imagery (0.5 h temporal resolution; 4 km spatial resolution; 2000 to present); (c) the National Climatic Data (NCDC) B1 IR imagery (3 h temporal resolution; 8 km spatial resolution; 1981 to 2008); (d) the Tropical Rainfall Measuring Mission (TRMM) 3B42 product (0.25° spatial resolution; 3 h temporal resolution); and (e) the NOAA Climate Forecast System v2 (CSFv2). Estimates of the pentadal rainfall from cold cloud duration (CCD)-based satellite data are calibrated with the TRMM 3B42 product using linear regression. The predictions of the regression models are expressed as a percentage of normal rainfall and multiplied by the corresponding precipitation climatology to produce CHIRP (Toté et al., 2015). CHIRPS then incorporates in situ precipitation observations obtained from the Global Historical Climate Network (GHCN) and the Global Summary of the Day dataset (GSOD) (Funk et al., 2014). CHIRP and CHIRPS have a spatial resolution of 0.05° (about 5.3 km over the Amazon region), quasi-global coverage (50°S-50°N, 180°E-180°W) from 1981 to present (Funk et al., 2014). Monthly CHIRP and CHIRPS used here were from January 1981 to December 2019, which overlaps with the gauge data period (1975–2019). The number of gauges used in the CHIRPS dataset decreased in Brazil starting in 1985 and fell to a few dozen by 2013 (Fig. S1). In Rondônia, CHIRPS used a total of 58 gauges in 1981 and 5 in 2019 (Fig. S2). One main goal of this study is to augment the number of gauges used to calibrate CHIRPS by identifying and incorporating additional rain gauge data.

3.2. Rain gauge data and processing

The Brazilian National Water Agency (ANA)collects rainfall data for Brazil. Rain gauge data for the state of Rondônia are available at daily (81 gauges) and hourly (47 gauges) resolution from ANA's Hidroweb portal (available online at www.snirh.gov.br/hidroweb/). A total of 128 gauges were used for calibration and validation in this study. The average density is 0.53 gauges per 1000 km^2, which is significantly higher than that used in other studies (0.01 gauges per 1000 km^2 in Cavalcante et al. (2020), and 0.11 for the whole Amazon in Paca et al. (2020).

The gauges are distributed unevenly, with more gauges in areas cleared earliest during colonization. Although the date ranges of the data are different for each gauge (Table S1, S2), the collective rainfall gauge datasets cover the period from 1975 to 2019.

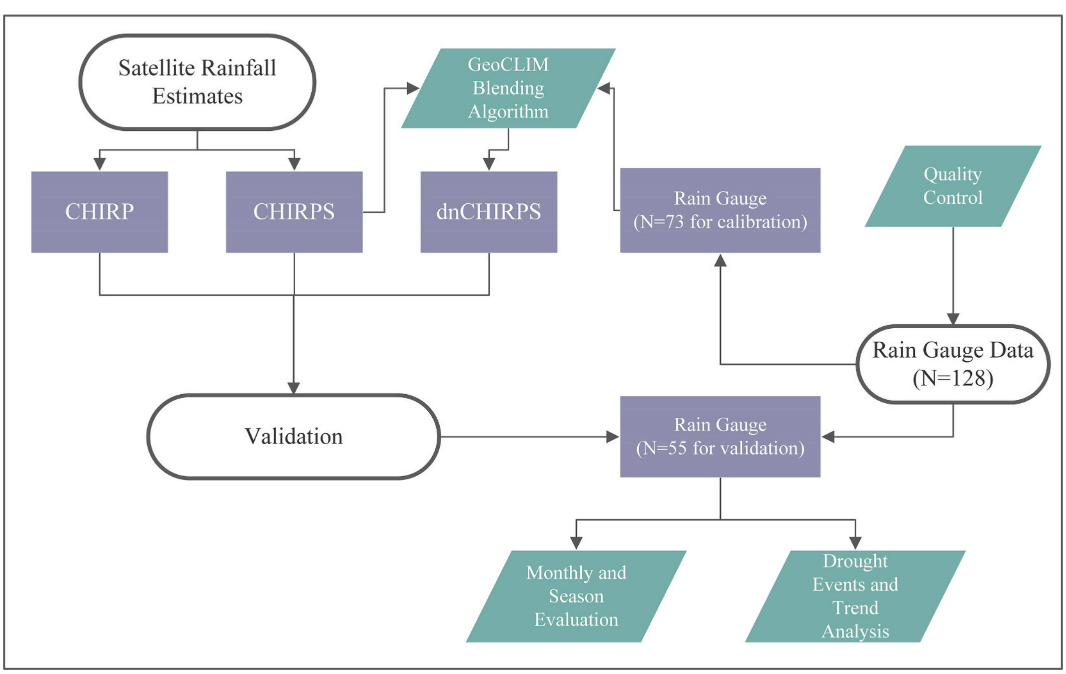

Fig. 2. Rainfall data processing and methodology flowchart.

Inventory and quality control of the rainfall gauge data was performed in three steps:

a) Calculate monthly rainfall from daily and hourly values to visualize gauge data availability as a percentage of days with data for each month and year (Fig. S3 and S4). Examine the monthly data quality for the 81 gauges with daily data and quality flags. Remove months with blank, uncertain, or estimated flags for any day in that month.
b) Gauges with telemetry and hourly data ($N = 47$) do not report data quality flags. Data for these stations were reviewed, and months with missing or incomplete data were removed. This procedure found and removed 432 zeros from 36 gauges.
c) Compare rainfall values from the gauge data with the interpolated gauge data. Identify and remove gauge data with clear quality issues (RMSE >100 mm/month, and annual rainfall <1000 mm). This step removed 31 annual values and 372 monthly values from 12 gauges.

For the final gauge dataset, the mean RMSE between gauge rainfall and the interpolated gauge rainfall was 33.5 mm/yr, with a small increase to 50 mm/yr in 2013 corresponding with the introduction of additional telemetry gauges (Fig. S5). The maximum RMSE at individual gauges for the station versus interpolated gauge comparison is 88 mm/yr. Out of 149 gauges, 21 gauges were completely removed due to missing data or data quality issues, leaving 128 gauges for analysis ($N =$ 81 daily and 47 hourly with telemetry). Of those 128 gauges in 1975–2019, 34 gauges had data for more than 20 years, 9 for 10–20, 40 for 5–10, and 45 less than 5 years.

3.3. dnCHIRPS data

The 128 rain gauges were randomly assigned for calibration ($N = 73$) and validation ($N = 55$). The dnCHIRPS rainfall dataset (0.05° × 0.05° resolution, 1981–2019) was developed by blending the 73 calibration gauges network into the CHIRPS product using the Geospatial Climate Data Management and Analysis (GeoCLIM) software (Bamweyana and Kayondo, 2018; Mwesigwa et al., 2017; Funk et al., 2015a), which is developed and maintained by the United States Geological Survey (USGS) and Family Early Warning Systems Network (FEWS NET) (Pedreros and Tamuka, 2017).

GeoCLIM uses the Background-Assisted Station Interpolation for Improved Climate Surfaces (BASIICS) algorithm, which blends CHIRPS with additional gauge data using a modified IDW that borrows some concepts from simple and ordinary kriging (Pedreros and Tamuka, 2017). We used modified IDW interpolation with the following parameters: 1.0 weight power, 100 km maximum effective distance, 0 (min) to 10 (max) gauges, 3.0 maximum ratio of the gauge to CHIRP value, and a 1.0 fuzz factor, which hides the location of the gauge by one pixel to avoid reverse-engineering the gauge-based pixel value (Pedreros and Tamuka, 2017). The search radius was set to 500 km, but since the study area is relatively small with sufficient gauge density, this parameter does not impact the calibration result. The blending process involved the following steps, following Funk et al. (2015b): a) Extract raster values for each gauge point; b) calculate the ratio of the gauge value to the value at the raster (CHIRP); c) if the ratio is greater than Max ratio, set the ratio to Max ratio. The ratio was greater than the Max ratio only 99 out of 9722 gauge-month values, suggesting it had limited impact on the results; and d) interpolate ratios and multiply the interpolated ratios by the original CHIRP values. The resultant monthly product is available from 1981 to 2019 and has the same spatial resolution as CHIRP and CHIRPS (0.05°). Changes in the number and distribution of gauges of time, especially introduction of new gauges, can introduce artifactual trends if the mean CHIRP climatology is biased so we tested the sensitivity of dnCHIRPS and resulting trends in precipitation to using only those gauges in the calibration set with data over the whole period of interest ($N = 8$).

Table 1
Equations of statistical metrics.

Name	Formula
Pearson correlation coefficient	$r = \frac{N(\sum CG) - (\sum C)(\sum G)}{\sqrt{\left[N\sum C^2 - (\sum C)^2\right]\left[N\sum G^2 - (\sum G)^2\right]}}$ (1)
Mean error	$ME = \frac{1}{N}\sum(C - G)$ (2)
Normalized root mean square error	$NRMSE = \frac{\sqrt{\frac{\sum(C-G)^2}{N}}}{\overline{G}}$ (3)
Percent bias	$\mathrm{PB} = 100\frac{\sum(C-G)}{\sum G}$ (4)

G: Gauge data; C: Satellite estimate; N: Number of data pairs.

3.4. Evaluation of the calibrated product

The remaining gauges ($N = 55$) of the gauge network were used for validation. Extracted values from the satellite data (CHIRP, CHIRPS, dnCHIRPS) at all valid gauge values (14,998 pairs) were cross validated using the BASIICS blending process. The BASIICS algorithm carries out a least-square regression between rainfall from rain gauges and satellite values at the rain gauge locations (Pedreros and Tamuka, 2017). We carried out point-to-pixel comparisons that use the rainfall estimates at the pixel in which the rain gauge is located. This method has been widely used in evaluating satellite rainfall estimates (Katsanos et al., 2016; Shrestha et al., 2017; Cavalcante et al., 2020), though it often overestimates error due to problems with comparing measurements at a point with a much larger pixel area. This scaling issue is particularly problematic in areas with isolated convective activity, including the Amazon. The relatively fine resolution (0.05° × 0.05°) of the CHIRP(S) rainfall datasets reduces but does not eliminate the problems associated with point-to-pixel comparison compared with coarse-resolution rainfall grids (Shrestha et al., 2017). The performance of the three satellite rainfall products was assessed using several metrics, including the Pearson correlation coefficient (r), mean error (ME), normalized root-mean-square error (nRMSE), and percent bias (PB) (Table 1). Trend magnitude (mm/yr) was determined using linear regression.

4. Results and discussion

4.1. Monthly and seasonal evaluation

The gauge-blended satellite rainfall products (dnCHIRPS and CHIRPS) performed consistently better than the satellite-only dataset (CHIRP, $R^2 = 0.67$, $r = 0.82$) (Fig. 3a) in predicting monthly rainfall across all months. dnCHIRPS ($R^2 = 0.80$, $r = 0.89$), which included between 15 and 68 more gauges than CHIRPS from 1981 to 2019, performed slightly better than CHIRPS ($R^2 = 0.76$, $r = 0.87$) when including all months. CHIRPS overestimated rainfall in months with low rainfall totals (< 250 mm), and all three datasets underestimated rainfall in months when the monthly total was more than 300 mm (Figs. 4 and 5). This implies that all the three datasets over-smoothened the rainfall field, and that dnCHIRPS can better represent the extremes of rainfall.

Other validation studies have had similar results (Cavalcante et al., 2020; Qin et al., 2014). Paredes-Trejo et al. (2017) used 21 rain gauges to validate CHIRPS in north-eastern Brazil and found underestimation of high values. Underestimation of high rainfall values was also observed in Venezuela, which was explained by the low rain detection capability during the wet season due to the tendency of CHIRP to misclassify rainfall events (Paredes Trejo et al., 2016).

CHIRP, CHIRPS, and dnCHIRPS all have similar annual cycles in mean monthly precipitation, but dnCHIRPS was more similar to rain gauges in August and during the wet season (Jan-Mar) (Fig. 5). During wet seasons, the correlations (r) between satellite and rain gauge data (r)

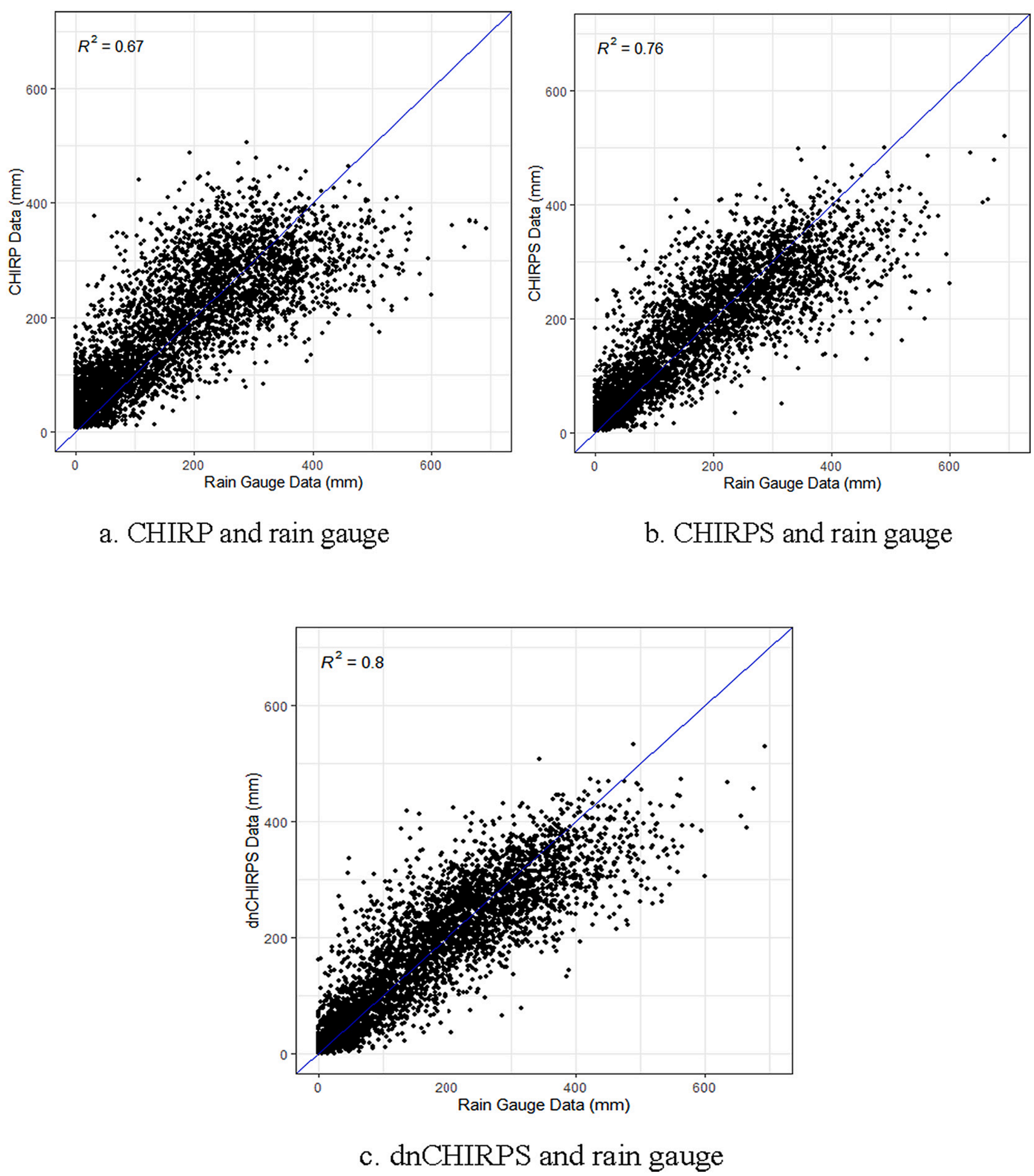

Fig. 3. Scatter plot of monthly rainfall from satellite rainfall products and ground-based rain gauge data ($N = 55$) from 1981 to 2019. The blue line indicates 1:1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

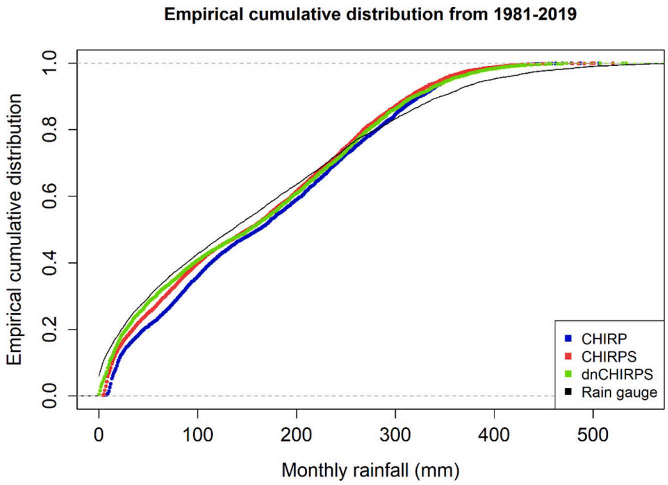

Fig. 4. Empirical cumulative distribution of monthly rainfall from satellite products and from validation rain gauge observations from 1981 to 2019.

are typically lower for CHIRP and CHIRPS, while the dnCHIRPS is highly correlated with gauge data in almost all months (Fig. S6). dnCHIRPS (0.21) has a lower mean nRMSE than CHIRP (0.48) and CHIRPS (0.39) every month (Fig. 6). For the JJAS (June to September) dry season, dnCHIRPS has much lower nRMSE, while CHIRP and CHIRPS have many high outliner points for JJAS. For August, dnCHIRPS has a significantly lower (nRMSE <0.1) and fewer outliners compared with CHIRP (nRMSE >0.25) and CHIRPS (nRMSE >0.1). dnCHIRPS performed better during the dry season compared with CHIRP and CHIRPS, which tend to overestimate low rainfall amounts (Saeidizand et al., 2018).

CHIRP (10.0 mm/month ME, 23.6% PB) and CHIRPS (−0.08ME, 7.4% PB) have higher and more variable mean ME and PB compared with dnCHIRPS (−0.01ME, 1.1%PB) (Fig. 7). Large ME values also occur during the wet seasons (December to February) in CHIRPS and CHIRP (Fig. 7). The highest errors in wet seasons could be caused by larger chances of non-raining clouds that could produce brief localized showers (Saeidizand et al., 2018). Overall, dnCHIRPS performed better in capturing extreme rainfall events during the dry seasons compared with CHIRP and CHIRPS at the monthly scale.

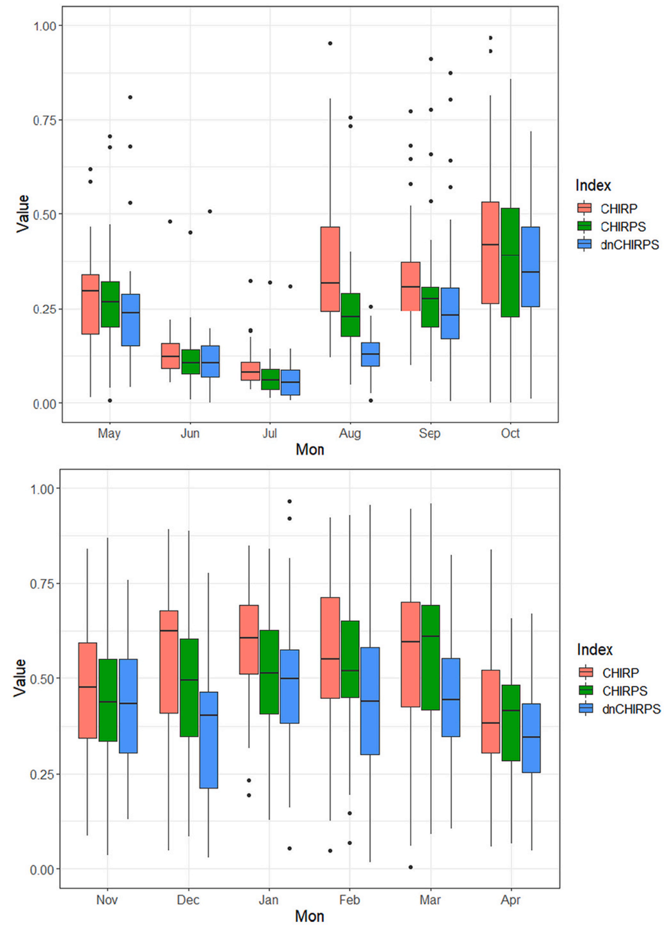

Fig. 6. Boxplots of nRMSE of the satellite products compared with validation gauges ($N = 55$) for each month: (top) Dry season (May-Oct). (bottom) Wet season (Nov-Apr). The black line on the box indicates the median.

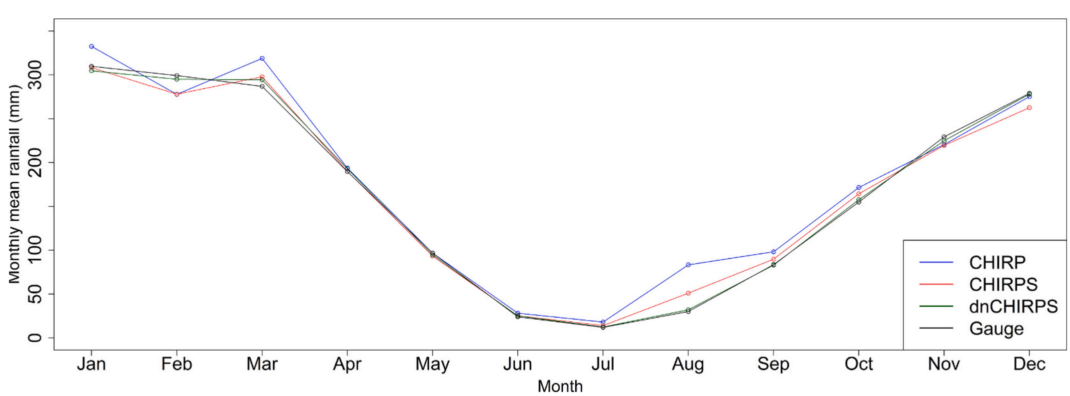

Fig. 5. The Monthly State-wide mean rainfall estimated from satellite products and validation gauge data from 1981 to 2019.

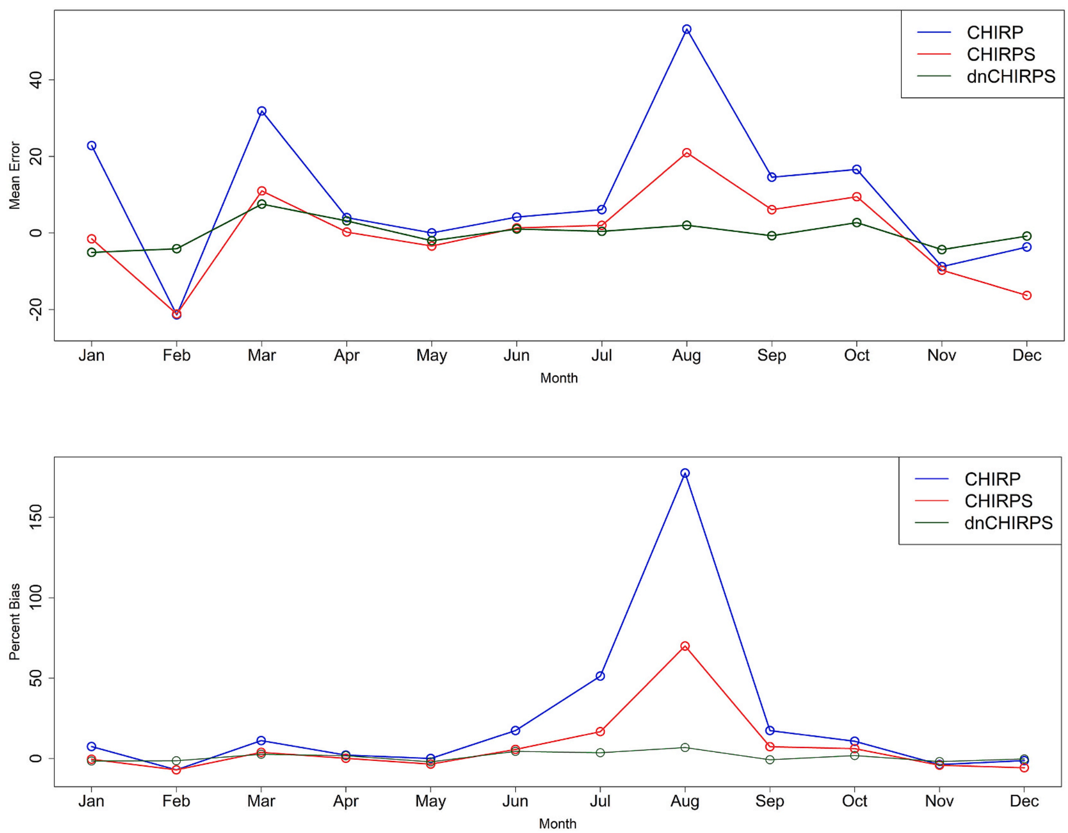

Fig. 7. Mean monthly error (mm) and percent bias of the satellite products compared with rain gauges from 1981 to 2019.

4.2. Drought events and Trend analysis

Large areas of the Amazon basin, including Rondônia, experienced severe droughts in 2005, 2010 and 2015. Panisset et al. (2018) found that a precipitation deficit was evident in JJAS for 2005 and 2010 drought events. This is supported by the low JJAS rainfall values in 2005 and 2010 from CHIRPS and dnCHIRPS (Fig. 8), though 2008 also had very low JJAS precipitation. dnCHIRPS had lower JJAS rainfall than CHIRPS during drought years, suggesting that CHIRPS may underestimate drought severity. In the dry season in some years, years without basin-wide drought as identified by Marengo et al. (2016) showed low rainfall in Rondônia (e.g. 1988, 2006–2008), suggesting the local droughts have occurred despite non-drought at the basin scale.

Maps of the temporal trends (Pearson correlation coefficients and regression slopes) provided by CHIRP, CHIRPS, and dnCHIRPS identify areas where the changes were statistically significant (Figs. 9 and 10). CHIRP identifies only increases in rainfall in the western part of the state. CHIRPS maps a small area of decreasing dry season rainfall in the northern part of the state and large areas of decreasing (north) and increasing (west) annual rainfall. dnCHIRPS shows a similar pattern in trends in annual rainfall as CHIRPS, but dnCHIRPS shows a more severe and widespread decreasing trend in dry season rainfall over the agricultural area of the state (Figs. 1 and 9). The decreasing trend is robust but slightly weaker when excluding gauges with records shorter than the whole study period (Fig. S7), suggesting that the gauges with short records enhanced the magnitude of the trend. The decreasing trends in the dry season and annual rainfall are consistent with other Amazon-basin wide studies (Arvor et al., 2017; Silva Junior et al., 2018; Paca et al., 2020), though our findings in Rondônia show larger decreases than others (e.g., Paca et al., 2020), who used CHIRPS. De Sales et al. (2020) found that deforestation of protected areas in the north and west of the state would increase rainfall over the west and north-western parts of the state but decrease dry season rainfall in the existing agricultural region, which is consistent with Khanna et al. (2017) and with our dnCHIRPS results. Deforestation increases sensible heat fluxes and atmospheric instability for enhanced convection and moisture flux convergence over the deforested areas but induces a regional dipole that reduces rainfall outside of the region of enhanced convection (Khanna et al., 2017; De Sales et al., 2020). Our high-resolution satellite-based precipitation estimates using a dense rain gauge network (dnCHIRPS) improve the identification of trends in dry season rainfall.

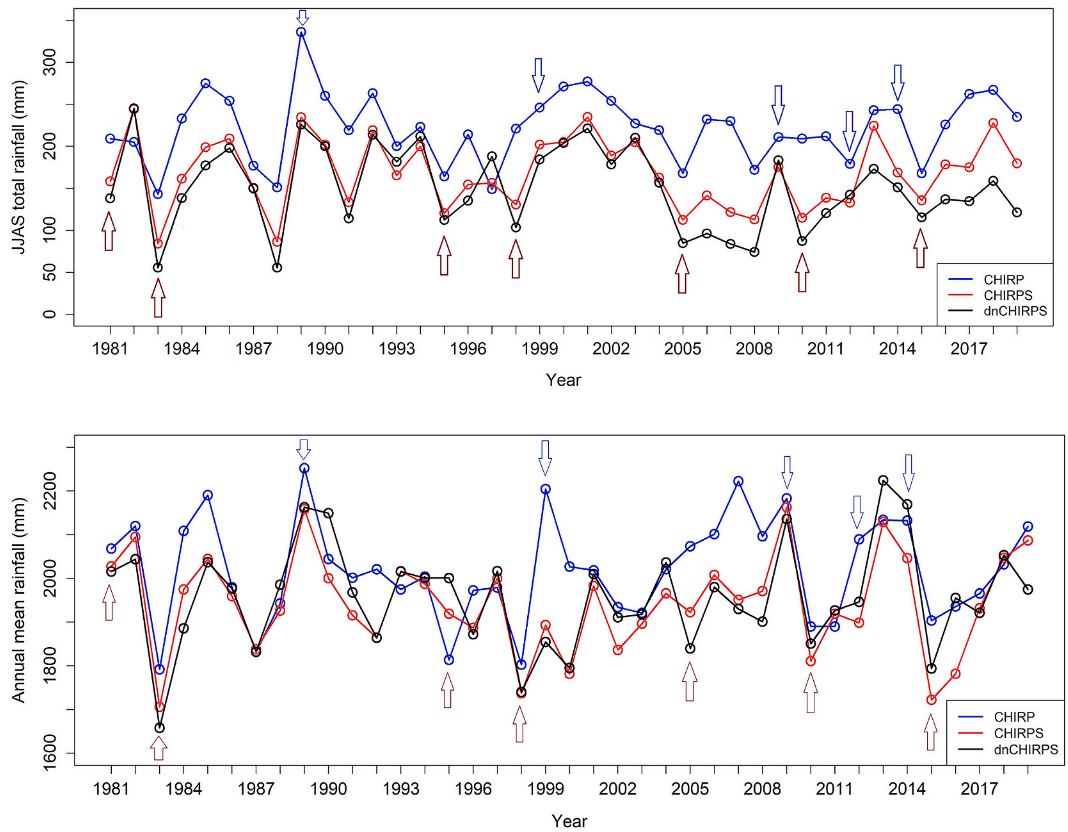

Fig. 8. JJAS dry Season and annual state-wide mean rainfall for the satellite products from 1981 to 2019. Red arrows indicate droughts and blue arrows indicate wet years (Marengo et al., 2016). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

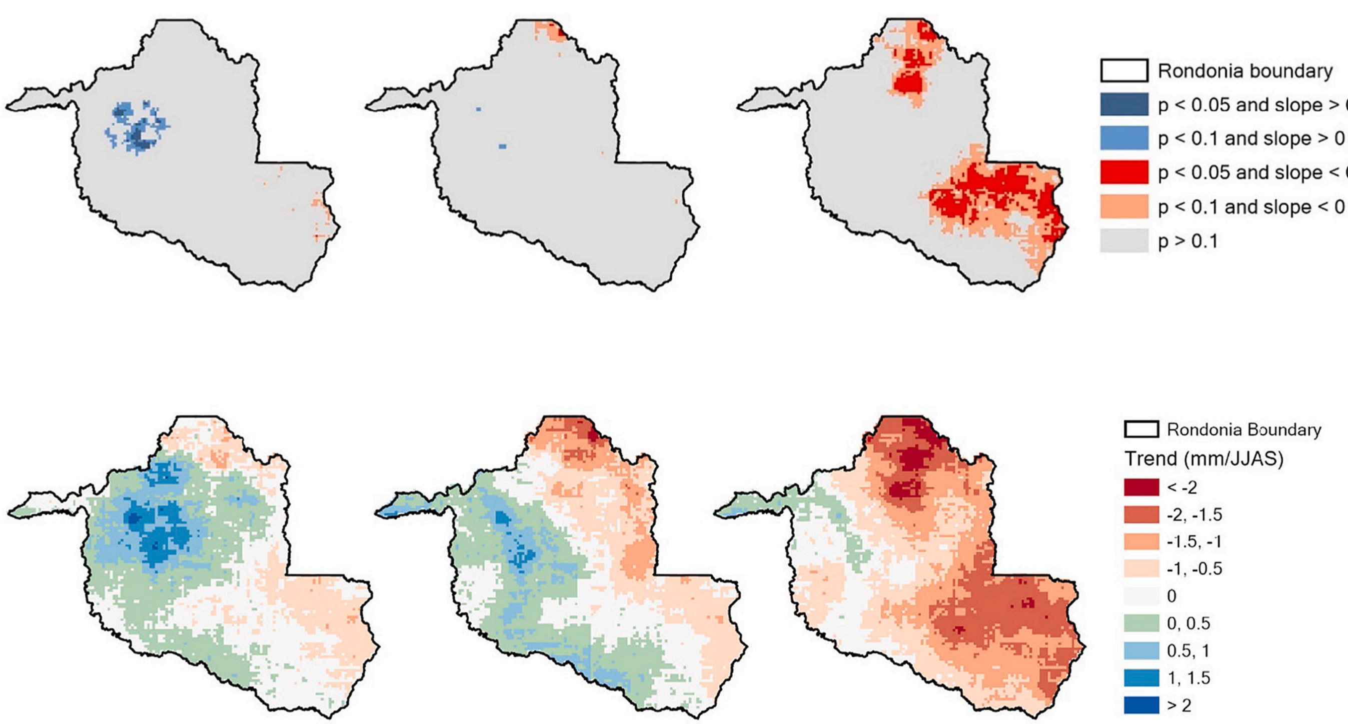

Fig. 9. Trends in JJAS total rainfall in CHIRP (left), CHIRPS (middle) and dnCHIRPS (right) over 1981 to 2019, including the *p*-value and trend sign (top) and trend magnitude (bottom).

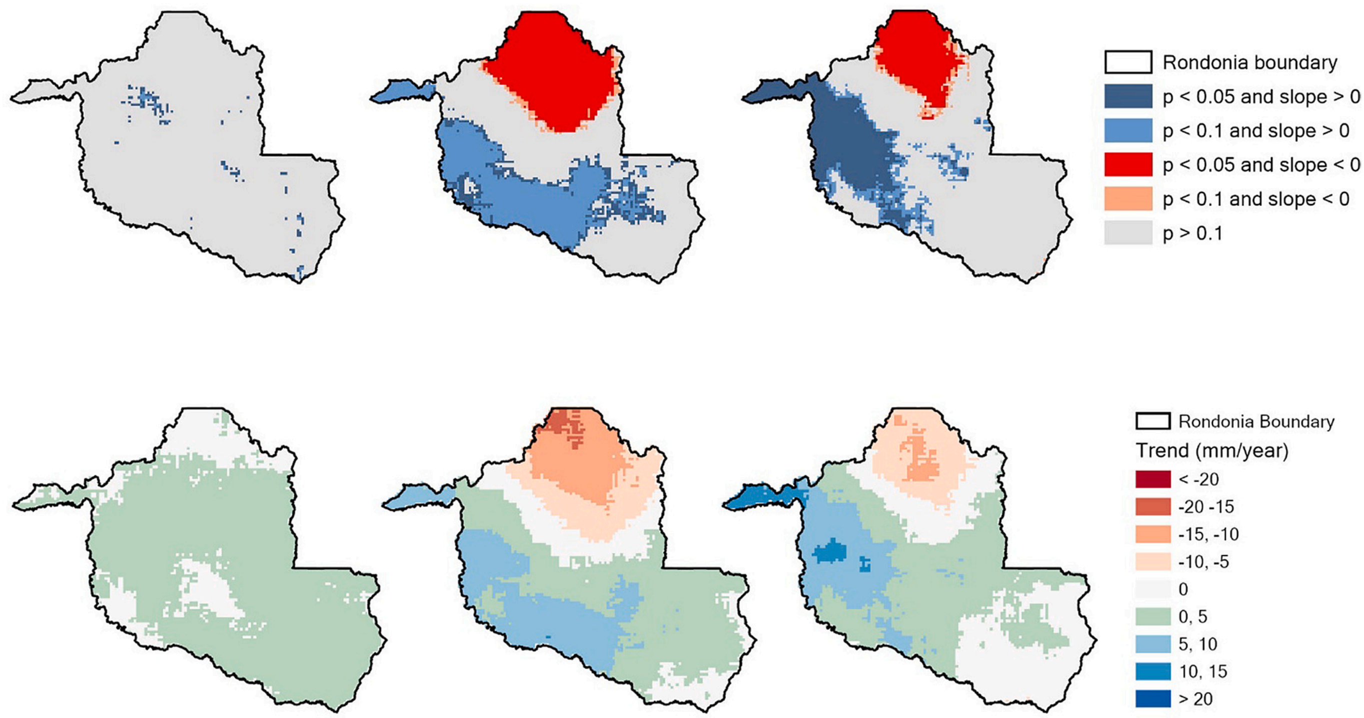

Fig. 10. Trends in annual rainfall from CHIRP (left), CHIRPS (middle) and dnCHIRPS (right) from 1981 to 2019, including the p-value and trend sign (top) and trend magnitude (bottom).

5. Summary and conclusion

We have documented spatial patterns and trends in monthly rainfall estimates using satellite-based rainfall estimates calibrated and validated with a dense network of rain gauge observations over the state of Rondônia in the Brazilian Amazon for 1981–2019. Satellite-based datasets with no (CHIRP) or little gauge data (CHIRPS) overestimated low rainfall amounts during dry seasons and drought events. dnCHIRPS, calibrated with a dense rain gauge network, had improved accuracy during months with extreme high and low rainfall. We conclude that a dense rain gauge network is necessary to accurately document the spatial pattern and magnitude of rainfall during dry seasons and droughts and that a large fraction of this agriculturally important region has experienced reduced dry season rainfall, which was not documented by existing datasets. Future research should incorporate additional rain gauge data into CHIRPS for other agriculturally important regions of the Amazon basin.

Data availability

CHIRPS and CHIRP data were obtained from https://www.chc.ucsb.edu/data/chirps. The gauge data were obtained from https://www.snirh.gov.br/hidroweb/apresentacao. DnCHIRPS rainfall data are available from https://zenodo.org/record/5034210.

Declaration of Competing Interest

No potential conflict of interest was reported by the authors.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.atmosres.2021.105741.

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