

Research Article

Using CHIRPS Dataset to Assess Wet and Dry Conditions along the Semiarid Central-Western Argentina

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The Climate Hazards group Infrared Precipitation with Stations (CHIRPS) dataset was conceived as a tool for monitoring drought and environmental change over land. Recent validation efforts along South America have assessed its suitability for reproducing the main spatial and temporal features of precipitation. Nevertheless, little has been done regarding the ability of CHIRPS for the assessment of wet and dry conditions, particularly in areas where in situ precipitation records are scarce. In this paper, we investigated the performance of CHIRPS for monitoring wet and dry events along the semiarid Central-Western Argentina. Using the Standardized Precipitation Index (SPI), we compared the CHIRPS database with records from 49 meteorological stations along the study area for the period 1987–2016. Results indicate that the CHIRPS dataset adequately reproduced the temporal variability of SPI on multiple timescales (1 month, 3 months, and 6 months), particularly in the region dominated by warm season precipitation. The large overestimation of the seasonal precipitation in the region dominated by cold season precipitation can introduce errors that are reflected in the performance of CHIRPS over the western portion of the domain. The frequency of wet and dry classes was accurately reproduced by CHIRPS on timescales larger than 1 month (SPI1), given the existence of a wet bias that produces an underestimation of the frequency of zero values. This bias is further translated to the evaluation of the SPI1 during the spatial and temporal assessment of historical dry (1998) and wet (2016) events, especially for the classification of extreme dry/wet months. The results from the evaluation indicate that CHIRPS is a suitable tool for assessing dry and wet conditions for timescales longer than 1 month and can support decision-making process within the hydrometeorological agencies over the region.

1. Introduction

A wide range of satellite-derived precipitation products have emerged in the last decades, providing a spatial coverage that is superior to gauge products, considering that rain gauges had the obvious queries such as the density of site networks, the continuous time series, and the financial limitation [1]. Some of these products are the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) [2], the Climate Prediction Center Morphing (CMORPH) technique [3], the Global Satellite Mapping of Precipitation (GSMaP) [4], the TRMM Multi-satellite Precipitation Analysis (TMPA) 3B42RT [5], and the Multisource Weighted-Ensemble Precipitation (MSWEP) [6]. A comprehensive overview of these products can be found in Beck et al.'s studies [7].

To satisfy the demand of studies and applications of climate and drought, some of these satellite-based estimations provide long-term precipitation records. Some of the products with the most extensive records are the MSWEP [6], the PERSIANN-CDR [8], and the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) data archive [9]. The CHIRPS database comprises a quasi-global (50°S–50°N, 180°E–180°W), 0.05° resolution, and 1981 to near-present gridded precipitation time series. This dataset merges three types of information: global climatology, satellite estimates, and in situ observations [10], generating several precipitation products with time steps from 6-hourly to 3-monthly aggregates.

This database was mainly used for the assessment of monthly, seasonal, and annual precipitation variability in several regions of the world. Monthly CHIRPS estimations

were applied for drought monitoring in Nepal [11], Chile [12], and China [1]. The research of López-Carr et al. [13] used 3-month accumulations to identify changes in the growing season precipitation patterns over Africa. Trends in CHIRPS annual rainfall estimations were compared with gridded gauge-only precipitation datasets and climate models simulations from the CMIP5 dataset [14]. The daily version of CHIRPS also gained attention recently. Examples of its use can be found in the detection of trends of extreme precipitation indices [15], the assessment of the relation between weather regimes and wet/dry conditions along East Africa [16], and the evaluation of the evolution of dry-day frequency and its impacts on Amazonian seasonal rainfall [17].

The performance of these satellite-based products needs to be evaluated over different regions of the world in order to identify retrieval errors and biases [18]. The Central-Western Argentina (CWA) is a region where the interplay between the complex topography and the atmospheric circulation determines a wide range of precipitation features, from intense winter orographic precipitation [19], extreme summer precipitation events leading to the occurrence of landslides along the Andes range [20], and hailstorms over the lowlands [21] to multiannual severe drought events [22, 23]. Considering these multiple characteristics over the CWA, the lack of ground observations makes mandatory the use of high-resolution satellite-based precipitation products in order to provide a better understanding of precipitation variability and change. A recent study performed the validation of CHIRPS for a 30-year period along the CWA, analysing the representation of the main climatological features of precipitation [24]. The CHIRPS dataset captured the rainy season characteristics over the region, considering the Mediterranean climate features over the Andes ranges and the monsoonal regime in the lowlands. Moreover, CHIRPS achieved better results in the region with summer precipitation maximum, given that precipitation was largely overestimated during the cold semester maximum. In view of this performance, the CHIRPS database was used for the assessment of a glacier collapse over the Central Andes of Argentina in a region with scarce meteorological information [25]. The CHIRPS estimations also gained attention as input for climate monitoring tools. Six countries in southern South America have established the World Meteorological Organization Regional Climate Center (RCC-SSA) that involves a strong collaboration between weather services and academic institutions [26]. The RCC-SSA periodically generates CHIRPS precipitation estimates maps on pentadal and monthly time steps, providing relevant information for decision-making needed for agricultural activities and water management purposes.

Besides the efforts for the use of the CHIRPS database as a tool for regional precipitation monitoring, few validation studies evaluated its suitability for the assessment of dry and wet conditions. Guo et al. [27] found that CHIRPS can properly capture the drought characteristics at various timescales with the best performance at the three-month timescale. Zambrano et al. [12] concluded that, in order to use the CHIRPS dataset to monitor drought intensity conditions, the product should be calibrated to adjust for the

overestimation/underestimation of rainfall geographically. Recently, Gao et al. [1] and Zhong et al. [28] indicated that CHIRPS successfully captured the spatial patterns of drought over China. These studies also show that wet conditions are not focus of assessment, which could be attributed to the design of CHIRPS for agricultural drought monitoring [9]. Nevertheless, over the study area, the occurrence of wet conditions affects the farming and particularly the quality of the grapes, which require plenty of solar radiation to achieve sufficient quality for wine production [29]. Moreover, during wet conditions, the probabilities for the occurrence of deep convection episodes during the warm season increases, which strongly affects the cultivated areas over the CWA, causing big damages and economic losses, particularly during hailstorms over the vineyards [30]. These factors make the assessment of both dry and wet conditions mandatory over the study area.

The objective of this study is to assess the suitability of CHIRPS precipitation estimations for the representation of wet and dry periods in the CWA. For this assessment, the Standardized Precipitation Index (SPI) [31] was selected as an indicator for the definition of wet and dry conditions. The SPI will be calculated based on rain gauges observations and CHIRPS estimations considering several timescales. The performance of CHIRPS will be evaluated through a comparison of the spatiotemporal characteristics of wet and dry events over the study area over the last 30 years. This assessment is being conducted in a region where observed precipitation is at low spatial density, the information from rain gauges is not always available, and time series are often interrupted, facts that highlight the crucial nature of validating satellite precipitation estimations for extreme precipitation monitoring. It is expected that the outcomes of this study will constitute a significant contribution for the improvement of regional monitoring of wet and dry conditions.

2. Materials and Methods

2.1. Study Area. The CWA is a semiarid region located leeward of the Andes ranges, between 30°S and 40°S (Figure 1). This area is characterized by a strong influence of topography on the regional and local climate. The climate at high elevations has a Mediterranean regime with higher precipitations during the cold season (April to September) and dry warm seasons (October to March), in response to the seasonal displacement of the Southeastern Pacific High [32]. North of 35°S, the Andes is a considerable topographic barrier with peaks exceeding 6000 m.a.s.l., preventing the wet Pacific air masses arriving at the eastern slopes [33]. Due to the strong rain shadow effect, climate in the east of the Andes is arid to semiarid, where convective warm season rainfalls favored by moist air masses from the Amazon and Atlantic basins play a relevant role [34]. South of 35°S, precipitation is mainly generated by the passage of cold fronts moving eastward from the Pacific [35], with a strong west-east precipitation gradient.

The agroindustrial activities in CWA depend largely on grape production, an activity only possible through

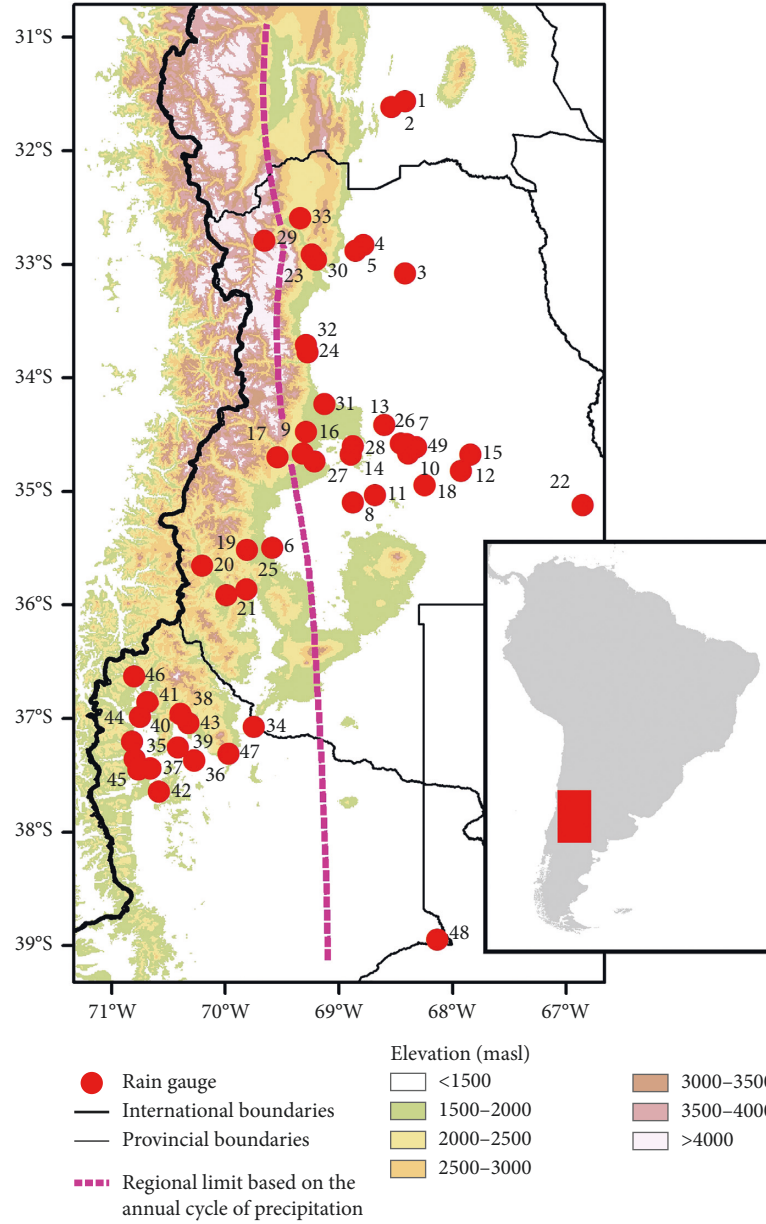


FIGURE 1: Map of the Central-Western Argentina, with the location and ID (see Table 1 for details) of the rain gauges used for the validation of CHIRPS. The dashed line represents the division between the rainy season characteristics: the stations located west of the line are dominated by winter precipitation, while the stations located east of the line are dominated by summer precipitation.

irrigation, considering the arid to semiarid climate of the region. The interannual rainfall variability over this region has been partially related to El Niño-Southern Oscillation (ENSO), with El Niño events providing large precipitation (both snow and rainfall) amounts and La Niña events accounting for drought situations [22, 36].

2.2. Data. Monthly precipitation data from 49 hydrometeorological stations located along the CWA were obtained through the Water Resources Agency of Argentina and the National Weather Service. The location of these rain gauges is shown in Figure 1, and the detailed information of each station can be found in Table 1. This database was built for

the assessment performed by Rivera et al. [24], including quality control procedures and the detection of inhomogeneities. A common period of 30 years, between 1987 and 2016, was selected based on the availability and quality of precipitation records and the spatial representativeness of the stations. Missing precipitation values, ranging from 1 to 27 nonconsecutive months, were replaced by applying linear regressions with neighbouring stations, only for reference stations that explain $>80\%$ ($R^2 > 0.8$) of the temporal variability of precipitation. The behaviour of precipitation over the study area was shown to be homogeneous both over the region dominated by summer precipitation [22, 29] and the region dominated by winter precipitation [33]. This was further verified with the use of rotated principal components

TABLE 1: Geographic and climatic features of the selected meteorological stations over the period 1987–2016.

ID	Name	Lat. (°S)	Lon. (°W)	Mean annual precipitation (mm)	Wet season
1	San Juan	31.57	68.42	98.2	Summer
2	San Juan INTA	31.62	68.53	99.7	Summer
3	San Martín	33.08	68.42	253.7	Summer
4	Mendoza Aero	32.83	68.78	236.3	Summer
5	Mendoza Observatorio	32.88	68.85	261.6	Summer
6	Malargüe	35.50	69.58	327.8	Winter
7	San Rafael	34.58	68.40	360.6	Summer
8	La Angostura	35.09	68.87	256.5	Summer
9	La Jaula	34.67	69.32	252.3	Summer
10	Rama Caída	34.67	68.38	347.5	Summer
11	El Nihuil	35.03	68.67	268.4	Summer
12	Villa Atuel	34.82	67.92	335.5	Summer
13	Capitán Montoya	34.58	68.45	361.5	Summer
14	Puesto Canales	34.67	68.89	293.0	Summer
15	Puesto Carmona	34.68	67.84	541.5	Summer
16	Arroyo Hondo	34.48	69.28	287.1	Summer
17	Las Aucas	34.70	69.54	253.3	Winter
18	Las Malvinas	34.94	68.24	278.4	Summer
19	Los Mayines	35.66	70.20	458.8	Winter
20	Bardas Blancas	35.87	69.81	379.4	Winter
21	Arroyo La Vaina	35.92	69.99	356.9	Winter
22	Puesto Las Moras	35.12	66.85	516.3	Summer
23	Guido	32.92	69.24	223.3	Summer
24	Valle de Uco	33.78	69.27	472.0	Summer
25	Pincheira	35.52	69.81	360.9	Winter
26	Las Vertientes	34.42	68.59	400.4	Summer
27	Juncalito	34.74	69.21	338.4	Summer
28	Puesto Morales	34.60	68.87	313.4	Summer
29	Polvaredas	32.79	69.65	178.6	Winter
30	Potrerrillos	32.96	69.20	240.1	Summer
31	Puesto Papagayos	34.23	69.12	321.4	Summer
32	La Remonta	33.71	69.29	531.6	Summer
33	Uspallata	32.59	69.34	147.6	Summer
34	Buta Ranquil	37.07	69.75	184.3	Winter
35	El Cholar	37.44	70.65	525.0	Winter
36	Chos Malal	37.37	70.27	217.6	Winter
37	Vilu Mallín	37.46	70.76	481.5	Winter
38	Cajón Curileuvú	36.96	70.39	476.7	Winter
39	El Alamito	37.26	70.42	247.6	Winter
40	Las Ovejas	36.98	70.75	718.0	Winter
41	Varvarco	36.86	70.68	627.0	Winter
42	El Huecu	37.65	70.58	432.9	Winter
43	Tricao Malal	37.04	70.32	366.5	Winter
44	Los Miches	37.21	70.82	607.8	Winter
45	Chochoy Mallín	37.36	70.79	516.0	Winter
46	Pichi Neuquén	36.63	70.80	778.5	Winter
47	Auquínco	37.32	69.97	336.3	Winter
48	Neuquén	38.95	68.13	204.9	Summer
49	San Rafael	34.61	68.32	439.1	Summer

analysis (RPCA) [37] applied in the S-mode with varimax rotation (not shown), a methodology that allowed to obtain the regional separation observed in Figure 1 after assigning each station to the component upon which it loads most highly [38]. Moreover, time series of regional precipitation are significantly uncorrelated [39], highlighting the presence of different water vapor sources over the region that are dependent of the season of the year. Even when every gap filling routine introduces errors to the precipitation estimation, we assume that the strong homogeneity within the

regions guarantees an adequate estimation of the real precipitation totals.

The spatial pattern of mean annual precipitation shows the semiarid condition of the study area, with values ranging from less than 150 mm/year north of 32°S to over 700 mm/year between 37° and 39°S, at the high elevations of the continental divide (Figure 2, Table 1). A narrow region along the central-east portion of the Mendoza province (approximately from 34° to 35°S) exhibits a relative maximum of precipitation, with values higher than 400 mm/year. South of

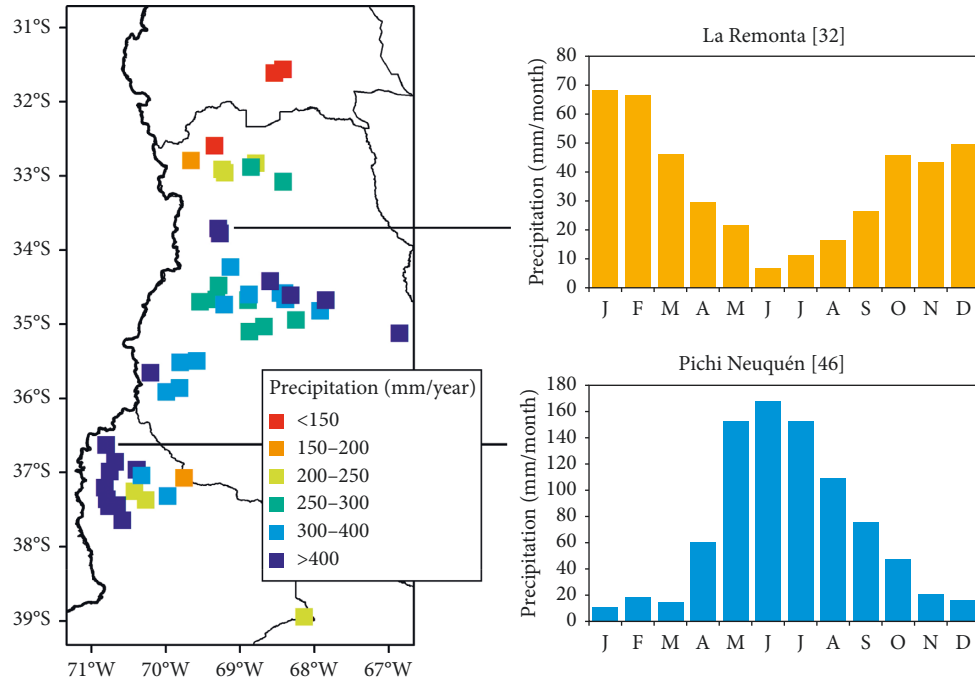


FIGURE 2: Spatial distribution of the mean annual precipitation over the study area, together with the annual precipitation cycle at two reference stations.

36°S, there is a strong precipitation gradient from west to east due to the rain shadow effect of the Andes (Figure 2). The clear distinct seasonality in precipitation over the CWA is illustrated for two selected locations (Figure 2). The annual cycle of precipitation in La Remonta shows a monsoonal regime, dominated by convective warm season rainfalls associated with the southward movement of the South American low-level jet (SALLJ) from northern Argentina [40] and the moisture transport from the southeast of Brazil and Uruguay or even directly from the Atlantic Ocean [41]. Conversely, the annual cycle in Pichi Neuquén shows a Mediterranean regime, with higher precipitation during the cold season associated with a strong water vapor transport from the Pacific Ocean in the pre-cold-front environment of extratropical cyclones [19, 42].

Gridded monthly precipitation estimates from the CHIRPS, developed at the University of California at Santa Barbara (UCSB) Climate Hazards Group (CHG) in collaboration to the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) center, were used to identify its accuracy reproducing extreme precipitation events along the CWA. Data from 1987 to 2016 were obtained through the CHG web page (<http://chg.geog.ucsb.edu/data/chirps/index.html>). As described by Funk et al. [9], the CHIRPS algorithm (i) is built around a 0.05° climatology that incorporates satellite information to represent sparsely gauged locations, (ii) incorporates monthly 1981-present 0.05° infrared cold cloud duration-based precipitation estimates, (iii) blends station data to produce a preliminary information product with a latency of about 2 days after the end of a pentad and a final product with an average latency of about 3 weeks, and (iv) uses a novel blending procedure incorporating the spatial

correlation structure of infrared cold cloud duration estimates to assign interpolation weights. This dataset was found to reproduce adequately several characteristics of precipitation over South America [12, 17, 43] and particularly over the CWA, showing a good agreement for the representation of the seasonal and interannual variability of precipitation and its spatial patterns [24].

3. Methods

In order to identify the occurrence of dry and wet events, we used the SPI, a widely accepted index as a universal tool for drought monitoring and assessment. Based on a comparison among six precipitation-based drought indices, the SPI was selected as the most adequate for analysing meteorological droughts along southern South America [44]. For the calculation of the SPI, time series of 1-month, 3-month, and 6-month accumulations were generated and fitted to a two-parameter gamma distribution function, following previous recommendations for the study area [22] and in other regions [12, 13, 27]. Finally, an equiprobability transformation from the cumulative density functions to the standard normal distribution with the mean of 0 and the variance of 1 were performed to obtain the SPI. Therefore, the values of the SPI are expressed in standard deviations, with positive SPI values indicating greater than median precipitation and negative values indicating less than median precipitation. Three dry and wet categories and a normal category can be defined based on the SPI values, as shown in Table 2, following the classification of Lloyd-Hughes and Saunders [45]. As mentioned in the introduction, at the present time, monitoring of wet and dry events has been performed by the RCC-SSA using CHIRPS for the calculation of SPI for

TABLE 2: Standardized Precipitation Index (SPI) categories.

Index value	Category
≥ 2.00	Extremely wet
1.50 to 1.99	Severely wet
1.00 to 1.49	Moderately wet
-0.99 to 0.99	Normal
-1.49 to -1.00	Moderately dry
-1.99 to -1.50	Severely dry
≤ -2.00	Extremely dry

timescales of 3 and 6 months (http://www.crc-sas.org/en/monitoreo_precipitacion_chirps.php).

The 30-year period selected for this study provides rain gauges and CHIRPS records that are long enough for an accurate estimation of the SPI values, as recommended by the World Meteorological Organization [46]. For the comparison between the SPI based on rain gauge observations and CHIRPS estimations, we used the Pearson correlation coefficient and the mean absolute error. The correlation coefficient measures the linear relationship strength between the satellite estimations and the rain gauges observations, bounded by -1 and 1 with an optimal value of 1 . The mean absolute error provides information on the average magnitude of error estimations, considering both systematic and random errors [24].

4. Results

4.1. Regional Behaviour of SPI Based on CHIRPS and Rain Gauges. For the comparison of the SPI based on the CHIRPS database and rain gauges data, the study area was divided according to the main regional features of the annual precipitation cycle: a region dominated by warm season (WS) precipitation, with a monsoonal regime associated with convective rainfalls over the lowlands and a relatively dry cold season; and a region dominated by cold season (CS) precipitation, with a Mediterranean regime close to the higher elevations of the Andes (see Figure 1). The time series of SPI at timescales of 1 month, 3 months, and 6 months for the WS and CS regions are shown in Figures 3 and 4, respectively.

The temporal evolution of the SPI based on CHIRPS estimations shows a good agreement with rain gauge observations, capturing the occurrence of the main dry and wet periods and its severity in both regions. For the WS region (Figure 3), the correlation coefficient between the SPI is higher than 0.8 ($p < 0.01$) for the three timescales considered, while this value ranges between 0.74 and 0.77 ($p < 0.01$) for the CS region. In line with the results obtained considering the correlation coefficients, the mean absolute error is slightly larger for the CS region (between 0.53 and 0.57) compared to the WS region (between 0.47 and 0.48).

The extremely wet period recorded between 2015 and 2016 along the WS region was well captured in timing by CHIRPS, although with an overestimation of its intensity in all the timescales (Figure 3). On the other hand, CHIRPS estimations detected the maximum severity period of the extreme drought between 2003 and 2004 along the WS

region, although the intensity was underestimated compared to the observations. This behaviour is similar to the observed during the dry period of 2005-2006 (Figure 3).

For the CS region, the occurrence of wet periods recorded between 2000 and 2003 is represented by CHIRPS estimations, particularly for SPI3 and SPI6, with an overestimation of its severity (Figure 4). CHIRPS-SPI captured the dry periods of 1989, 1995-1997, and the extreme drought of 1998-1999, with a good agreement with the observed SPI. The extreme drought of 1999 affected the hydropower generation over Patagonia due to hydrological drought conditions that were also recorded over CWA [47]. The onset of this drought event was well identified by CHIRPS estimations and also the timing and severity of the maximum drought intensity (Figure 4). Nevertheless, the drought demise estimated by CHIRPS was anticipated by several months when compared with rain gauges-SPI (February 1999 versus September 1999). This condition could be attributed to a large overestimation of precipitation over the CS region compared with rain gauge data [24].

The observed difference in the agreement between CHIRPS-SPI and rain gauges-SPI over WS and CS regions can be associated with the large overestimation of monthly precipitation estimated from CHIRPS over the CS region (Figure 5). This result can be further attributed to the overestimations for the months of April to September, especially in zones above 1000 m.a.s.l. [24]. Monthly precipitation from CHIRPS over the WS region shows a slight underestimation and, thus, a better agreement between rain gauges-SPI and CHIRPS-SPI over the WS region.

4.2. SPI Classification for Wet and Dry Categories. Given that the SPI values fit a standard normal distribution, these values lie within one standard deviation at approximately 68% of the time, within two standard deviations 95% of the time and within three standard deviations 98% of the time [48]. In this sense, it is expected that approximately 16% of the months (~ 58 months) would be classified as dry (wet) months, given that this value corresponds to the probability of $\text{SPI} \leq -1.0$ ($\text{SPI} \geq 1.0$). In order to evaluate this requirement, we calculated the number of months with dry and wet conditions for each rain gauge and its corresponding CHIRPS pixel. Figure 6 shows the box plots for the number of months with dry and wet conditions for the SPI1, SPI3, and SPI6. The most relevant difference between rain gauge-SPI and CHIRPS-SPI classes is found for the timescale of 1 month considering dry conditions. In most of the rain gauges, the SPI values tend to underestimate the expected number of dry months. This can be related to the presence of zero values, given the arid and semiarid characteristics of the study area and its marked seasonal precipitation cycle. When a high frequency of zero values occurs, SPI tends to be nonnormally distributed, with a lower bound in the SPI time series at short timescales [49], thus failing to indicate drought occurrences. This is not observed considering CHIRPS estimations, given that this product tends to underestimate the occurrence of zero values. To illustrate this, Figure 7 shows the number of months with zero values for each rain gauge and CHIRPS

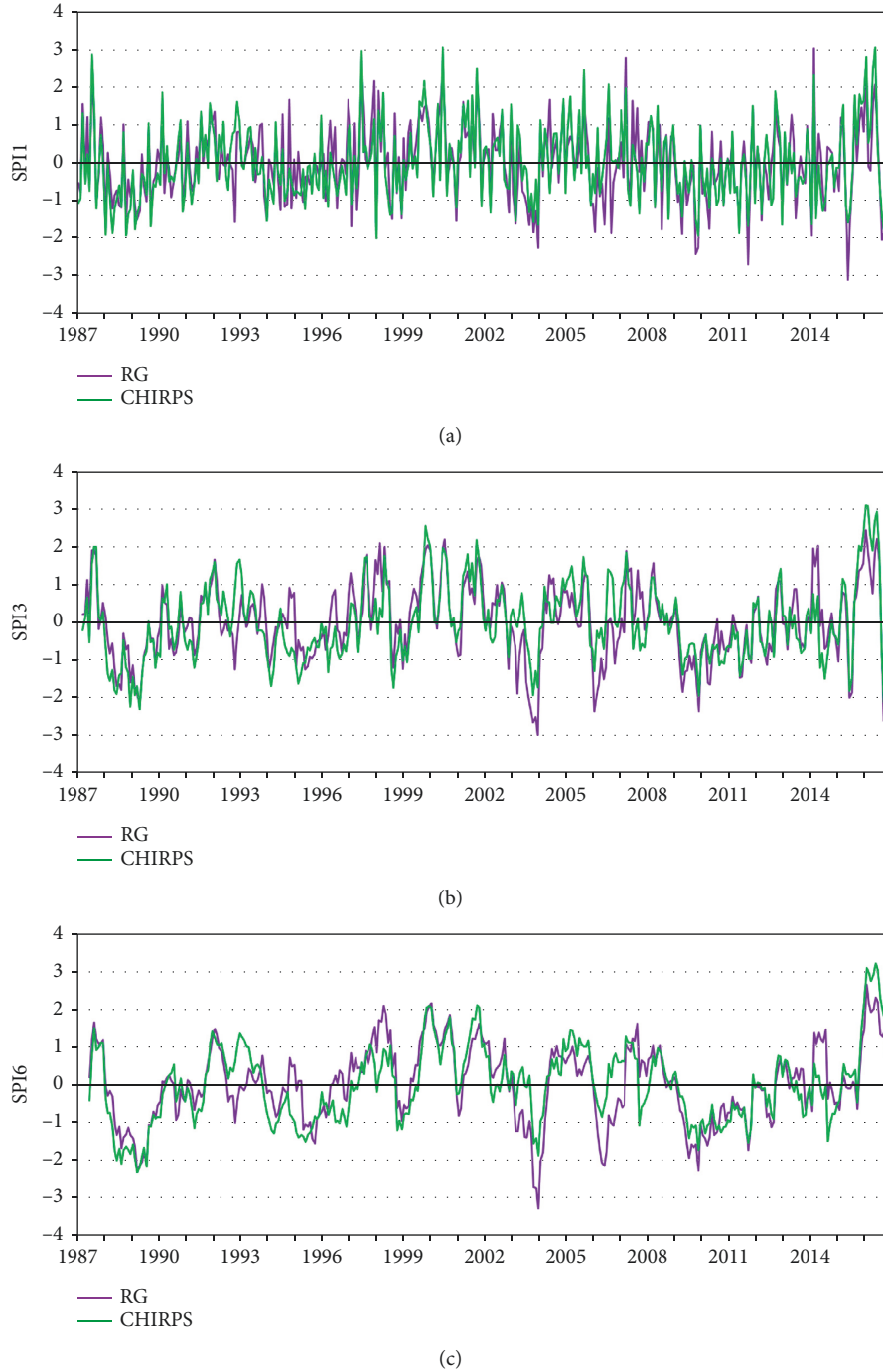


FIGURE 3: SPI time series for the WS region based on CHIRPS and rain gauges (RG) during 1987–2016: (a) SPI1, (b) SPI3, and (c) SPI6.

pixel. The differences observed in the SPI1D between rain gauges and CHIRPS can be attributed mainly to the underestimations over the CS region, although all the CWA exhibit the same underestimation pattern by CHIRPS. The lack of zero values can arise from the screening procedure developed to remove “false zeros” in the CHIRPS estimations [50], a bias previously reported by Zambrano et al. and Katsanos et al. [12, 51].

Regarding the remaining timescales and wet and dry categories, CHIRPS estimates and precipitation from rain gauges show a similar behaviour, although with larger

regional dispersion considering the SPI6 (Figure 6). It must be noted that, for most of the timescales and SPI categories, the median number of months is slightly larger than the expected probabilistic value, a condition previously documented considering the SPI based on the two-parameter gamma distribution [52].

Temporal evolution of the number of pixels/rain gauges affected by dry conditions based on CHIRPS estimations.

From a vulnerability point of view, the situations when a great portion of the study area is under dry or wet conditions must be considered. In this sense, for each month from

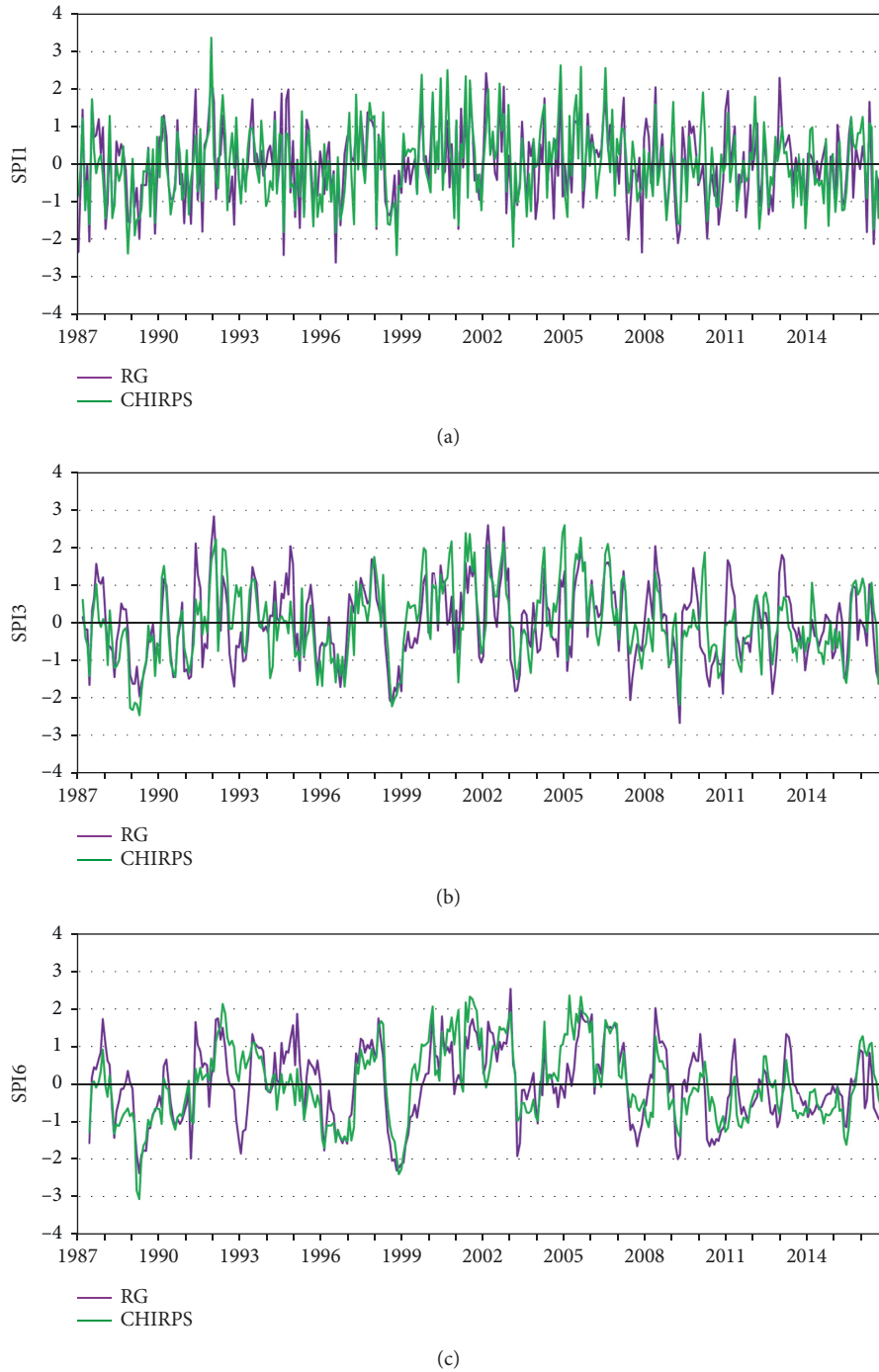


FIGURE 4: SPI time series for the CS region based on CHIRPS and rain gauges (RG) during 1987–2016: (a) SPI1, (b) SPI3, and (c) SPI6.

January 1987 to December 2016, we obtained the number of pixels with dry conditions. Figure 8 shows the temporal evolution of this regional index for the SPI1, SPI3, and SPI6 and the moderately (yellow), severely (orange), and extremely (vermillion) dry categories (see Table 2). According to CHIRPS estimations, the CWA experienced large-scale dry conditions particularly during the periods 1988–1989 and 1998–1999 (Figure 8). As the timescale for the calculation of the SPI increases, the high-frequency temporal

variability in the time series decreases, allowing a better identification of the main dry periods considering the SPI6.

We repeated the procedure considering the time series of SPI based on rain gauges observations. This allowed calculating the difference between the CHIRPS and rain gauges areal estimations of dry conditions. The temporal evolution of this difference, for each timescale and dry category, is shown in Figure 8. Positive values indicate that CHIRPS is overestimating the number of pixels/rain gauges

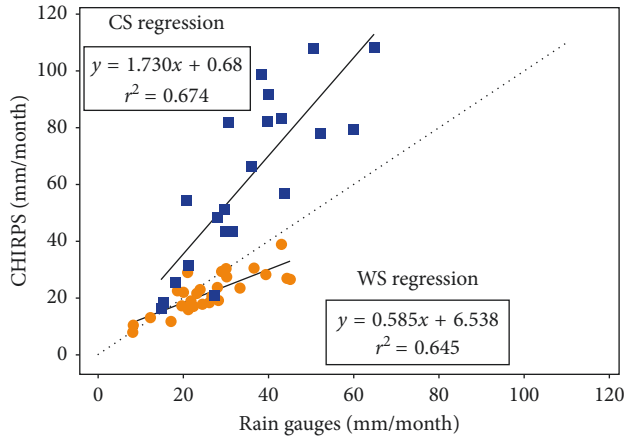


FIGURE 5: Scatter plot comparing the 49 rain gauge data with the corresponding grids of CHIRPS estimations in mm/month over the 1987–2016 period. Circles indicate the values of the stations located over the WS region, and squares indicate the values of the stations located over the CS region. The black lines indicate the linear regression fits. The dashed line represents a 1:1 relation.

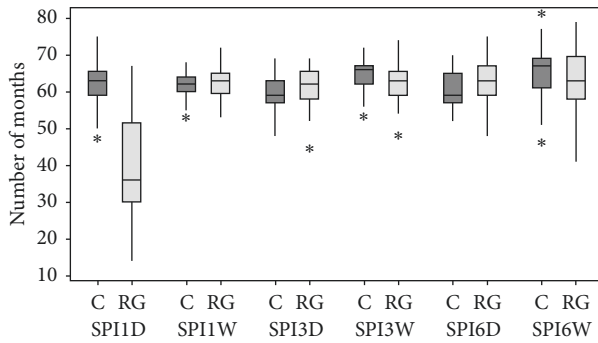


FIGURE 6: Boxplot of the number of months with dry and wet conditions (SPInD and SPInW, respectively, with $n = 1$ -month, 3-month, and 6-month timescale) for the SPI based on CHIRPS estimations (C) and rain gauges (RG) observations. Dry months were defined when $SPI \leq -1.0$, and wet months were defined when $SPI \geq 1.0$. Each boxplot shows the median and first and third quartiles, while the whiskers extend to the data values that are 1.5 times the interquartile range above or below the quartiles. Outliers are represented by*.

with dry conditions, while negative values show an underestimation. Considering the SPI1, during most of the 1987–2016 period, the time series based on CHIRPS precipitation show an overestimation of the dry affected area. This is particularly evident during the large-scale dry periods identified in Figure 8. The result is in line with the observed bias in the number of months with dry conditions (Figure 6), suggesting that the SPI1 based on CHIRPS estimations is not adequate for meteorological drought monitoring over arid and semiarid regions. Similar temporal evolution is observed considering the differences between CHIRPS and rain gauges for SPI3 and SPI6, with large areal overestimation during 1988–1989 and a clear underestimation during 2003, particularly for the extremely dry category (Figure 9).

The monthly sum of simultaneously affected stations enables the identification of the large events and their durations, but does not show the regional patterns of meteorological drought and its severity [47]. Figure 10 shows a comparison of the spatial extension of the dry conditions recorded during October 1998 based on rain gauges and CHIRPS-SPI for the three timescales selected. As expected based on previous results, CHIRPS shows a large overestimation of the dry conditions considering SPI1, with a large number of pixels under severely dry and extremely dry category in comparison with the rain gauges-SPI1. Considering the spatial patterns based on SPI3 and SPI6, CHIRPS estimations accurately reproduce the observed dry conditions, both in location and intensity (Figure 10).

Temporal evolution of the number of pixels/rain gauges affected by wet conditions is based on CHIRPS estimations.

Following the assessment performed on the previous section, we repeated the methodology to analyse the areal patterns corresponding to wet conditions. Figure 11 shows the temporal evolution of the number of pixels/rain gauges affected by wet conditions considering the SPI1, SPI3, and SPI6 and the moderately (light blue), severely (blue), and extremely (dark blue) wet categories (see Table 2). A large fraction of the CWA was affected by wet periods based on CHIRPS estimations during 1999–2003, 2005–2008, and 2016. This is particularly evident considering the CHIRPS-based SPI6 (Figure 11). It is remarkable the large number of pixels affected by extremely wet conditions during 2016, a result that can be attributed to the major El Niño event of 2015/16 considering the precipitation response to this mode of climate variability events over CWA [22].

The temporal evolution of the difference between the number of pixels/rain gauges under wet conditions based on CHIRPS-SPI and rain gauges-SPI is shown in Figure 12. Similarly to what was found for the assessment of dry conditions, the cases where widespread wet conditions are observed by CHIRPS show a large overestimation in the number of affected pixels/rain gauges. This is particularly evident for the severely wet and extremely wet categories considering the SPI3 and SPI6 between 1999 and 2007 and during 2015–2016 (Figure 12). The comparison of the spatial pattern based on rain gauges-SPI and CHIRPS-SPI during the month of April 2016 shows a similar location of the wet categories, although CHIRPS tends to overestimate the wet categories classifying a large number of pixels under extremely wet conditions in comparison with the categories based on rain gauges (Figure 13).

The spatial distribution of both dry and wet conditions is critical for impact studies. The results from this comparison allowed identifying the strengths and weakness of CHIRPS estimations for wet and dry monitoring. Even when there is a tendency towards an overestimation of both dry and wet regional events, the spatial distribution of wet and dry cases was accurately captured by CHIRPS-SPI. Nevertheless, the bias in the SPI categorization can limit the usefulness of CHIRPS for dry or wet declaration. Nowadays, the WMO RCC-SSA offers climate services in support of the National Meteorological and Hydrometeorological Services (NMHS) and other users from the countries located in the southern

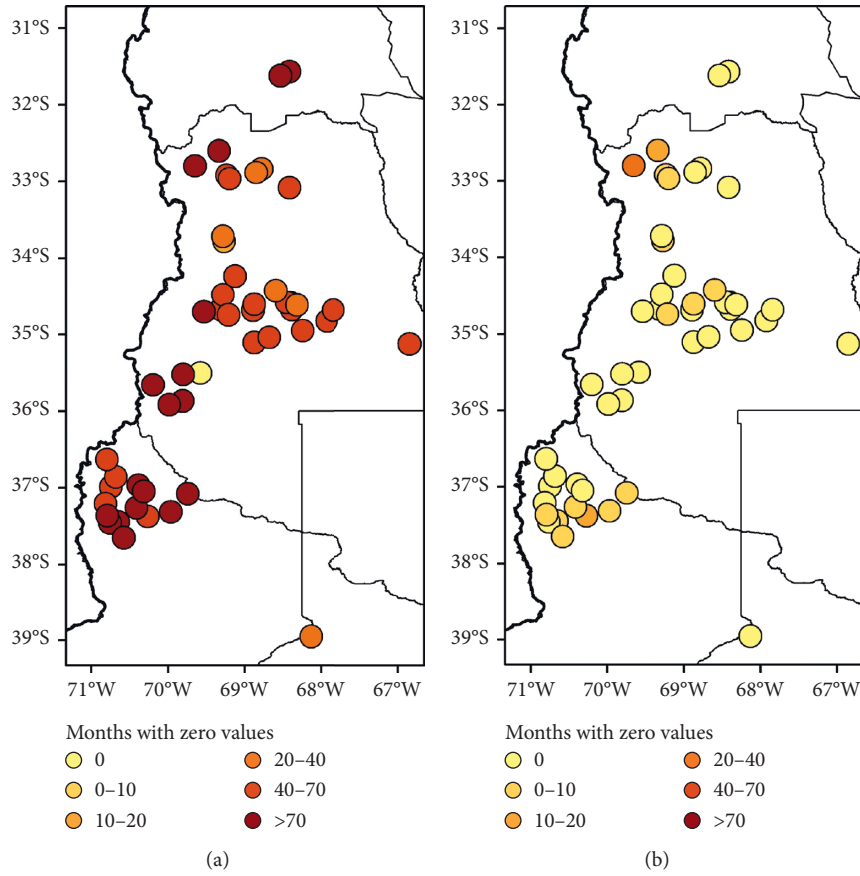


FIGURE 7: Frequency of zero precipitation months for each (a) rain gauge (RG) and (b) CHIRPS pixel.

South American region. Some of its monitoring tools are based on CHIRPS precipitation estimations, making the assessment performed in this paper a baseline to improve climate services over the region.

5. Discussion

Satellite remote sensing is increasingly being used as a complementary source of information to in situ monitoring networks and, in many cases, is the only feasible source [53]. Considering the importance of the water management for the sustainable regional development in arid and semiarid areas, much effort has gone into the development and use of satellite-based precipitation estimations for this purpose. In this sense, the performance of the CHIRPS dataset for the identification of wet and dry events was evaluated in the CWA, a semiarid region, with two distinct precipitation regimes based on available precipitation records from rain gauges, using a point-to-pixel comparison for the period 1987–2016.

Several indicators have been developed during recent decades for the monitoring of dry and wet events, based both on in situ information and remote sensing estimations, targeting aspects for meteorological, agricultural, hydrological, and socioeconomic dry and wet declaration. Each indicator has its own inherent strengths and weaknesses, and its utility is often tailored for a specific application or

decision-making activity [54]. For this study, the SPI was used as a tool for the identification of wet and dry events, based on its performance for drought and wet monitoring over southern South America [22, 44, 55, 56]. This choice is also relevant given the simplicity of the SPI, considering that is calculated only based on precipitation data, being one its main advantages [57]. Considering that CHIRPS estimations only provide precipitation estimations and the meteorological stations over the study area only measure temperature in few reference stations, belonging to the National Weather Service, we consider unfair to use an index that rely on more variables for its calculation, for example, the Standardized Precipitation and Evapotranspiration Index (SPEI) [58]. In this sense, Quesada-Montano et al. [59] highlighted that the selection of the precipitation database was more important than the selection of the drought index. The use of CHIRPS precipitation estimates for drought monitoring based on the SPI has gained attraction nowadays, as shown by studies performed in Indonesia [60], China [1, 28], Nepal [11], Morocco [54], Southeast Asia [27], Central America [59], and Chile [12].

Uncertainties in the comparison of the SPI time series based on rain gauges and CHIRPS estimations arise from the input precipitation data. In the case of the observations, precipitation data have large latency (~3 months), which makes it unpractical for real-time decision-making. The sparse and uneven distribution of rain gauges also provides a

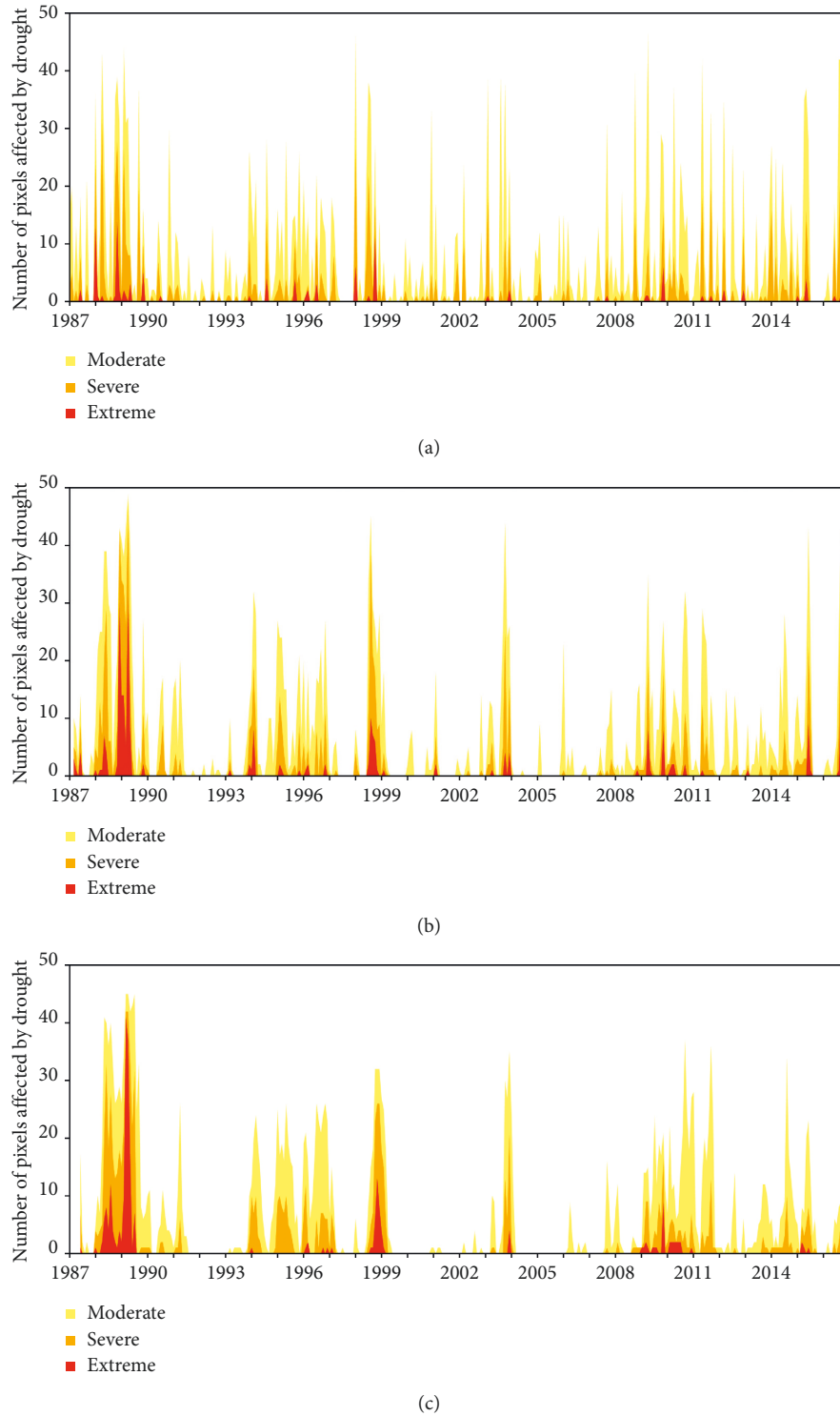


FIGURE 8: Temporal evolution of the number of pixels affected by dry conditions for the different dry categories and SPI timescales: (a) SPI1, (b) SPI3, and (c) SPI6.

source of uncertainty, even when the selected stations represent in an adequate way the main characteristics of precipitation over the CWA. A larger number of rain gauges can be used to overcome this limitation, however, with shorter records and without reaching the 30-year record

recommendation for the estimation of the SPI parameters [46]. Moreover, gap filling methods like the linear regression used here are subject to uncertainty in the estimation of missing data. Nevertheless, given the limited number of missing months and the homogeneous behaviour of regional

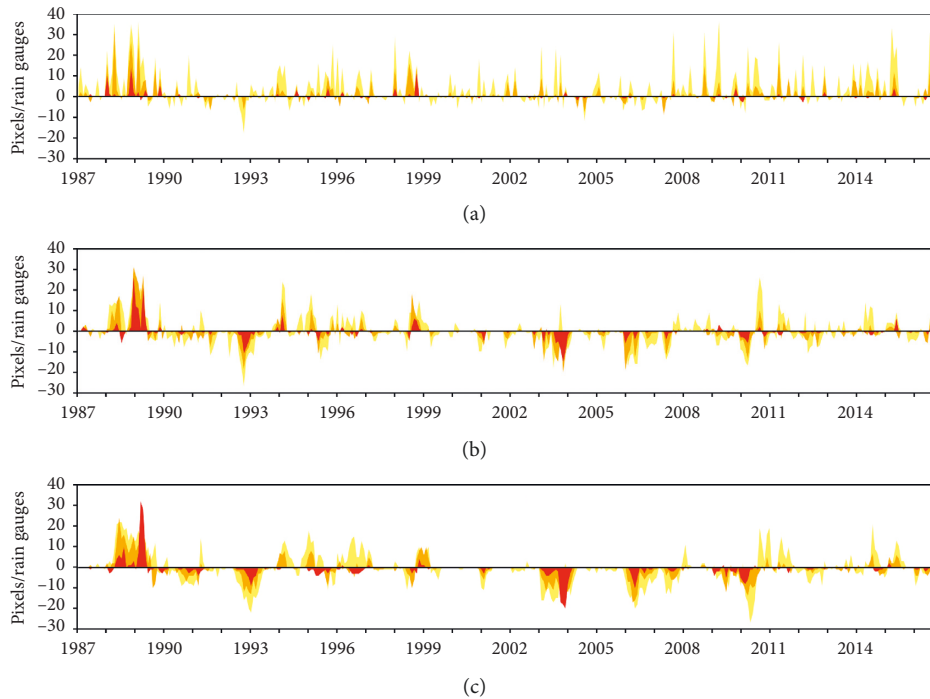


FIGURE 9: Temporal evolution of the difference between the number of CHIRPS pixels and the number of rain gauges with dry conditions for the different dry categories and timescales: (a) SPI1, (b) SPI3, and (c) SPI6.

precipitation, we consider that this contribution to uncertainty is negligible.

Regarding the CHIRPS estimations, one of the main sources of uncertainty arises from the anchor stations used for the blending procedure, as pointed out by Rivera et al. [24]. Firstly, in order to verify the independence of this validation, we analysed the temporal evolution of the anchor stations used in the blending procedure of CHIRPS. All the Argentinean stations were provided by the National Weather Service and obtained through either the Global Historical Climate Network (GHCN), the Global Summary of the Day (GSOD), and the World Meteorological Organization's Global Telecommunication System (GTS), as can be observed in ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/diagnostics/monthly_station_data/. The maximum number of anchor stations during the period 1987–2016 is 12 (Figure S1, supplementary material), far from the 49 stations used in this study. A closer look to these data indicates that several of these anchor stations were discarded from our validation, like San Carlos, Uspallata, Chacras de Coria, or Cipolletti, most of them due to data issues (not shown). In this sense, we can conclude that at least 41 of the analysed stations were not included for the CHIRPS generation, which indicates that our validation can be considered as independent. Given that CHIRPS estimations are based on the use of stations from three different sources, another issue to report is the multiplication of anchor stations. In order to illustrate this, we analysed the anchor stations located over the domain 31° to 39° S and 68° to 70° W during the month of July 2015 (data accessed through <ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/diagnostics/>

[monthly_station_data/2015.07.csv](ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/diagnostics/monthly_station_data/2015.07.csv)). We found that the list indicates a total of 14 anchor stations; nevertheless, Neuquén has 3 different precipitation values for that month (Neuquén Aero from GHCN 7 mm, Neuquén Aero from GSOD 7.8740001 mm, and Neuquén Airport 7.4 mm), with 3 different locations as can be seen in the latitude and longitude. The same problem can be observed for Mendoza Aero, San Juan, San Rafael, San Martín, and Malargüe. Therefore, even when the list shows the records from 14 stations, there are only 6 valid precipitation values. To evaluate how this duplication or triplication of information affects the final CHIRPS estimations is beyond the scope of this study, however, this must be considered as a potential main source of uncertainty.

6. Conclusions

This paper addressed some relevant features that need to be taken into account before using satellite precipitation products for regional dry and wet monitoring. Based on the SPI calculated on timescales of 1 month, 3 months, and 6 months, we used the quasi-global high-resolution CHIRPS monthly precipitation estimations to evaluate its utility over Central-Western Argentina from 1987 to 2016. This comparison was performed considering high-quality observations from 49 rain gauges over the study area. The main conclusions of this assessment can be summarized in the following:

- (i) From a regional perspective, SPI time series based on CHIRPS accurately reproduce the occurrence of

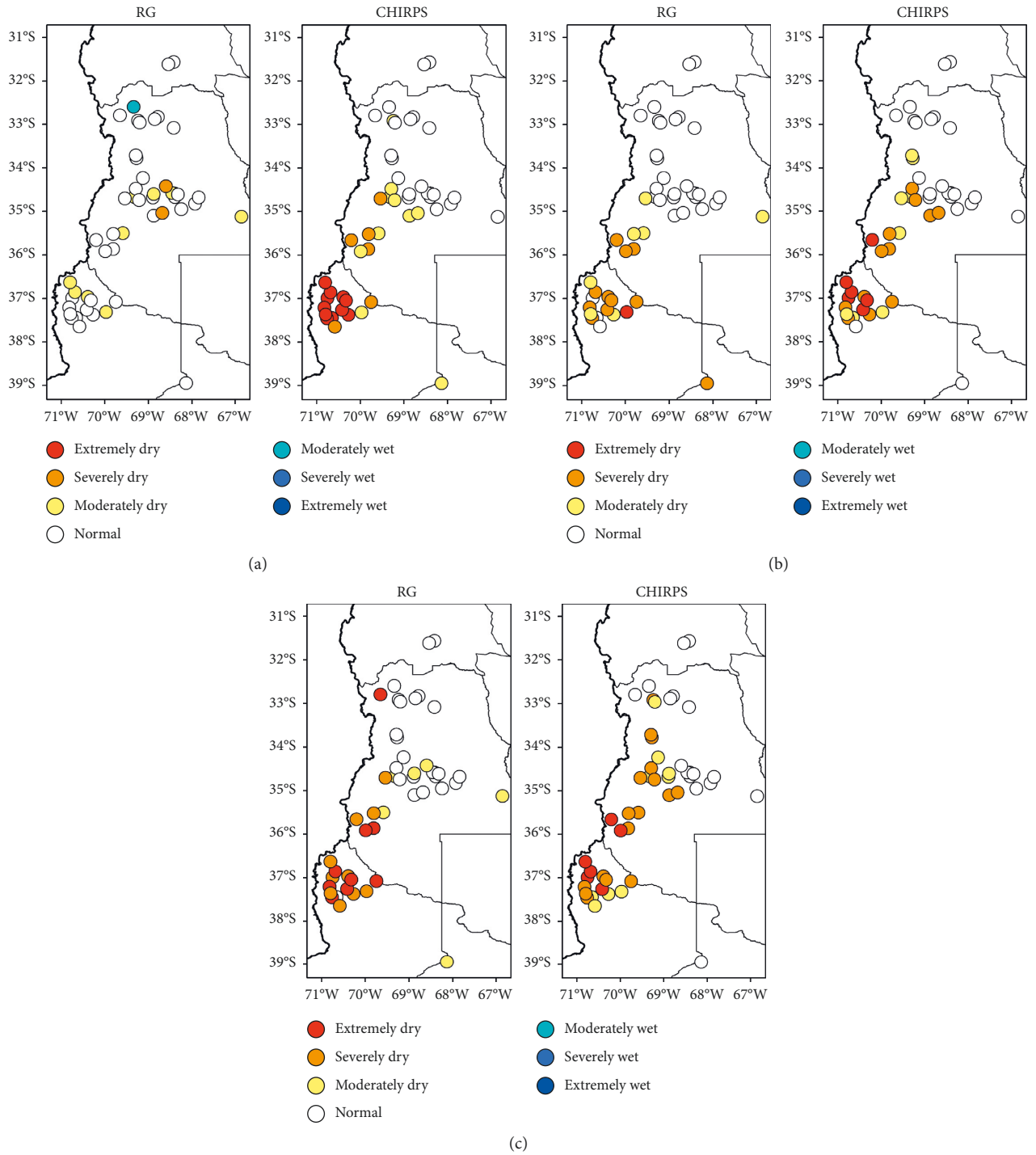


FIGURE 10: Spatial distribution of the SPI categories for timescales of (a) 1 month, (b) 3 months, and (c) 6 months during October 1998 considering rain gauges (RG) and CHIRPS estimations.

wet and dry conditions over the CWA. Considering the stations located in the region dominated by summer precipitation, the correlation between observations and CHIRPS estimations is significant ($r > 0.8$, $p < 0.01$). Even when the product exhibits a marked wet bias over the region dominated by winter precipitation, the temporal variability of the SPI resembles the observations ($r > 0.78$, $p < 0.01$),

showing the suitability of the product for the SPI calculation.

- (ii) For the monitoring and assessment of dry conditions over arid to semiarid regions like the CWA, it is recommended that the timescale for the calculation of the SPI based on CHIRPS estimations needs to be larger than 1 month. This is related to the bias in the frequency of zero values in

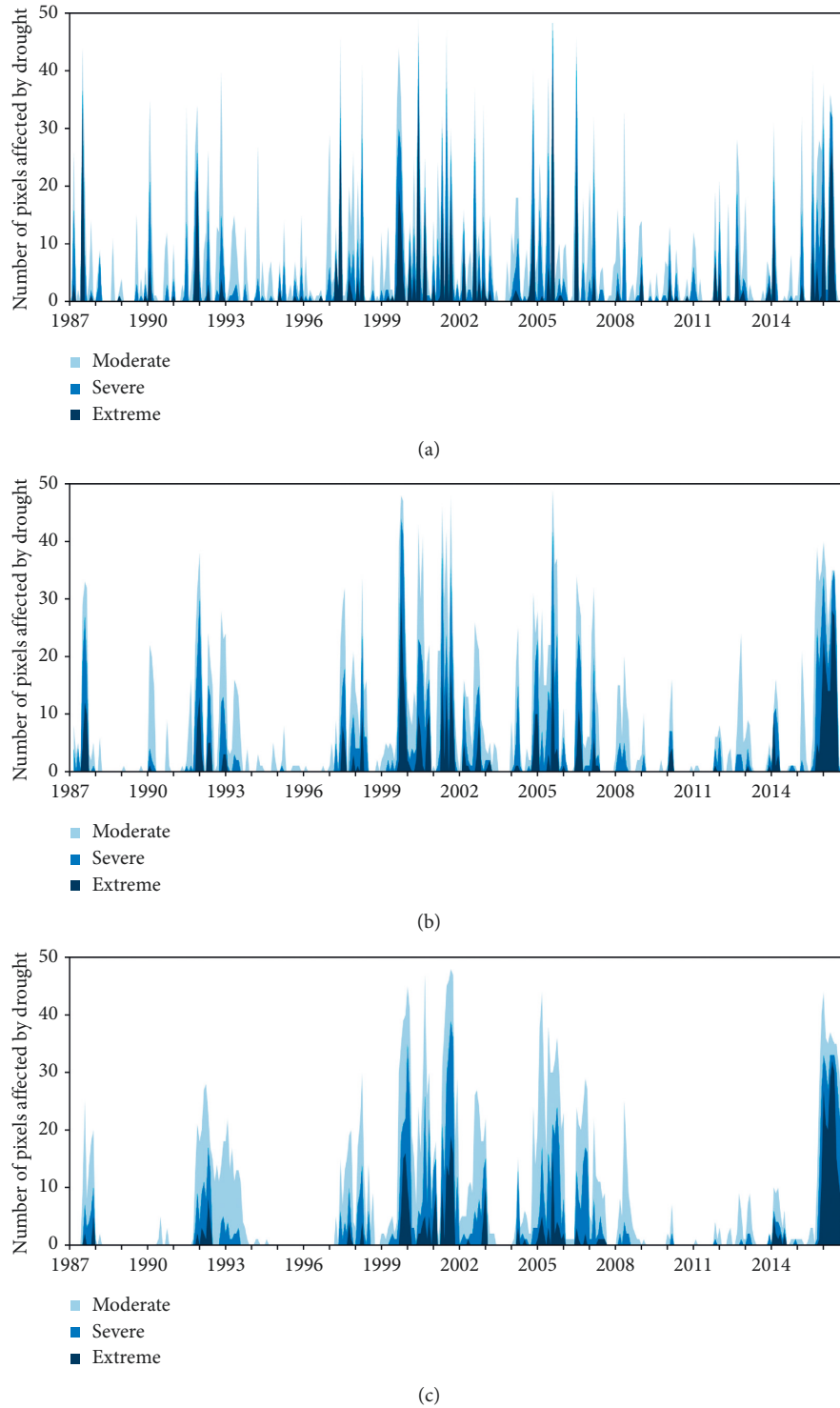


FIGURE 11: Temporal evolution of the number of pixels affected by wet conditions for the different wet categories and SPI timescales: (a) SPI1, (b) SPI3, and (c) SPI16.

comparison with the rain gauge observations, which fictitiously avoid the lower bounded SPI time series and lead to a normally distributed SPI.

- (iii) The spatial pattern of selected wet and dry cases was accurately reproduced by CHIRPS, although there was a bias in the SPI categories towards extreme

conditions. This drawback can affect its suitability for drought and excess declaration by the regional agencies. In this sense, the values for severe and extreme dry and wet classes based on CHIRPS-SPI should be complemented with in situ information for a more precise quantification of drought intensity.

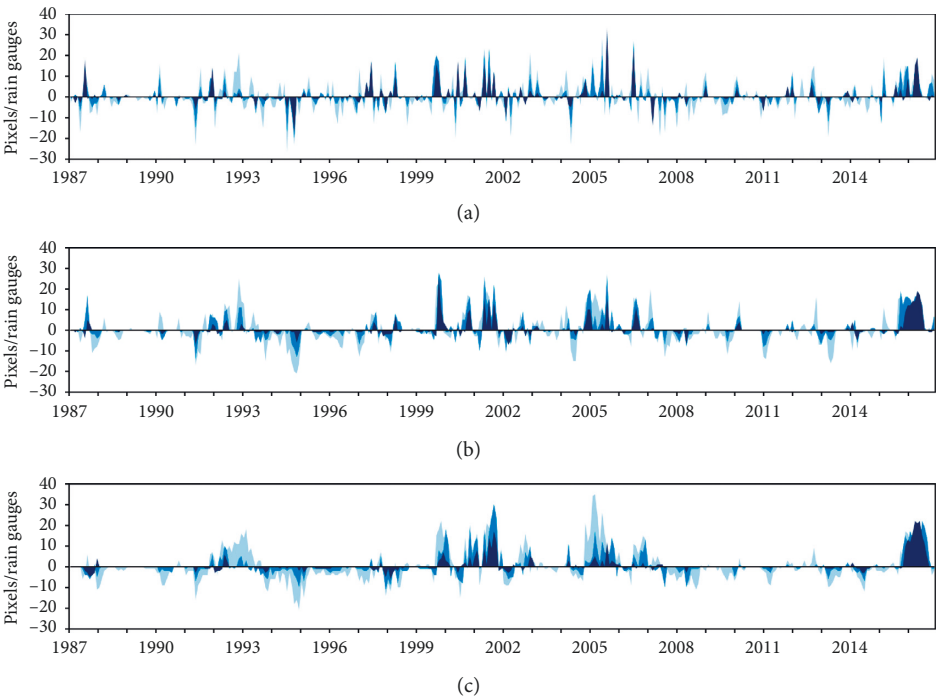


FIGURE 12: Temporal evolution of the difference between the number of CHIRPS pixels and the number of rain gauges with wet conditions for the different wet categories and timescales: (a) SPI1, (b) SPI3, and (c) SPI6.

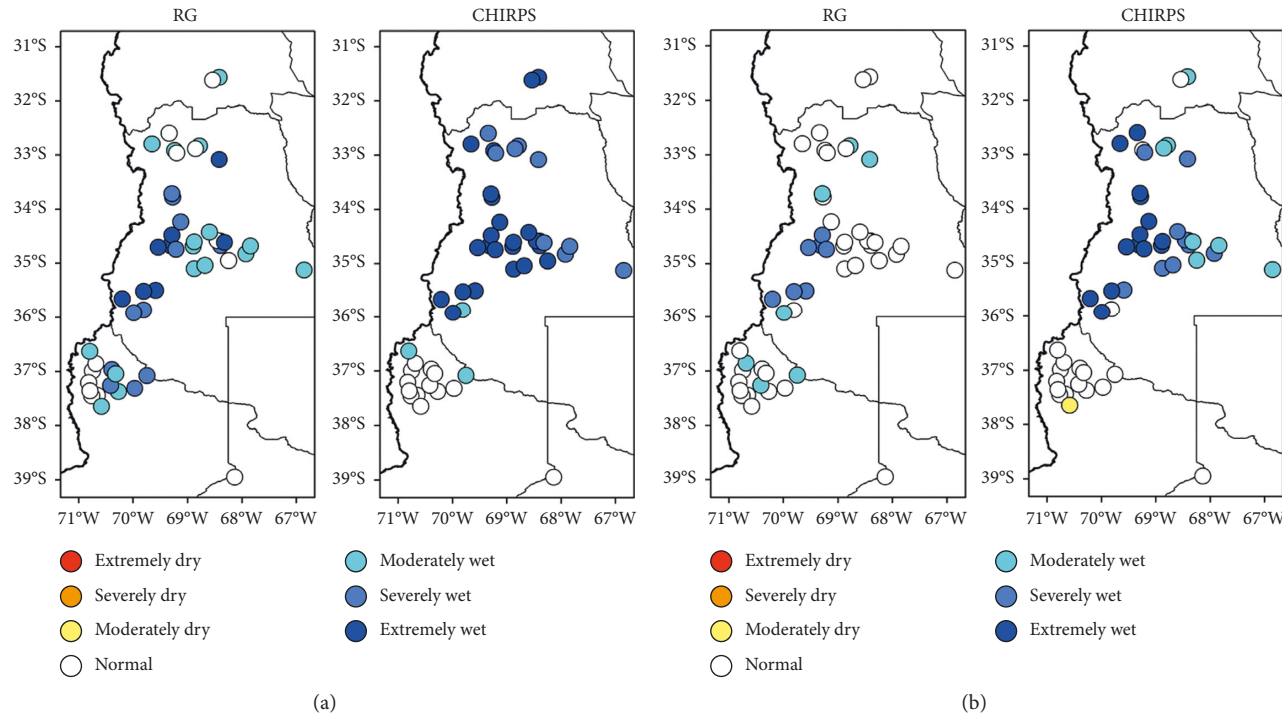


FIGURE 13: Continued.

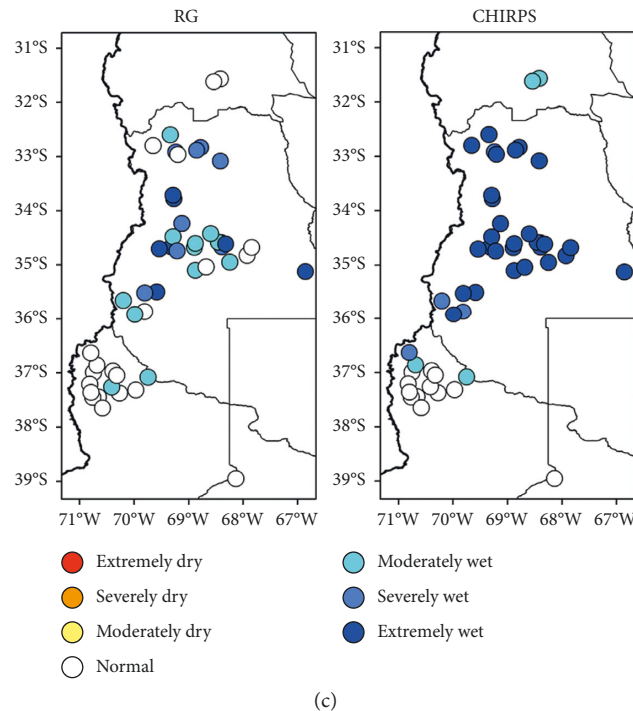


FIGURE 13: Spatial distribution of the SPI categories for timescales of (a) 1 month, (b) 3 months, and (c) 6 months during April 2016 considering rain gauges (RG) and CHIRPS estimations.

Considering the relatively short latency (~ 3 weeks) of the final CHIRPS product, available after blending with several station sources, its adequate performance for the identification of wet and dry events over the study area, and the sparse and uneven distribution of rain gauges along the CWA, this study provides a promising prospect of hydro-meteorological utility of CHIRPS estimations. Given the ongoing efforts for precipitation monitoring and declaration of drought and flood conditions, this assessment can provide some insights into regarding the use of CHIRPS for the SPI calculation and application over an arid to semiarid region, making extensible the results to other similar areas with complex topography.

Future research should focus on the methodological aspects of the SPI calculation, considering several choices of probability distribution functions for the representation of precipitation. Moreover, operational thresholds for the definition of dry and wet conditions can also provide valuable information for decision-making, given that drought and flood monitoring is of paramount importance considering the socioeconomic activities over the region. Future validation studies should also include the Climate Hazards Group Infrared Precipitation (CHIRP) satellite-only product, given its short latency (available 2 days after the end of a pentad) and its performance after 1992 [11].

Data Availability

Monthly precipitation records from 41 of the analysed sites can be accessed online through the Integrated Hydrological Database from the Water Resources Agency of Argentina

(<http://bdhi.hidricos.gob.ar>). The records from the remaining 8 sites can be freely requested to the National Weather Service of Argentina through its Meteorological Information Center (cim@smn.gob.ar). The code for the calculation of the Standardized Precipitation Index can be obtained at <http://drought.unl.edu/droughtmonitoring/SPI/SPIProgram.aspx>. The CHIRPS products can be accessed through <ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0>.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Supplementary Materials

Figure S1: number of anchor stations used for the estimation of CHIRPS dataset in the domain 31° – 39° S; 67° – 71° W. Period 1987–2016. (*Supplementary Materials*)

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