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Spatiotemporal analysis of monthly precipitation and temperature estimates from CHIRPS and Worldclim in the Sonora River Basin, Mexico

Ildefonso Narváez-Ortiz[1], Rocío Alexandra Ortiz-Paz[2], Claudio César Hernández-Vásquez[3]

1. Agroforestry Engineering Program, International University of the American Tropics, Yopal, Casanare, Colombia.
2. Colombian Corporation for Agricultural Research – Agrosavia, C.I. La Selva, Colombia.
3. Universidad Autónoma Chapingo, State of Mexico, Mexico.

Abstract: Context: Precipitation and temperature estimates for the Sonora River basin in Mexico are analyzed using raster data from Chirps and WorldClim. These platforms can compensate for the lack of data due to limited or nonexistent instrumentation, providing information for territorial planning and decision-making.

Knowledge gap: Despite the information generated from remote sensors that facilitate the interpolation and estimation of climatic variables in areas without direct measurements, doubts persist about the accuracy of interpolated raster data compared to climatological records obtained on land, especially in areas of low station density and geographical diversity.

Purpose: The main objective is to evaluate the accuracy of Chirps' precipitation estimates and WorldClim's maximum and minimum temperature estimates, using monthly records from 19 climatological stations in the Sonora River basin during the period 1981-2013.

Methodology: Data were collected from Chirps and WorldClim and compared with records from weather stations using the Absolute Value of Relative Error (PBIAS) and the Ratio of Standard Deviation (RSR). R code routines were used.

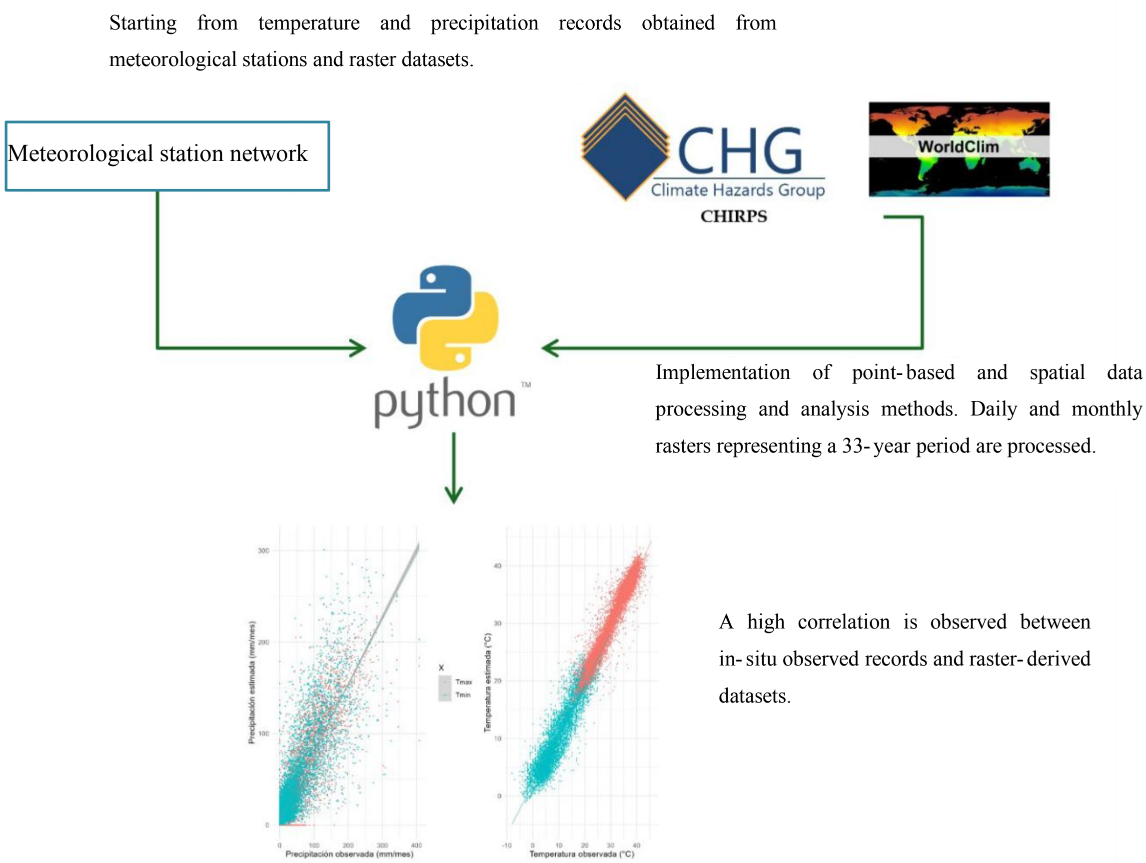
Results and conclusions: The results show that the Chirps and WorldClim estimates have a "Good" to "Very Good" fit. However, cases of underestimation and overestimation were identified, mainly in temperatures. Temperature estimates showed a high degree of fit, while precipitation estimates were more varied. Raster data platforms are reliable for climate and planning studies in the region.

Key words: climate; interpolation; low instrumentation; climatological stations; Rasters

1 Introduction

The traditional way to obtain climatological data necessary for studying hydrometeorological phenomena such as droughts and floods is through observations of records from in-situ weather stations. This method, used for years, has serious limitations, both spatial and temporal, due to the lack of uniformity in the geographical distribution of the stations. Furthermore, in many cases, the weather records contain data entry errors and missing data (Dinku, 2019; Infante and Zárate, 2012). Missing data are a recurring problem at most weather stations in Mexico and cause limitations when conducting analyses and modeling. The World Meteorological Organization (WMO), in its *Guide to Climatological*

Practices (WMO, 2018), offers detailed information on various methods for missing data, but they require a particular and detailed analysis of use and application (Herrera Oliva et al., 2017).



Graphic summary (Source: authors)

In Mexico, temperature and precipitation data are often obtained from meteorological station records; however, the Chirps and WorldClim platforms are satellite-based tools for accessing reliable, quasi-global historical climatological records with high spatiotemporal resolution (Paredes Trejo et al., 2016; Paredes-Trejo et al., 2021; Zakeri & Mariethoz, 2024). Chirps and WorldClim are being used more frequently in water resource management studies and crop and livestock planning (Romero & Alfaro, 2024; Romero-Hernández et al., 2024; Shumilo & Skakun, 2024). They are also important in drought monitoring (Tikuye et al., 2024) and in estimating groundwater recharge (Belay et al., 2024).

Globally, several studies have been conducted to evaluate the accuracy of records compared to ground-based stations. Shrestha et al. (2017) assessed the accuracy of Chirp and Chirps in the Koshi River basin in Nepal and found that the records show acceptable accuracy with variations depending on geographical configurations, i.e., better accuracy at higher altitudes. Rivera et al. (2019) compared wet and dry conditions in the semi-arid central-west of Argentina and concluded that Chirps is a promising tool for hydrometeorological studies, while also suggesting further study of its application for calculating indices such as the SPI. Shen et al. (2020) conducted a global assessment of the accuracy of Chirps, concluding that it shows acceptable accuracy but that caution should be exercised when dealing with records prior to 2000. López-Bermeo et al. (2022) evaluated the accuracy of Chirps at a regional level in the department of Antioquia, in Colombia, found that the accuracy varies depending on the climatic diversity and geographical conditions, evidenced under and over estimates, however, they concluded that it is an acceptable tool as a source of information for annual and interannual precipitation studies, but it is not recommended with daily data.

Therefore, the objective of this study is to evaluate the accuracy of the precipitation estimates of Chirps and of precipitation, maximum temperature and minimum temperature of WorldClim in the Sonora River basin, Mexico, using as a reference data set the monthly records of 19 climatological stations in the period from 1981 to 2013.

2 Materials and methods

Study area. The Sonora River basin is located in the central-northeastern region of the state of the same name and is defined by the geographic coordinates 28°5'19.23" and 30°59'18.56" north latitude and 109°52'8.92" and 111°37'52.81" west longitude. It extends from the coast of the Sea of Cortez from sea level to 2,411 meters above sea level, with a total area of 26,827 km². The study area comprises the middle and upper parts of the basin with a territorial extension of 21,220 km² (Figure 1).

Average annual rainfall varies between 300 and 600 mm, with two rainy seasons, the most significant occurring in summer and associated with the effects of the North American monsoon. The average temperature ranges between 12°C and 24°C, with the lowest temperatures recorded in mountainous areas and the highest in areas near the city of Hermosillo (SMN, 2019).

Climatological information. Two data sources were used for the precipitation, maximum temperature, and minimum temperature variables (P, Tmax, and Tmin): i) historical records from climatological stations located within the study area and ii) raster databases from the Chirps and WorldClim products. The Chirps platform consists of a series of rasters representing daily precipitation, and WorldClim integrates rasters with monthly values of precipitation, maximum temperature, and minimum temperature.

Chirps (Climate Hazards Group InfraRed Precipitation with Station data) and World-Clim (Kyrgyzbay et al., 2023) rely on ground-based stations to validate estimates using infrared technology. They have daily precipitation data in formats such as NetCDF and TIFF from 1981 to the present, with a spatial extent that includes latitudes from 50°S to 50°N and all longitudes at a resolution of 0.05°. It is managed by the U.S. Geological Survey (USGS) and the University of California, Santa Barbara (UCSB) (Funk et al., 2015; Kyrgyzbay et al., 2023). WorldClim is a dataset platform that provides climate variables including temperature, precipitation, solar radiation, wind speed, and water- vapor pressure in TIFF format. It is available at spatial resolutions ranging from 30 arc- seconds to 10 arc- minutes, with a temporal coverage from 1961 to the present (Fick & Hijmans, 2017; Hijmans et al., 2005; Perrin et al., 2020). It is built upon the interpolation of meteorological station observations alongside additional sources such as NASA, NOAA, and national meteorological services.

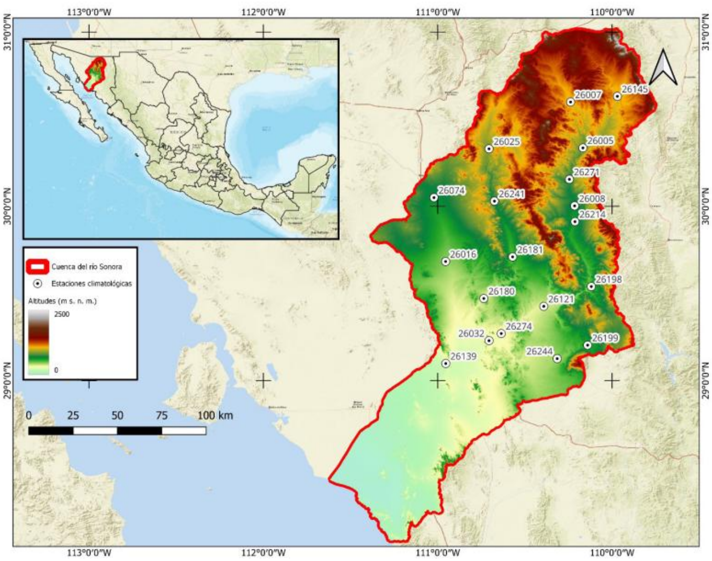


Figure 1. Location of the study area and climatological stations (Source: authors.)

Climatological stations. Monthly records (observed) were obtained from 19 climatological stations (in situ) (Figure 1, Table 1) belonging to the National Meteorological Service (SMN, 2019). The climatological data set corresponds to 33 years of observation (1981-2013) and was subjected to strict quality control regarding its continuity, variability and magnitude (Hernández-Vásquez et al., 2020).

Table 1. Geographical and climatic characteristics of the climatological stations (Source: authors.)

Station ID	Station	Elevation	Latitude (N)	Longitude (W)	P (mm)	Tmáx (°C)	Tmín (°C)
26005	Arizpe	836	30°20'08"	110°10'03"	474.5	29.4	10
26007	Bacanuchi	1,049	30°35'56"	110°14'18"	489.1	28	7.4
26008	Banamichi	675	30°00'12"	110°12'54"	459.7	30.7	13.3
26016	Carbo	464	29°41'03"	110°57'18"	374.6	31.2	13
26025	Cucurpe	853	30°19'50"	110°42'21"	524.7	29.6	10.3
26032	El Orégano	279	29°13'48"	110°42'21"	410.6	33.8	14.1
26074	Querobabi	661	30°03'02"	111°01'17"	394	31.2	11.3
26121	Ures	385	29°25'37"	110°23'31"	375.6	31.8	9.1
26139	Hermosillo II	221	29°05'56"	110°57'14"	363.5	32.2	17.7
26145	Bacoachi	1,049	30°37'54"	109°58'12"	465.5	28	8.2
26180	El Cajón	390	29°28'19"	110°44'09"	414.2	32.1	11.7
26181	Rayón	560	29°42'38"	110°34'14"	500.5	30.6	11.8
26198	Mazocahui	449	29°32'26"	110°07'09"	517.6	31.4	11.2
26199	Pueblo de Álamos	589	29°12'15"	110°08'25"	498.8	30.8	11.7
26214	Huepac	644	29°54'46"	110°12'47"	496.5	30.1	9.7
26241	Meresichic	712	30°01'50"	110°40'30"	521.8	28.5	11
26244	Rancho Viejo	450	29°07'37"	110°18'54"	458.6	31.1	12.4
26271	Sinoquipe	740	30°09'20"	110°14'42"	504.5	30.5	11.6
26274	Topahue	300	29°16'15"	110°38'09"	418.6	33.1	12.9
P = Average annual precipitation Tmáx = Average maximum temperature. Tmín = Average minimum temperature							

Raster products. The rasters were obtained for the same period as in the in-situ stations. From Chirps (Funk et al., 2015) (www.chc.ucsb.edu/data/chirps) precipitation data were acquired on a daily time scale (12,053 rasters) with a spatial resolution of 3 arcminutes and from WorldClim (www.worldclim.org/data) precipitation, maximum temperature and minimum temperature data were obtained on a monthly time scale (396 rasters of each variable) with a spatial resolution of 2.5 arcminutes (Figure 2).

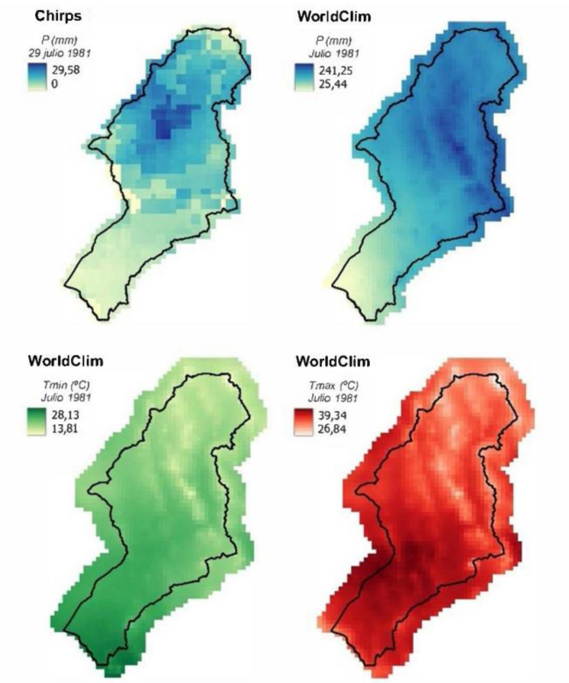


Figure 2. Example of a raster layer with Precipitation (P), Minimum Temperature (Tmin) and Maximum Temperature (Tmax) data from Chirps and WorldClim (Source: authors.)

Analysis tools. The preparation of rasters, organization and extraction of data was done using code routines with the Python programming language (QGIS Development Team, 2023; Van Rossum & Drake, 2009) and the QGIS 3.16.9-Hannover program (QGIS Development Team, 2023).

The layers representing precipitation and temperature were downloaded from the servers https://climateserv.servirglobal.net/map (Chirps) (Funk et al., 2015) and https://www.worldclim.org/data/monthlywth.html (WorldClim). The former provides raster layers of daily precipitation, and the latter provides raster layers of monthly precipitation, maximum temperature, and minimum temperature. The raster layers were prepared using QGIS 3.X (QGIS Development Team, 2023) and its built-in Python console, where code routines were generated using the GDAL (GDAL/OGR contributors, 2024), NumPy (Harris et al., 2020), and Pandas (Pandas development team, 2020) modules.

Using Python routines, the rasters were cropped according to the polygon of the study area to obtain files of similar size and weight. To obtain the average monthly temperature, the maximum and minimum temperature rasters for each of the 396 months were summed and divided by two.

Once the monthly precipitation and temperature rasters were prepared, three-dimensional matrix arrays were generated using Python and the Numpy (Harris et al., 2020) and Pandas (Pandas Development Team, 2020) modules. The X and Y axes represent the latitude and longitude coordinates, locating the pixels of each raster, and the Z axis represents the time in months during the study period 1981-2013. Using the iloc property of the Pandas module (Pandas Development Team, 2020), the data series at a given point on the X and Y axes was extracted based on the geographic coordinates of each of the 19 stations considered in this study.

Three three-dimensional matrices were generated: two for precipitation (CHIRPS and WorldClim) and one for mean temperature (WorldClim), summarizing the climatic variables in time and space. Data series for the locations of the 19 meteorological stations shown in Table 1 were extracted and exported to a comma-delimited file. For each of the 19 stations, four series were obtained: observed monthly temperature and precipitation records, Chirps precipitation, and WorldClim precipitation and temperature.

From each three-dimensional matrix, the value corresponding to the pixel where the coordinates of the location of each of the 19 weather stations coincided was taken, forming daily precipitation series with data from Chirps and monthly series of precipitation, maximum temperature, and minimum temperature with data from WorldClim. The daily series (Chirps) were summed to obtain the total accumulated precipitation at the monthly level. The time series with the data of the climatological variables from the rasters and the weather stations were saved in comma-separated text files.

Statistical analysis was performed using the R programming language (R Core Team, 2025). Text files were processed, and the fit of the series was evaluated using correlations and the indices presented in Table 2. Precipitation series from Chirps and WorldClim were analyzed against stations, as were minimum and maximum temperature series from WorldClim against stations. Data and results were visualized using the ggplot library (Wickham, 2016). Daily precipitation series from Chirps were summed to obtain monthly values that could be compared with precipitation, minimum and maximum temperatures from WorldClim and the 19 meteorological stations.

Indices for evaluating goodness-of-fit. The goodness-of-fit between raster-derived data and precipitation and temperature data recorded at in-situ climate stations was assessed using the percent bias (PBIAS) (Shen et al., 2020) and RSR. RSR is defined as the ratio of the root-mean-square error to the standard deviation of observations (Moriasi et al., 2007; Shrestha et al., 2017). The aforementioned indices are calculated using Equations 1 and 2, respectively.

$$PBIAS=\frac{\sum(R_{est}-R_{sat})}{\sum(R_{est})}*\ 100$$

$$RSR=\frac{\sqrt{\sum(R_{est}-R_{sat})^2}}{\sqrt{\sum(R_{est}-\overline{R}_{est})^2}}$$

where R_{est} is the record of the in situ climatological station and $\overline{R}_{est}$ is the average of the period considered for the in situ station, R_{sat} is the series with the estimates of the climatological variables from the Chirps or WorldClim satellites. The *PBIAS* and *RSR* values were interpreted qualitatively based on the categories proposed by Moriasi et al. (2007) presented in Table 2.

Table 2. PBIAS and RSR value ranges for qualitative interpretation (Source: authors)

Classification	RSR
Very good	0 to 0.5
Good	0.5 to 0.6
Satisfactory	0.6 to 0.7
Unsatisfactory	> 0.7
Classification	PBIAS (%)
Unsatisfactory	< -55
Satisfactory	-55 to -30
Good	-15 to -3
Very good	-15to 15
Classification	RSR
Good	15to 30
Satisfactory	30 to 55
Unsatisfactory	> 55

Furthermore, the PBIAS allows us to determine whether the compared series is underestimated or overestimated based on its value. If the value is less than 20, it is considered underestimation, and when it is greater than 20, it is considered overestimation (López-Bermeo et al., 2022).

3 Results and discussion

Adjustment of raster estimates. A statistical evaluation was performed on the adjustment of estimates based on interpolations and mixed data with records from climatological stations, in order to analyze the capacity of platforms with raster data to capture and store historical climate information.

The statistical evaluation (PBIAS and RSR) of the fit of the climatological variable estimates (P, Tmax, and Tmin) is presented in Table 3. In general, and based on the categories presented in Table 2, the precipitation and temperature estimates from Chirps and WorldClim show a "Good" and "Very Good" fit, with occasional "Satisfactory" results and no "Unsatisfactory" fits, compared to the historical records of ground-based weather stations. Statistical indices less than -20 or greater than 20 for PBIAS (López-Bermeo et al., 2022), and greater than 0.6 for RSR, correspond to data where remote sensors overestimate or underestimate temperature series and precipitation peaks. The results obtained are consistent with the conclusions of Bai et al. (2016) and Katsanos et al. (2016) and Peng et al. (2020).

Table 3. Fit statistics (Source: authors.)

Station	Station vs Chirps		Station vs WorldClim					
	P		P		Tmin		Tmax	
	PBIAS	RSR	PBIAS	RSR	PBIAS	RSR	PBIAS	RSR
26005	-7.574	0.433	0.263	0.527	9.567	0.376	-0.797	0.283
26007	-5.112	0.417	0.787	0.530	24.522	0.328	-0.501	0.157
26008	-4.139	0.386	-1.425	0.470	-5.158	0.220	-0.203	0.224
26016	-2.748	0.544	-3.011	0.597	-6.487	0.265	0.675	0.198
26025	-20.548	0.484	-5.830	0.515	2.505	0.441	-1.593	0.503
26032	-16.082	0.478	-11.495	0.559	-2.251	0.255	-2.668	0.295
26074	-22.424	0.583	-13.926	0.644	-1.320	0.192	-4.587	0.354
26121	25.811	0.672	19.724	0.644	49.668	0.653	2.530	0.399
26139	-29.539	0.614	-18.368	0.651	-18.876	0.603	0.383	0.175
26145	-8.772	0.452	-1.398	0.531	19.504	0.434	0.795	0.346
26180	-20.097	0.527	-6.801	0.586	13.523	0.275	1.068	0.199
26181	-20.385	0.472	-10.298	0.524	6.625	0.251	1.052	0.238
26198	-19.883	0.463	-0.778	0.550	10.144	0.274	-1.464	0.263
26199	-5.053	0.399	10.838	0.495	-0.669	0.231	0.729	0.320
26214	-9.594	0.418	-7.780	0.513	37.958	0.557	2.596	0.307
26241	-13.019	0.521	-8.728	0.587	8.946	0.491	5.344	0.543
26244	-7.965	0.373	4.833	0.473	-3.328	0.224	3.223	0.312
26271	-13.775	0.432	-9.099	0.469	4.472	0.266	-2.707	0.278
26274	-15.141	0.544	-13.228	0.613	7.229	0.203	0.467	0.209

The dispersion of station records and their equivalent raster estimates is presented in Figure 3. Precipitation shows greater dispersion than temperature, both with Chirps and WorldClim; that is, there is a greater difference between the observed data and the raster estimates. Unlike the findings of López-Bermeo et al. (2022), in this study, Chirps tends to overestimate when considering the values from the 19 analyzed stations, possibly related to the difference in precipitation volume between Colombia and northern Mexico, where arid or semi-arid regions predominate (Bai et al., 2018). On the other hand, WorldClim tends to slightly underestimate monthly precipitation values. Regarding minimum and maximum temperatures, its estimates show a high degree of fit, with slight overestimation. The fit of the temperature estimates provided by WorldClim is remarkably high. According to the interpretation categories, they are "Very good" (Figure 3), evidenced by having a narrow confidence interval (gray band: 95% confidence interval).

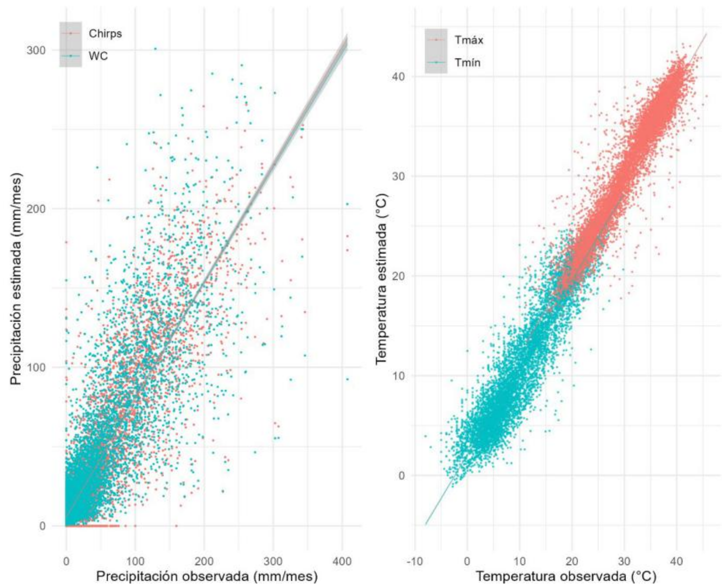


Figure 3. Dispersion of records from in-situ stations vs. rasters (Source: authors.)

The linear fit of the station records, compared to the interpolated values in rasters (Table 4), confirms the qualitative interpretations. The expected intercept value for an ideal fit is zero; however, values range from -0.76 to 3.03, corresponding to the variations present in the series, which manifest as underestimation or overestimation. Precipitation in both Chirps and WorldClim shows a larger intercept than temperature, due to the scale of the records. A similar situation is found in the correlation coefficient, where the largest fits, around 0.9, are found in temperature, while precipitation is around 0.7.

Table 4. Linear model of stations compared to rasters (Source: authors.)

	Intercept	Slope (Standard Error)	95% confidence interval of the slope	R2	P- value
PP Chirps	3.03	1.05 (0.0065)	1.03 - 1.06	0.78	p < 0.0001
PP WC	2.71	0.97 (0.0073)	0.96 - 0.99	0.7	p < 0.0001
T min	-0.76	1.01 (0.0042)	1.001 - 1.018	0.88	p < 0.0001
T max	-0.13	1 (0.0038)	0.995 - 1.009	0.9	p < 0.0001

The geographical distribution of the seasons with their respective qualitative interpretation of the fit is shown in Figures 4 and 5. No pattern of association between the degree of fit and altitude is determined, possibly because the variability in terms of altitude is not significant and is less than 1000 m above sea level (Katsanos et al., 2016)

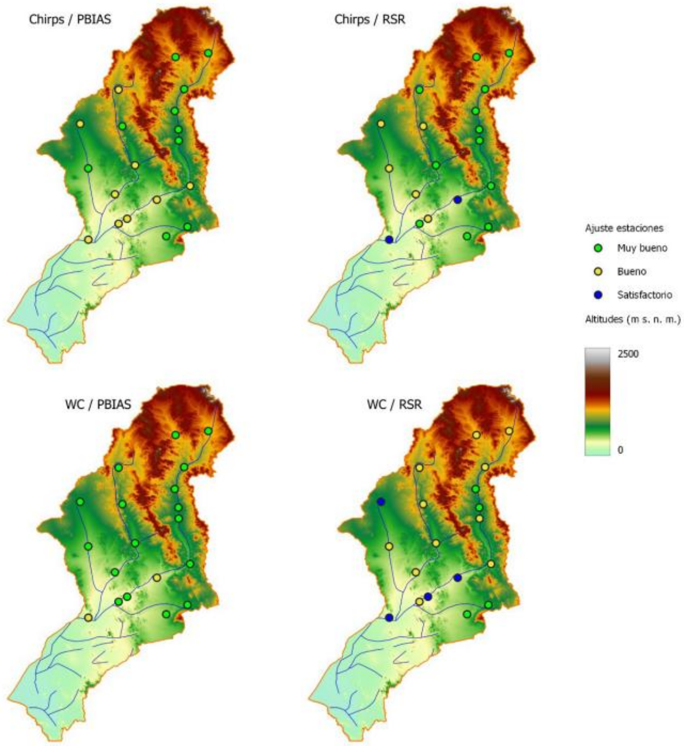


Figure 4. Fit performance of raster- derived precipitation records (Source: authors.)

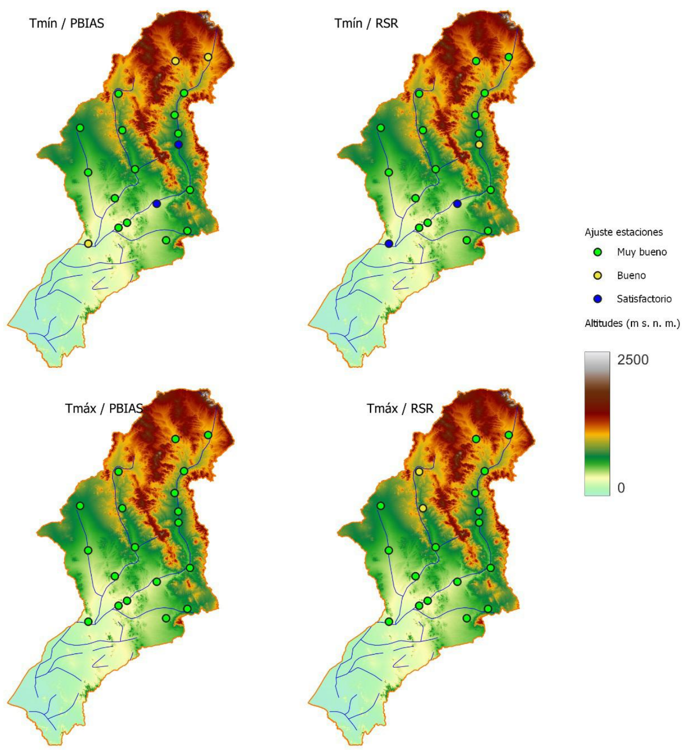


Figure 5. Fit performance of raster- derived temperature records (Source: authors.)

The precipitation and temperature series with a "Very Good" fit are presented in Figure 6. Greater dispersion can be observed in the precipitation records than in the temperature records; this trend is similar in WorldClim and Chirps. In the dispersion of the minimum temperature, a line tends to form above 45°, which indicates a high level of fit.

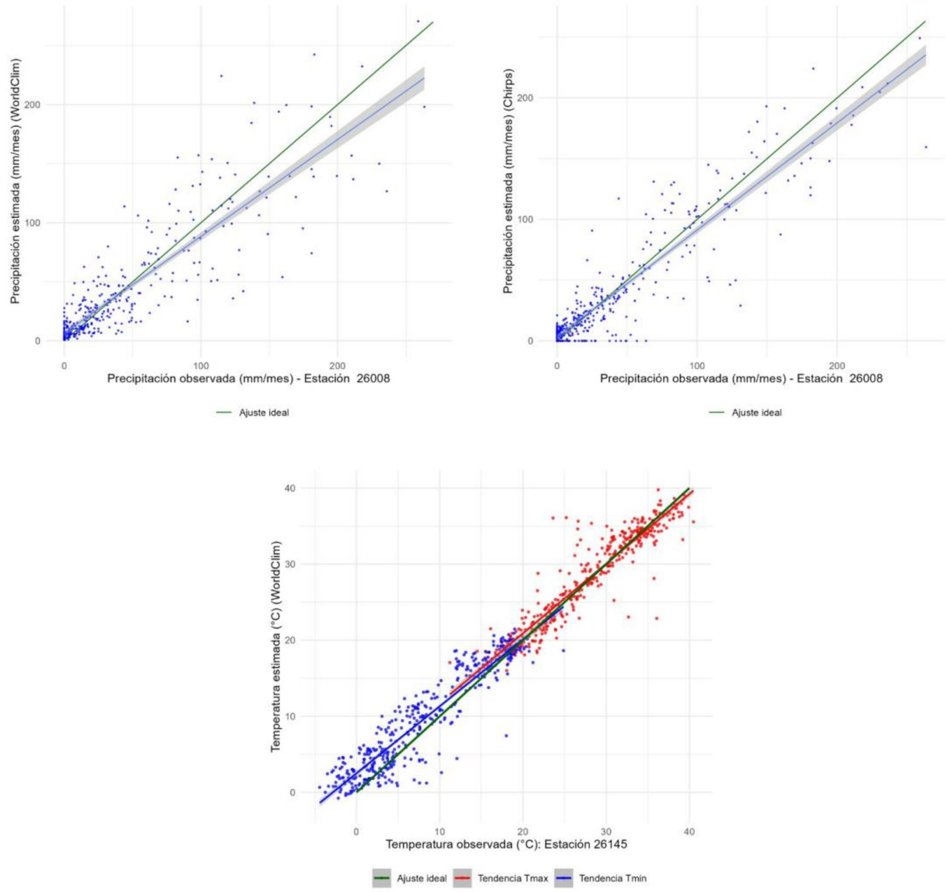


Figure 6. Series with "Very good" fit: Precipitation WorldClim and Chirps – Station 26145, Temperature – Station 26198 (Source: authors)

Regarding the precipitation estimated using Chirps, there were five cases of underestimation and one case of overestimation, according to the ranges proposed by López-Bermeo et al. (2022). The precipitation records obtained by remote sensors at stations 26121 and 26139 showed the lowest degree of fit, due to the greater dispersion that leads to a tendency toward overestimation or underestimation (Figure 7). The proportion of outliers that contribute to overestimation or underestimation is small relative to the total; however, the greater dispersion influences the statistics, indicating a poor fit.

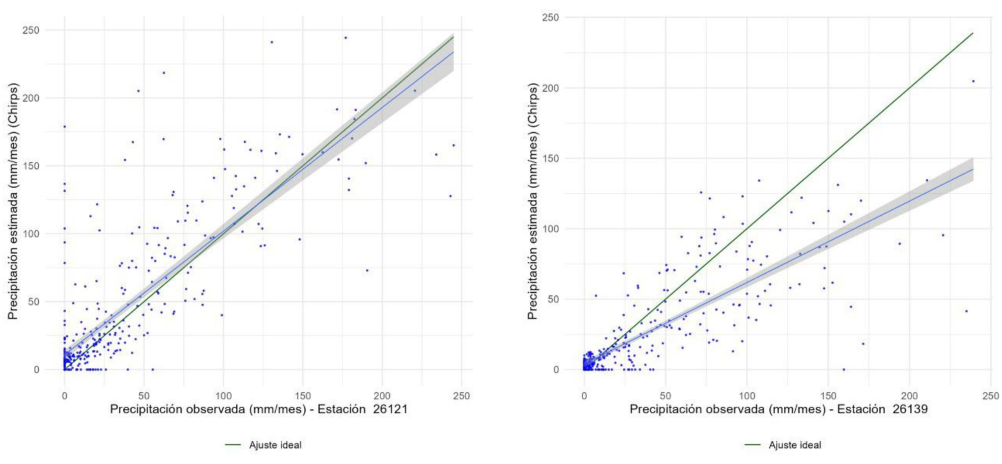


Figure 7. Precipitation time- series with low fitting performance: Left – Station 26121, Right – Station 26139 (Source: authors.)

In the case of WorldClim's maximum temperature estimates, the adjustments are "Good" or "Very Good," whereas the minimum temperature series show cases where the adjustment is "Satisfactory", due to overestimation (Figure 8). However, remote sensing estimates are representative of temperature behavior and can be used for studies or territorial planning, considering rescaling and adjustment for systematic errors (Hempel et al., 2013; Poggio et al., 2018).

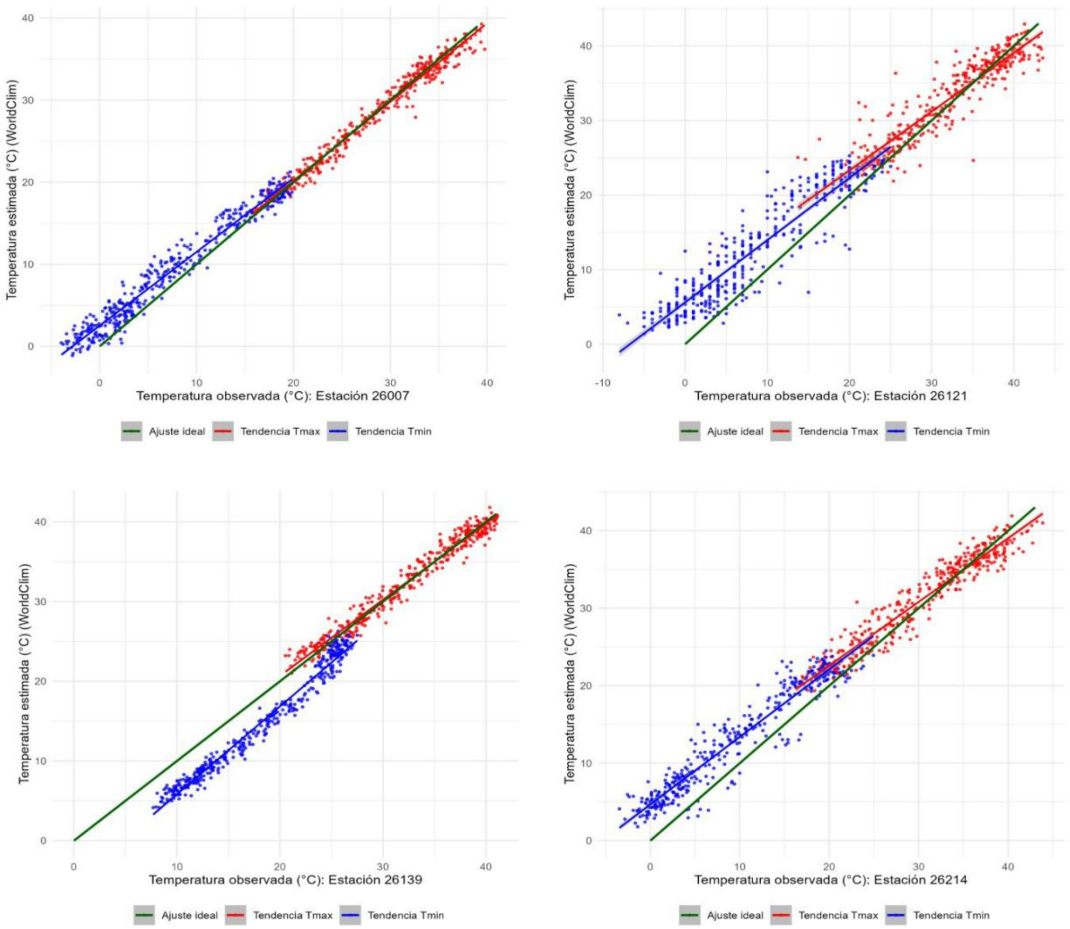


Figure 8. Poorly- fitted time- series of minimum and maximum temperature (Source: authors.)

Temperature series exhibit systematic errors that overestimate or underestimate the observed value (Figure 8). The degree of fit and applicability of data and analysis results based on remote sensors can be optimized by performing systematic error correction with methods such as the ISI-MIP (Inter-Sectoral Impact Model Intercomparison Project) (Hempel et al., 2013; Méndez, 2016).

4 Conclusions

Historical precipitation and temperature records from the Chirps and WorldClim raster databases are highly reliable and can be used in hydrological and climate studies for agricultural planning or land-use planning. Temperature estimates tend to incorporate systematic errors that underestimate or overestimate the variable's value; this behavior can be addressed with error correction strategies such as the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP). No significant association was found between the degree of fit of the estimates and altitude.

Furthermore, for the information contained in Chirps or WorldClim rasters to be increasingly used and leveraged by decision-makers, especially in territorial areas, it is essential to improve the management of the platforms and develop applications that facilitate their use. One alternative to improve the fit is to average neighboring pixels. Likewise, it is important to promote the implementation of tools and the use of open-source software to reach territorial entities that lack the resources to access information and technology.

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Conflicts of interest

The author declares no conflicts of interest regarding the publication of this paper.

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