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Articles

Estimation of daily design rainfall in Argentina from satellite-derived data

Estimación de las precipitaciones diarias de diseño en Argentina a partir de datos derivados de satélite

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Abstract

The results of the estimation of the daily design rainfall in Argentina are presented for 97 % of the continental national territory. This analysis was based on the processing of the Satellite-Derived Precipitation Data (DPDS) of the CHIRPS product (Climate Hazards Group InfraRed Precipitation with Station data), with a spatial resolution of 5 km and a temporal coverage of 37 years. The extraction of the Annual Maximum Daily Precipitation (pdMa) maps was carried out by means of *ad-hoc* codes developed through the Google Earth Engine platform. The pdMa series from CHIRPS were compared with those obtained from 64 rainfall stations provided by the National Meteorological Service (SMN), determining the slopes of the linear regression. These regression parameters were interpolated to the territory under study, to enhance the pdMa maps. These corrected maps were processed through codes developed in Python, to associate non-exceedance empirical probabilities and adjust the optimal theoretical probability distribution to each of the 106 778 pixels considered. From these results, daily design rainfall maps were generated for 2–100-year return periods. These results were validated against 30 stations from the National Water Information System, obtaining an acceptable agreement. It is considered that the results obtained will be useful in hydrological design, especially in regions that lack adequate rainfall records for a traditional statistical analysis.

Keywords: Statistical hydrology, geographic information systems, design rainfall.

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Resumen

Se presentan los resultados de la estimación de las precipitaciones diarias de diseño en Argentina para el 97 % del territorio nacional continental. Este análisis se basó en el procesamiento de los datos de precipitación derivados de satélite (DPDS) del producto CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data), con una resolución espacial de 5 km y una cobertura temporal de 37 años. La extracción de los mapas de precipitación diaria máxima anual (pdMa) se efectuó por medio de códigos *ad hoc* desarrollados a través de la plataforma Google Earth Engine. Se compararon las series de pdMa provenientes de CHIRPS con las obtenidas a partir de 64 estaciones pluviométricas provistas por el Servicio Meteorológico Nacional (SMN), determinando las pendientes de la regresión lineal. Estos parámetros de la regresión fueron interpolados al territorio bajo estudio para corregir los mapas de pdMa. Los mapas corregidos se procesaron a través de códigos desarrollados en Python para asociar probabilidades empíricas de no excedencia y ajustar la distribución teórica óptima de probabilidades a cada uno de los 106 778 pixeles considerados. A partir de estos resultados se generaron mapas de precipitaciones diarias de diseño para periodos de retorno comprendidos entre 2 y 100 años. Los resultados se validaron contra 30 estaciones provenientes del Sistema Nacional de Información Hídrica, obteniéndose un acuerdo aceptable. Se considera que los resultados obtenidos serán de utilidad en tareas de diseño hidrológico, en especial en las regiones que carecen de registros pluviométricos adecuados para un análisis estadístico tradicional.

Palabras clave: hidrología estadística, sistemas de información geográfica, lluvias de diseño.

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Introduction

Generalities

Hydrological systems are sometimes affected by extreme events, such as severe storms, floods and droughts. The magnitude of an extreme event is inversely related to its frequency of occurrence, that is, very severe events occur less frequently than more moderate events. The hydrological information used must be carefully selected in such a way that it satisfies the assumptions of independence and identical distribution. In practice, this is usually done by selecting the annual maximum of the variable under analysis, with the expectation that successive observations of that variable from one year to the next will be independent (Chow, Maidment, & Mays, 1994).

In water resources engineering, design rainfalls are defined as idealized pluvial events that reflect the demands of hydrometeorological origin to which infrastructure works would be subjected under a certain level of risk (Caamaño-Nelli & Dasso, 2003). They are characterized through three components: duration, intensity and non-exceedance probability, and arise from the statistical analysis of series of extreme values (maximum in this case) of real rainfall, usually recorded by rain gauges.

In Argentina, as in other countries, daily precipitation measurements are carried out using surface pluviometric stations. As a result, punctual or specific observations sometimes do not adequately represent the space-time variability of precipitating systems, which makes it necessary to incorporate other measurement sources that can improve this aspect (Vidal, Salio, & Pappalardo, 2011).

The regionalization of hydrological variables comprises a set of statistical inference techniques and probabilistic models, which use the set of observed data, spatially distributed at points in a region considered homogeneous, to estimate the quantiles associated with different probabilities of exceedance at any point within that region (Zamanillo, Larenze, Tito, Pérez, & Garat, 2008).

The regionalization of maximum rainfall in Argentina

Local validity procedures have been developed in various provinces of the country, that have allowed these sites to define standards in the choice of design rainfall. Among these cases we can mention: the work of

Caamaño-Nelli and Dasso (2003) for the province of Córdoba; the one carried out by Zamanillo *et al*. (2008) for the province of Entre Ríos; the one carried out by Fernández, Fornero and Rodríguez (1999) for the great Mendoza; the one presented by Weber and Guillén (2018) for the province of La Rioja; the one carried out by Catalini, García-Rodriguez, Caamaño-Nelli and Ordoñez (2014) extending the regionalization of maximum rainfall to the provinces of Santa Fe and San Luis; and the one developed by Guillén, Botelli, García and Catalini (2015), who present an extension of the regionalization methodology carried out in Córdoba, to an important part of the provinces of northern Argentina: Jujuy, Salta, Tucumán, Catamarca, Santiago del Estero, Chaco and Formosa.

One of the main limitations of the regionalization of design precipitation, based on the statistical analysis of series of pluviometric stations (especially when their spatial density is low) lies in the use of spatial interpolation methods. These methods generally cannot consider geographic variability by themselves, particularly those associated with orography and climate, by generating a continuous field of the interpolated variable. This limitation, which would be overcome with an adequate spatial density of pluviometric stations, is an important limitation in the validity of the application of these techniques in a country as large and geographically diverse as Argentina, with the aggravated factor of the limited availability of reliable and long-term data series.

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Devoto's method

A methodology available for obtaining Intensity-Duration-Frequency relationships of national coverage is described below. Devoto (2002) developed, based on information from 26 pluviographic stations, a method for estimating Intensity-Duration-Frequency (IDF) curves in Argentina for localities without information. Assuming valid the Gumbel probability distribution, a hyperbolic-type relationship between intensity and duration, and based on four parameters obtaineined from maps (average intense rainfall of 1- and 12-hours duration, and the corresponding coefficients of variation), it is possible to obtain synthetic IDF relations for the entire national territory. In this way, it becomes the only accessible and valid regionalization procedure throughout the territory.

The method assumes that, for each return period considered, there is a relationship between the intensity *i* (in mm/h) and the duration *t* of the storm (in minutes) given by:

$$i = \frac{a}{t^{b}+c} \qquad (1)$$

where *a*, *b* and *c* are parameters to be determined. Devoto (2002) assumes a constant value for b = 0.80, so that the parameters *a* and *c* are obtained from a pair of values i_1 and i_2 for the durations t_1 = 1 hour and t_2 = 12 hours. The associated rainfall X_1 and X_2 are obtained from the average rainfall *X* of that duration, its coefficient of variation *Cv* and the return period *Tr*, assuming the Gumbel distribution, as:

$$X = \bar{X} \cdot \left\{1 - \frac{0{,}5772}{1{,}282} Cv - \frac{1}{1{,}282} Cv \cdot ln\left[-ln\left(1 - \frac{1}{Tr}\right)\right]\right\} \quad (2)$$

Devoto (2002) assumes that the average intense rainfall of 1 h and 12 h duration, and their corresponding coefficients of variation, are continuous fields. Determining these values for the 26 pluviographic stations considered, and based on this, he publishes four contour maps for these magnitudes, from which he suggests obtaining, by linear interpolation, the corresponding values for any other site in the country. Figure 1 shows the average intense rainfall of 1- and 12-hours duration published by Devoto (2002) for the application of his methodology.

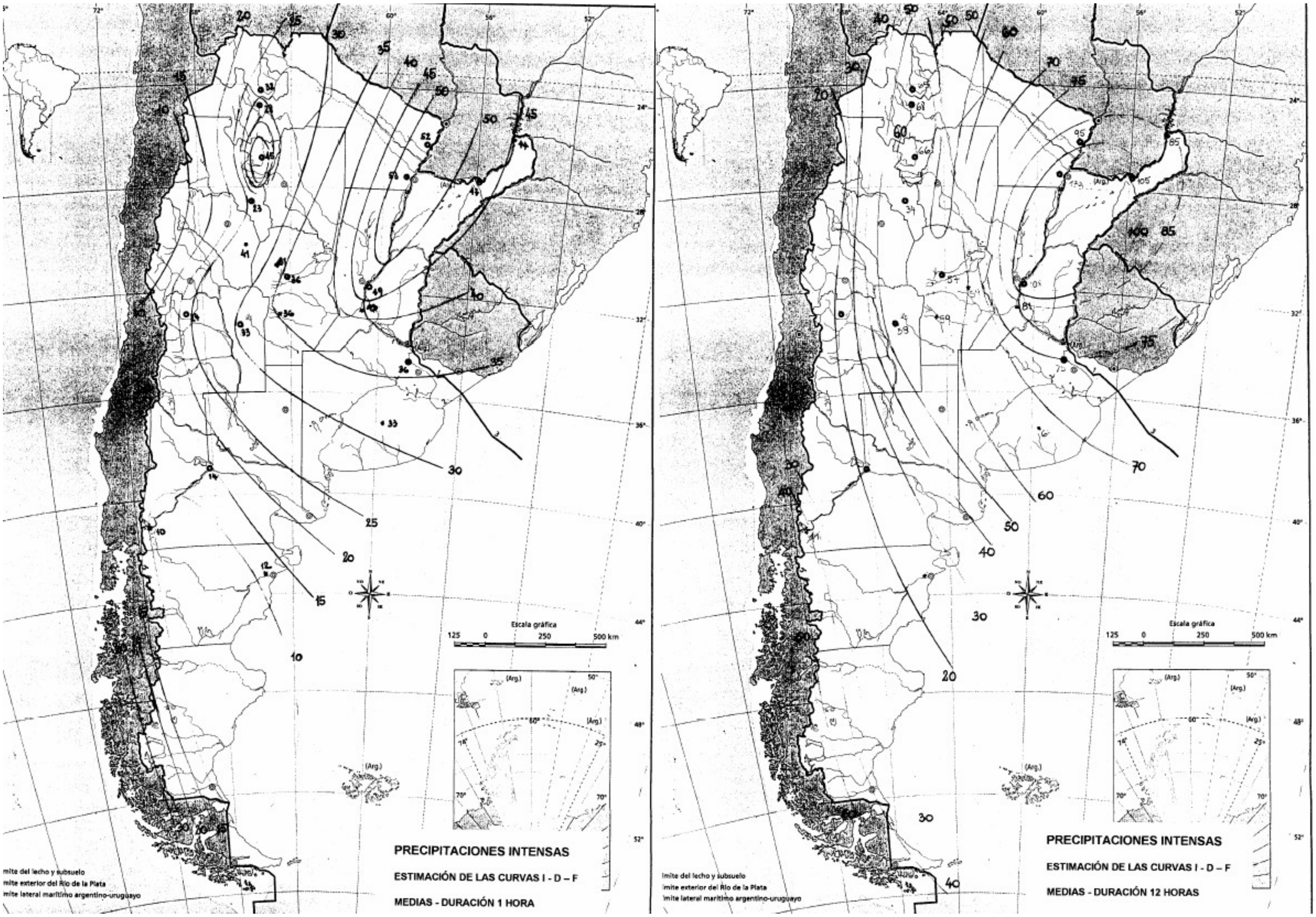

Figure 1. Average intense rainfall of 1 hour and 12 hours duration presented by Devoto (2002).

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Satellite-Derived Precipitation Data (DPDS)

In situ measurements have several drawbacks, such as incomplete areal coverage and deficiencies in most oceanic and sparsely populated areas. With advanced infrared (IR) and microwave (MW)-based instruments, satellite observations compensate for these deficiencies by providing coverage that is more spatially homogeneous and temporally complete for vast areas of the globe.

Intermittency, together with sampling in time and space, is the main challenge for observing precipitation. Rain gauges are essential to measure precipitation directly, but the global density of rain gauge stations is limited. In addition, the observations are interpolated to form gridded data sets to cover the entire globe; this smoothes out extreme values and affects long-term trends, especially in regions with scattered measurement points.

Satellite data provides adequate temporal resolution and fine spatial resolution with a wide coverage, allowing precipitation to be accurately estimated in some unmonitored regions, such as oceans, complex mountainous areas, and deserts (Sun *et al*., 2018).

Some DPDS sets are operationally available, including TRMM (Huffman *et al*., 2007), PERSIANN (Ashouri *et al*., 2015), CMORPH (Joyce, Janowiak, Arkin, & Xie, 2004), CFSR (Saha *et al*., 2014) and CHIRPS (Funk *et al*., 2015). In addition, products have been designed that combine satellite and field measurements to improve the precision of measurements of climatic variables; it is assumed that this approach maximizes the relative benefits of each type of data. Table 1 presents some Satellite-Derived Precipitation Data and their main characteristics.

Table 1. Characteristics of some Satellite-Derived Precipitation Data (DPDS).

DPDS	Resolution	Frequency	Coverage	Period
TRMM	0.25°	3 h/daily	35° S - 35° N	1998-2014
PERSIANN-CDR	0.25°	Daily	60° S - 60° N	1983-current
CMORPH	0.25°	30 min/3 h/daily	60° S - 60° N	2002-current
CHIRPS	0.05°/0.25°	Daily	50° S - 50° N	1981-current

The most frequent use of these technologies is usually monthly or weekly (Hurtado-Montoya & Mesa-Sánchez, 2014). Applications linked to daily rainfall are less frequent (Gebremichael & Hossain, 2010), mainly associated with the uncertainty of these estimates. In Argentina, several works have been carried out in this sense, especially with the TRMM product (Brito-Hoyos, 2015; Sepulcri, Di-Bella, & Moschini, 2009; Brizuela, Nosetto, Aguirre, & Bressán, 2015; Su, Hong, & Lettenmaier, 2008) with applications linked to hydrology, climate modeling and prediction. Tools have also been explored that facilitate the management of spatially distributed dynamic information, in a GIS environment (Bortagaray, 2018) or independently (Gavilán *et al*., 2019).

The applications of these products linked to the analysis of extreme precipitation events are less frequent, and the existing ones are mainly linked to the study of hurricanes and exceptional events (Miao, Ashouri, Hsu, Sorooshian, & Duan, 2015; AghaKouchak, Behrangi, Sorooshian, Hsu, & Amitai, 2011). Since the products already described have, in many cases, several decades of records available, they can be evaluated in terms of their ability to analyze extreme series; even in Argentina, these series are even longer than many of the traditional rainfall records (see, for example, Weber, González-Castillo, & Peña-Pollastri, 2017).

Objectives

As a general objective of this work, it is established to evaluate the usefulness of the CHIRPS Satellite Derived Precipitation Dataset (DPDS) in the generation of design daily precipitation fields in Argentina.

Specific objectives include:

- To develop tools that allow the automatic acquisition and analysis of precipitation data derived from satellites, in general, and from the CHIRPS product in particular.
- To analyze the degree of spatial and temporal correlation of these data with existing rainfall information in the country.
- To characterize statically the annual maximum daily precipitation (pdMa) series obtained from satellite-derived precipitation data.
- To generate daily pluviometric maps of the country from the satellite product considered, which adequately describe the spatial variability of

precipitation considering orographic and climatic effects in the vast Argentine territory.

Materials and methods

Rainfall information

For the development of this work, the daily pluviometric information provided by the National Meteorological Service (SMN) was used in 64 pluviometric stations whose geographical distribution can be seen in Figure 2. For each station, the month of minimum average monthly precipitation was determined, defining thus the beginning of the hydrological year in each one of them. This information was added as an additional attribute to a vector layer in a geographic model developed in the QGIS geographic information system.

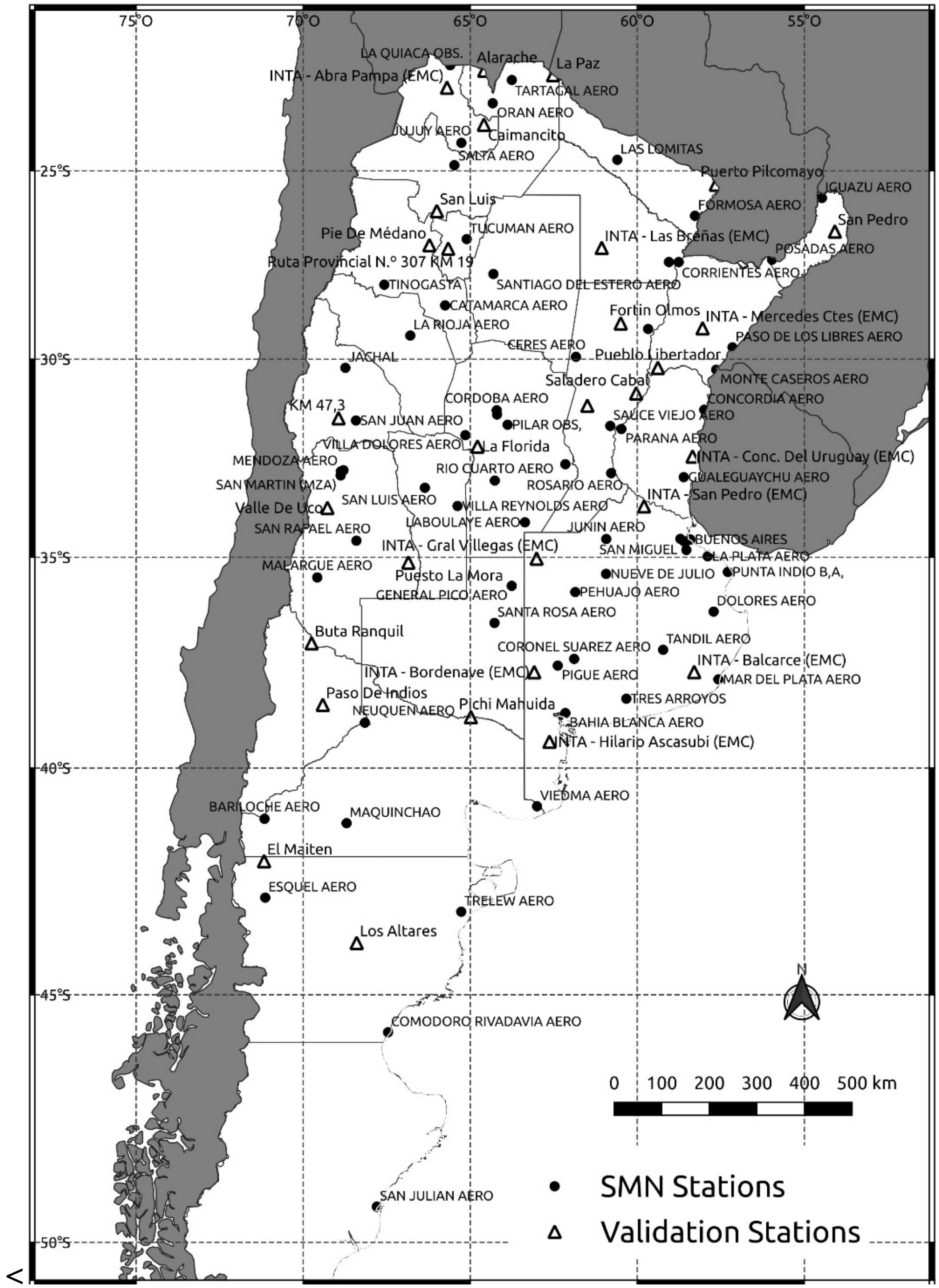

Figure 2. Rainfall stations of National Meteorological Service (•) and for validation (△) used in this work.

Additionally, a set of 30 pluviometric stations was considered for the validation of the results. These data are available to the public through the National Water Information System (previously called BDHi - Integrated Hydrological Data Base-) managed by the Secretariat of Infrastructure and Water Policy, dependent on the Ministry of Public Works. Nine of these stations belong to the network of meteorological stations of INTA (National Institute of Agricultural Technology) and the rest to the National Hydrological Network or provincial networks. These stations were selected in order to validate the response of the model in the geographic areas not covered by the SMN stations (Figure 2), with temporal coverage equal to or greater than that of the synthetic data used.

Satellite-derived precipitation data

Due to its spatial resolution, frequency, and temporal coverage, CHIRPS product (Funk *et al*., 2015) was chosen for this work.

CHIRPS (Climate Hazards Group InfraRed Precipitation with Stations) was born from the collaboration between the US Geological Survey (USGS) and the Earth Resources Observation and Science (EROS). CHIRPS is a quasi-global precipitation dataset of more than 30 years of continuous temporal coverage. CHIRPS incorporates 0.05° resolution satellite imagery (approximately 5.4 km) with data from in situ stations (reanalysis) to create gridded (raster) rainfall time series. The product used has a time resolution of 1 day, with continuous availability since 1/1/1981. The data is provided by the Climate Hazards Center, University of California, Santa Barbara (USA).

The CHIRPS precipitation estimate Is not tied only to weather stations, but instead combines weather stations with satellite-based precipitation estimates from NASA (National Aeronautics and Space Administration) and NOAA (National Oceanic and Atmospheric Administration). With this merger of resources, the bias suffered by rain gauge estimates in rural areas (due to lack of stations) and satellite data estimates in complex territories is avoided, obtaining an improved mixed product. CHIRPS offers freely available global precipitation information (between latitudes 50°S and 50°N). The data can be downloaded in global tiles in daily, bimonthly, quarterly temporal resolutions and in georeferenced BIL, TIF or NetCDF formats (Funk *et al*., 2015).

CHIRPS was developed to support the US Agency for Famine Early Warning Systems Network (FEWS NET). Taking advantages of approaches used in successful Thermal Infrared (TIR) precipitation products, such as the National Oceanic and Atmospheric Administration (NOAA) Precipitation Estimation (RFE2) and Africa RAINAT Climatology or TAMSAT African Precipitation Time Series and Climatology from the University of Reading (TARCAT). CHIRPS uses the Tropical Rainfall Measurement Mission Multi-Satellite Precipitation Analysis Version 7 (TMPA 3B42 v7) to calibrate global cold cloud duration (CCD) precipitation estimates (Funk *et al*., 2015).

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Digitization of Devoto's method

For comparative purposes, it was necessary to implement a digital version of the Devoto method (Devoto, 2002) described above, since this procedure is manual in its original version. For this, the four maps published by the author were georeferenced (average of intense rains of 1 and 12 hours, and their corresponding coefficients of variation) and their isolines were digitized. Then, by linear interpolation, and using the QGIS Geographic Information System, continuous raster fields were constructed for these magnitudes. Subsequently, using Map Algebra operations and for each return period considered (2, 5, 10, 20, 25, 50 and 100 years), rainfall X_1 and X_2 and the corresponding intensities i_1 and i_2 were determined for durations of 1 and 12 hours, applying equation (2). Assuming b = 0.80, the parameters a and c of equation (1) were determined for each return period, and from these parameters the precipitation of 24 hours was obtained; finally, these values were divided by the coefficient of the ratio of durations X24h/X1 day = 1.08 suggested by Caamaño-Nelli and Dasso (2003) as the mean value for the entire country.

In this way, seven continuous raster fields were obtained (one per return period) for the estimates of the design daily rainfall, based on the method currently available for the entire national territory.

Methodology

The methodology developed consisted of the steps indicated below and outlined in the flow chart of Figure 3. The tools and methods used to carry out the indicated steps are described below.

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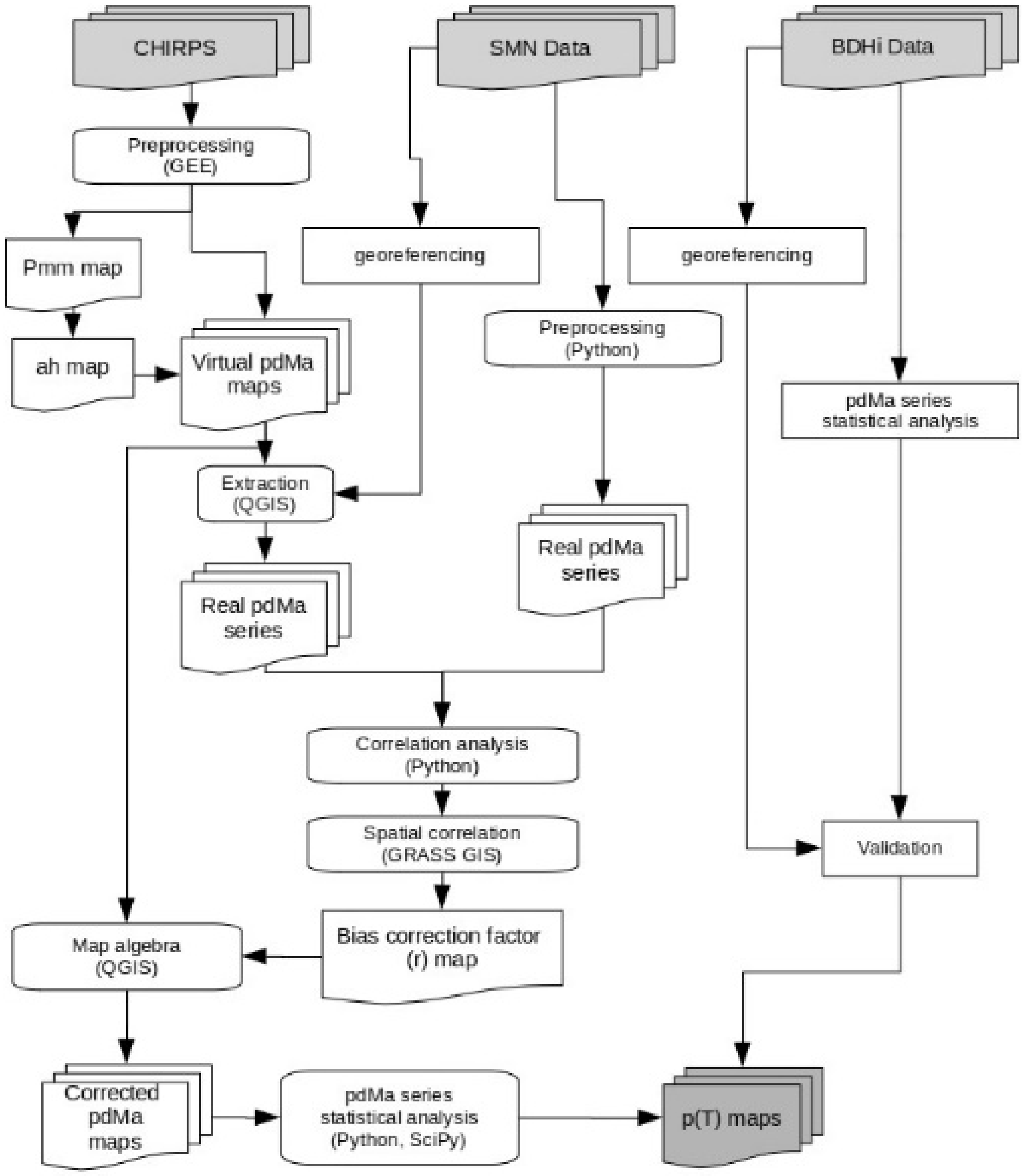

Figure 3. Flowchart of the methodology applied in this work.

DPDS pre-processing

This stage includes downloading and spatial and temporal clipping of the DPDS. From these, the maps of annual maximum daily precipitation (pdMa) and average monthly precipitation (pmm) are obtained. From the latter, the map of the hydrological year for the area of interest (identified by the start month) is determined.

Due to the natural massiveness of the information to be processed (Big Data), it was necessary to appeal to a tool that allows the automated management of large spatial data sources. This process was carried out through a set of ad-hoc codes developed in the Code Editor API of the Google Earth Engine -GEE- platform (Gorelick *et al*., 2017).

The processes were reduced to a spatial coverage between 18° and 50° South latitude, and 48° and 77° West longitude, allowing coverage of 97 % of the continental national territory, leaving the Tierra del Fuego province and the southern sector of the Santa Cruz province.

The temporary extension considered covered the period 1981 - 2017, in order to harmonize the joint development with the other activities, data sources and project objectives. This ensured a total of 36 hydrological years considered. In this way, considering the temporal and spatial extension of the data, a total of 132,296 series of synthetic precipitation in the country (one per pixel) of 13,514 days of extension were processed, that is, a total of 1,787,848,144 ($\sim 1.8 \cdot 10^{9}$) virtual pluviometric data.

Generation of the map of the hydrological year. The hydrological year is a 12-month period during which the various hydrological variables over a given hydrographic basin are considered and analyzed. The hydrological year does not necessarily coincide with the natural year, that is, the period that conventionally passes between January 1 and December 31 of the same year. This responds to the natural spatial variability of the climate (Linsley & Franzini, 1972).

One way to identify the hydrologic year is to find the successive 12-month period that provide most consistently, year after year, the greatest correlation between precipitation and surface flow and also shows negligible changes in storage (i.e., the groundwater and snow).

The beginning of the hydrological year can vary from one region to another, even within the same country. The temporal analysis of the hydrological variables, starting from the hydrological year, allows us to preserve the statistical hypothesis of independence, particularly in the analysis of series of hydrological extremes. In the absence of other variables, it is usually considered, for the definition of the beginning of the hydrological year, the month with the lowest average monthly rainfall.

Information processing algorithms were developed at GEE for this purpose. The raster maps thus generated were exported in GeoTIFF format with a spatial resolution of 5 km, similar to that of the base information. The maps resulting from the processes described above were processed locally using the QGIS Geographic Information System (QGIS Development Team, 2020). In this environment work, the visualization maps of the results were developed, as well as the extraction of the punctual values of: average monthly precipitation, annual average and month of the beginning of the hydrological year in correspondence with the pluviometric stations of the National Meteorological Service described above.

Generation of pdMa maps. For each of the 36 hydrological years considered, a raster map was generated containing the annual maximum daily precipitation (pdMa) in each pixel, using a code developed in GEE, based on the definition of the beginning of the hydrological year given by the map presented above, and using the information from CHIRPS (virtual pdMa). These pdMa maps were downloaded locally (as GeoTIFF files) and post-processed using QGIS software.

Preprocessing of pluviometric data from the National Meteorological Service (SMN)

The data was classified by season and both pdMa series (real series) and average monthly rainfall were extracted. Additionally, the 64 stations considered were adequately georeferenced.

Correlation analysis

In correspondence with each of the 64 SMN stations considered, the associated virtual series of annual maximum daily precipitation (pdMa) was extracted (using the QGIS software). In this way, two series of 36 values associated with each of the 64 stations considered were obtained: one from the SMN data (real series) and another from the CHIRPS data (virtual series).

Given that in the statistical analysis of the extreme value series, the first step consists of assigning non-exceedance empirical probabilities based on the position that each value of the series occupies in an ordered list, or plotting position (Castillo, 2012). It is possible to compare the real and virtual series after prior ordering: the ordered series preserve the statistical properties of interest of the original series and, therefore, have the same utility for the purpose of estimating daily design rainfall. Under this premise, this bias correction model was established:

$$pdMa_r = r.pdMa_v \tag{3}$$

where $pdMa_r$ is the real annual maximum daily precipitation (obtained from SMN data), $pdMa_v$ is the virtual annual maximum daily precipitation (obtained from CHIRPS data), and r is the slope of the linear regression line forced through the origin (in order to avoid negative images for the positive subdomain), which can be interpreted as a correction coefficient for systematic errors or bias correction that allows estimating real values of pdMa from virtual values. This analysis was performed for each of the 64 stations considered, and its results added as a new attribute to the SMN stations layer in QGIS.

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PdMa maps correction

From the 64 georeferenced values of the bias correction coefficient *r*, a bilinear spline interpolation was performed (Brovelli, Cannata, & Longoni, 2004), implemented in the GRASS GIS v.surf.bspline command (Neteler & Mitasova, 2013), generating a field of Values of *r* for the sector of the national territory considered, with the same spatial resolution as the virtual pdMa maps described above. As we said, this factor *r* represents a bias correction factor with which to correct virtual precipitations.

The 36 annual daily maximum precipitation maps extracted from the CHIRPS data were corrected by multiplying them, pixel by pixel, by the bias correction factor map described above, obtaining a new set of 36 pdMa-corrected maps ($pdMa_C$).

Statistical analysis

For the statistical analysis of the corrected pdMa series, a code was implemented in the Python programming language, using the SciPy (Virtanen *et al*., 2020), NumPy (Harris *et al*., 2020) and GDAL (GDAL/OGR contributors, 2021) libraries. This code processed, for each of the 132,296 active pixels considered, the pdMa series and generated the following maps as a result:

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- distr.tiff (integer): optimal theoretical probability distribution, as integer code
- param1.tiff, param2.tiff, param3.tiff (float): optimal parameters of the distribution given in the previous map
- R2.tiff (float): fit determination coefficient
- T2.tiff, T5.tiff, T10.tiff, T20.tiff, T25.tiff, T50.tiff, T100.tiff (float): daily design precipitation, estimated from the optimal distribution given in distr.tiff, for return periods of 2, 5, 10, 20, 25, 50 and 100 years, respectively

Statistical analysis of each extreme value series was carried out through the following steps:

1. *Extraction and ordering of the series and assignment of empirical probabilities.*

   For each pixel, the series of 36 $pdMa_c$ values was extracted, ordered and assigned a non-exceedance probability according to its plotting position:

$$F(x_m) = P(X < x_m) = \frac{m-b}{n+1-2b} \tag{4}$$

where

n is the number of records (36)

m is the position occupied by the value x_m in the ordered list

b is a parameter that allows selecting the formula to use.

In this case, the Gringorten formula was applied, with *b* = 0.44 (Castillo, 2012).

2. *Fitting of a theoretical probability distribution.*

From the 36 ordered pairs (x_i, $F(x_i)$), and using the statistical functions of SciPy, the Lognormal, Gumbel, GEV and Gamma probability distribution functions were fitted, whose probability density functions are given, respectively , by (Naghettini & Andrade-Pinto, 2007):

$$f(x) = \frac{1}{x\sigma_Y\sqrt{2\pi}} e^{-(1/2)[(lnx-\mu_Y)/\sigma_Y]^2}, x > 0 \quad (5)$$

$$f(x) = e^{-z-e^{-z}}, z = \frac{x-\mu_0}{\beta} \quad (6)$$

$$f(x) = \frac{1}{\sigma} t(x)^{\xi+1} e^{-t(x)}, \xi \neq 0 \Rightarrow t(x) = \left[1 + \xi\left(\frac{x-\mu}{\sigma}\right)\right]^{\frac{-1}{\xi}}, \xi = 0 \Rightarrow t(x) = e^{-(x-\mu)/\sigma} \quad (7)$$

$$f(x) = \frac{\lambda}{\Gamma(\alpha)} (\lambda x)^{\alpha-1} e^{-\lambda x}, x > 0 \quad (8)$$

In these formulae:

Y = ln(x) =is the natural logarithm of the random variable (pdMa)

μ, μ(Y) = are random variable mean and logarithms of the random variable mean, respectively

σ, σ(Y) = are random variable standard deviation and logarithms of the random variable standard deviation, respectively

μ0 = is the mode of the random variable

$\beta = \sigma \cdot \sqrt{6}/\pi$ = is the scale factor in the Gumbel distribution

ξ = Is the shape parameter of the GEV distribution

α = is the shape parameter of the Gamma distribution

$\lambda = \alpha \cdot \mu$ = is the inverse of the scale parameter of the Gamma distribution

Γ = is the gamma function, extension of the factorial concept to real numbers

Based on the empirically determined return periods (and therefore, on the non-exceedance probabilities), and on the optimal distribution found (and its parameters), the associated precipitations were determined pixel by pixel. Based on this, the determination coefficient R^2 was calculated according to Equation (9) (Canavos, 2003):

$$R^2 = 1 - \frac{\sigma_r^2}{\sigma^2} \tag{9}$$

where

σ^2_r is the residual variance

σ^2 the total variance, of the pdMa considered.

As a result of this process, we obtained: a georeferenced raster map with the optimal pixel-by-pixel distribution; another map with the coefficient of determination R^2 of the fit; three maps with the parameters of this distribution and seven maps of design rainfall (one for each return period considered).

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Results validation

For the validation of the results obtained in the previous process, series of daily precipitations of 30 selected stations were used (Figure 2) that were downloaded from the portal of the National Water Information System. At the same time, the stations were correctly georeferenced. These series were inspected to detect and eventually correct errors or inconsistencies. Then, and in a similar way to what was indicated above, the series of maximum annual daily rainfall was extracted, according to the local definition of the hydrological year.

Both for the adjustment of the theoretical distributions described above, and for obtaining the daily design rainfall associated with the different return periods considered (as well as its confidence interval, for a 90 % level), CumFreq statistical analysis software (Oosterbaan, 2019) was used.

For each of the 30 validation stations considered, CumFreq was applied, obtaining the optimal distribution (among the four considered: lognormal, Gumbel, GEV and Gamma), and for this, the design rainfall corresponding to return periods of 2, 5 , 10, 20, 25, 50 and 100 years; as well as the lower and upper limits of the 90 % confidence interval associated with the estimate.

Finally, the design precipitations obtained from the virtual series were compared with those obtained from the real series. A match was assumed to exist if the first falls within its confidence interval.

Results

Hydrologic year map

Figure 4 (left) shows a scatter plot of the monthly mean precipitation for the stations considered, comparing the values extracted from the real series (SMN stations) with the virtual series (generated from the CHIRPS DPDS). In the same figure, the identity line and the linear regression line of the mentioned data are superimposed. As can be seen, there is a very good correspondence between the real and virtual mean monthly precipitation ($R^2 = 0.97$). It should be noted that this figure represents a set of 768 ordered pairs, corresponding to 12 values for each of the 64 stations analyzed.

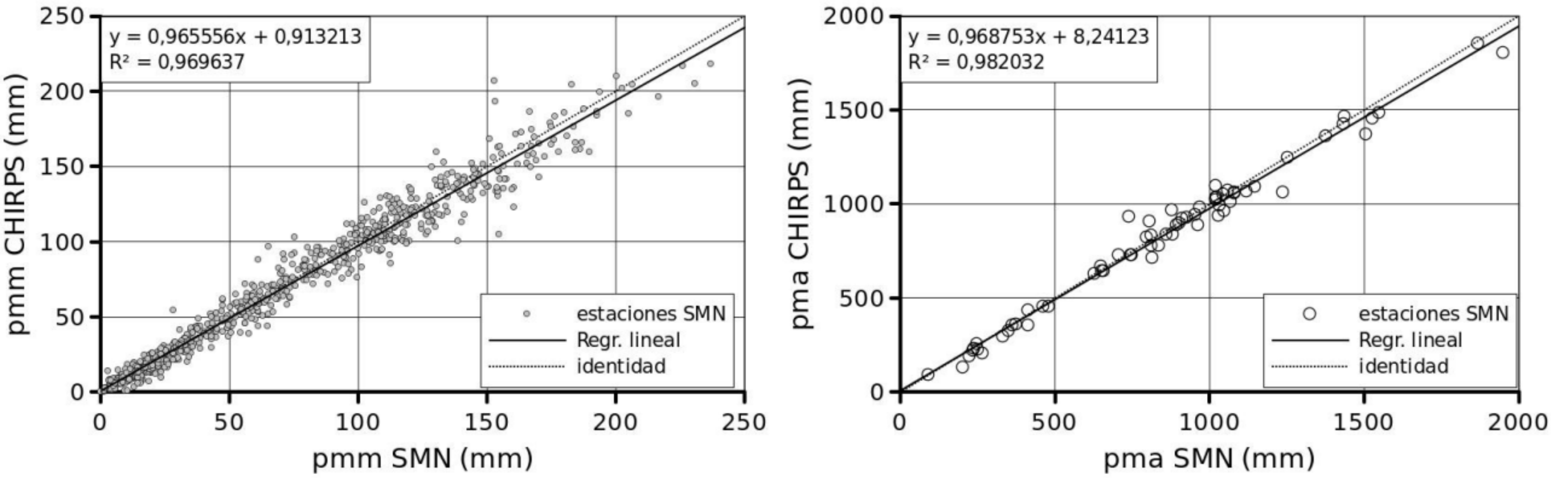

Figure 4. Average monthly (left) and annual (right) real (SMN) and virtual (CHIRPS) precipitation. Identity line (dashes) and linear regression (continuous) are overlaid, along with their equation and its determination coefficient R^2.

A similar analysis is presented on the right of the same figure, in this case for mean annual precipitation. The scatterplot now shows 64 ordered pairs (one per station considered). The regression line obtained (close to the identity) together with the coefficient of determination, show the good correspondence between the series.

In general, a good correspondence can be observed between the start month of the hydrological year obtained, for the stations considered, for the real (SMN) and virtual (CHIRPS) precipitation series, since, with the exception of four stations (Malargüe, Neuquén, Viedma and Puerto San Julián) the start month of the hydrological year between both series differ by no more than two months. Specifically, of the 64 stations, 36 (56 %) coincide in the start month of the hydrological year, 17 (27 %)

differ by one month, 7 (11 %) differ by two months and four (6 %) by more of two months.

Figure 5 (left) shows the spatial distribution of the hydrological year, classified by its start month, produced from the CHIRPS data. A great spatial variability of the results obtained can be observed; however, large regions with spatially homogeneous results can also be seen, which shows a certain consistency in the product obtained. The wide variability in the results in the Patagonian Steppe responds, once again, to the low degree of seasonality in the virtual precipitation series.

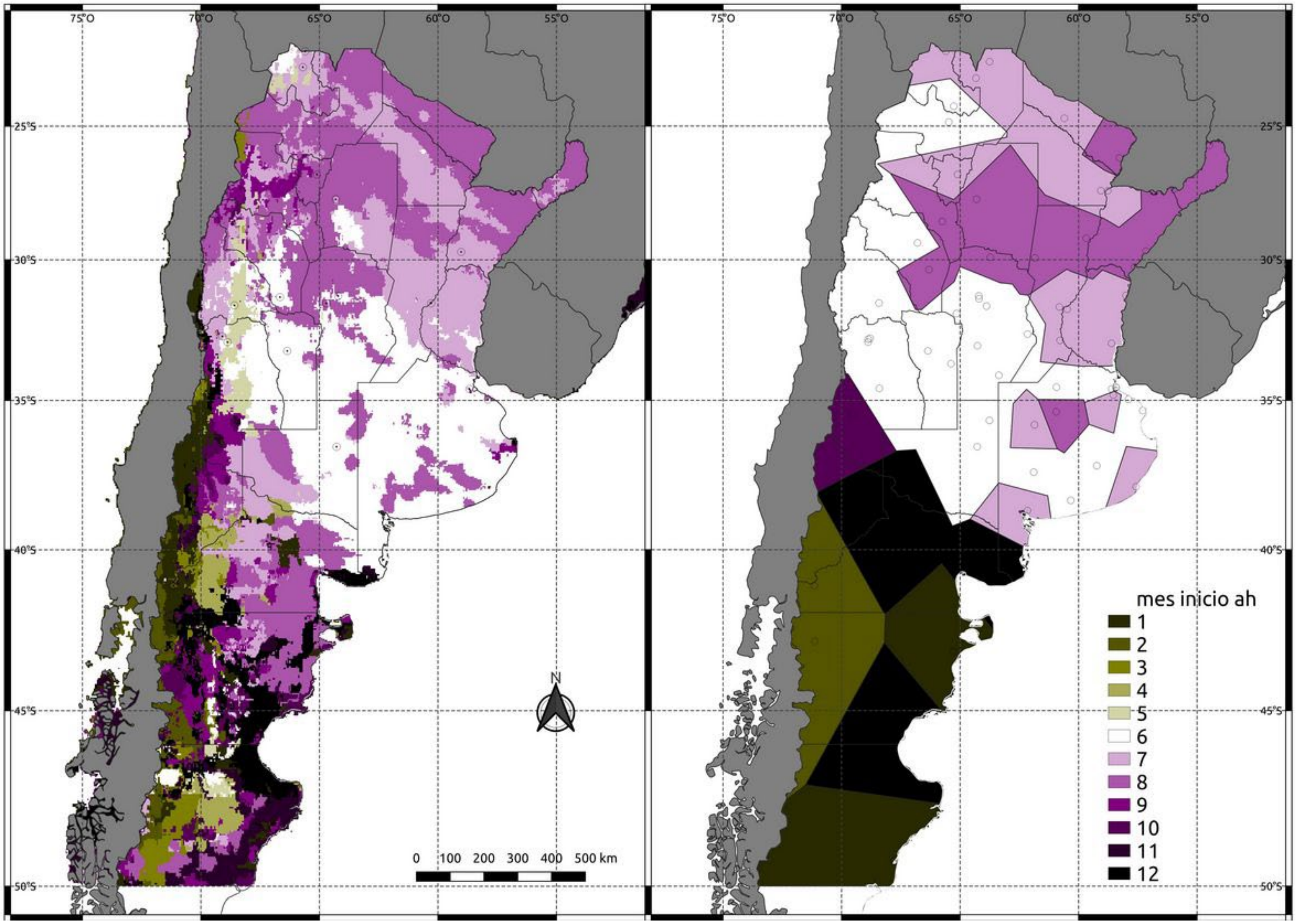

Figure 5. Map of the hydrological year of Argentina (expressed through its start month) obtained from CHIRPS data (left) and rainfall information from the SMN, by means of Voronoi tessellation and subsequent fusion of entities according to the results (right). The dots represent the SMN stations considered.

For comparison purposes, in Figure 5 (right) the same map is presented but obtained from the analysis of the monthly average rainfall point series of the SMN, in the 64 stations considered, and therefore spatially distributed based on a Voronoi Tessellation (Thiessen polygons), and merged based on the results obtained. This process was carried out by using the geographic information system QGIS. As can be seen, there is a general trend shared between what is presented in Figure 9: The Arid Diagonal marks a limit between two regions, the one located to the Northeast, with a hydrological year that begins in the months of June, July or August (winter) and the one located to the Southwest, coinciding with Patagonia, including the southern region of the province of Mendoza, with a hydrological year that begins in the summer months; however, the map obtained from the DPDS presents a spatial richness not detectable in its counterpart obtained from the SMN stations. In particular, a certain effect attributable to the orography is observed in the Cordillera and Pedemonte of the Cuyo region and in areas of the Puna de Catamarca and Jujuy that cannot be reproduced from the SMN local data.

Annual daily maximum precipitation (pdMa) maps

From the processing described above, 36 pdMa maps were obtained corresponding to each hydrological year considered. Figure 6 shows, as an example, the geographic distribution of the virtual pdMa for two specific hydrological years.

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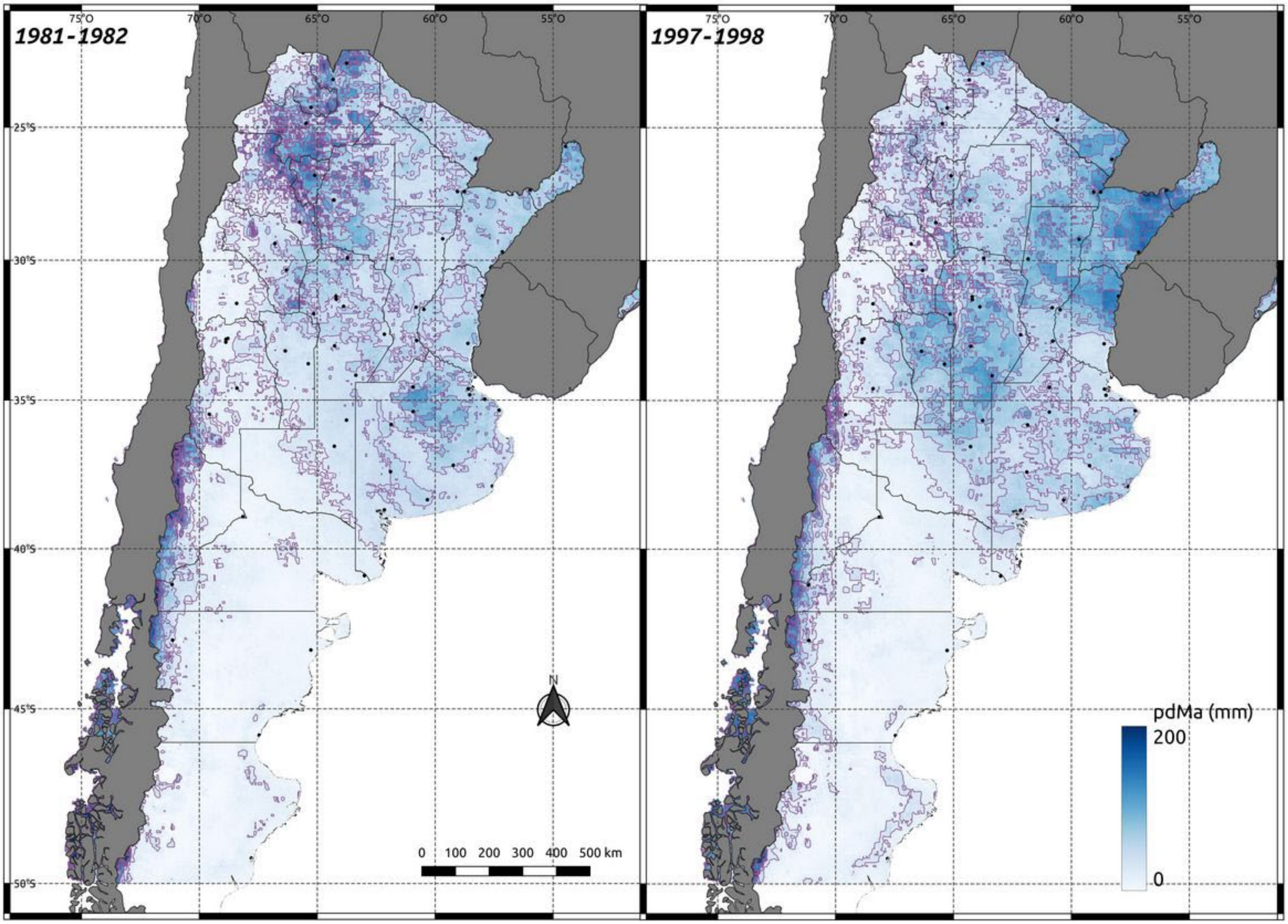

Figure 6. Virtual annual maximum daily precipitation (pdMa) maps for two hydrological years (1981-1982 on the left; 1997-1998 on the right) generated from CHIRPS data. Equidistance of isohyets: 25 mm.

Correlation analysis

A year-by-year (hydrologic) comparison of real and virtual pdMa's yields, for the set of 64 stations (2304 ordered pairs), the scatterplot shown in Figure 7 (left). A slight trend in the correlation can be observed; however, significant random variability is also observed, that is, CHIRPS does not reproduce the pdMa of a given year with sufficient precision, but rather with significant random errors. This can be observed in a more accentuated way when each series (station) is analyzed individually: as an example, Figure 8 (left) shows the analysis carried out for the Cordoba Observatory station.

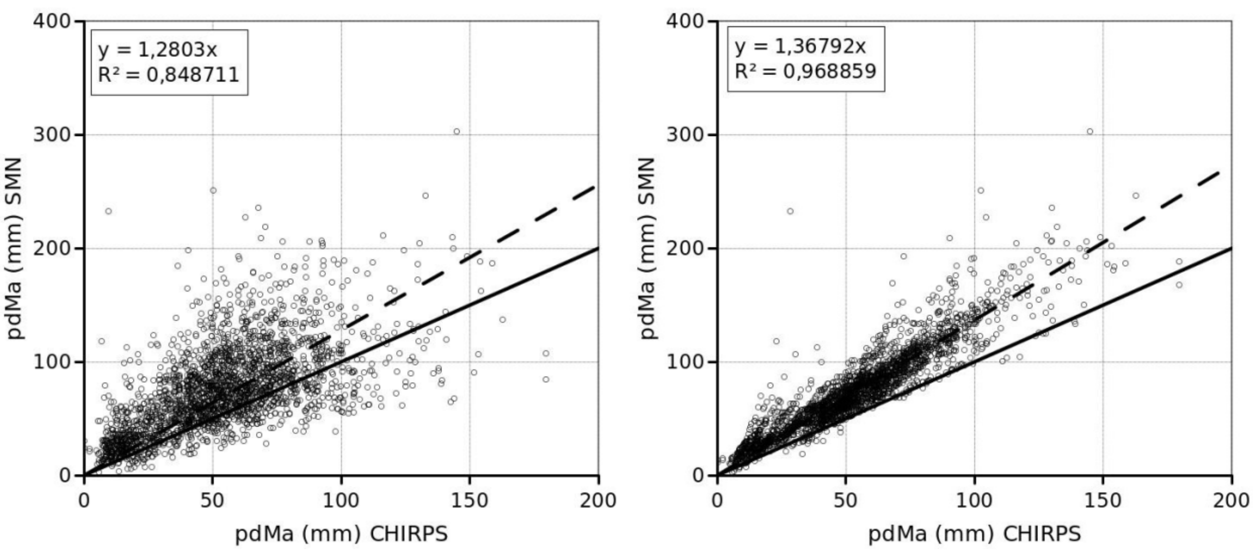

Figure 7. Real (SMN) *versus* virtual (CHIRPS) annual maximum daily precipitation (pdMa). On the left, the direct correspondence (year by year). On the right, that of the ordered series. The continuous line is the identity; the dashed line is the regression line through the origin.

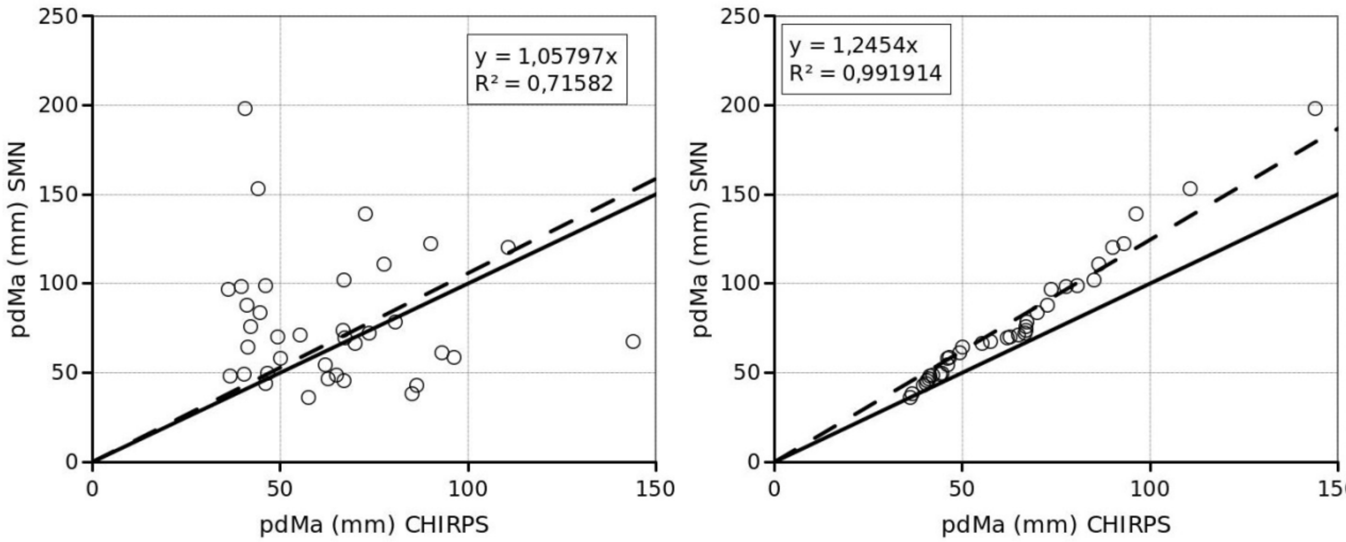

Figure 8. Real (SMN) *versus* virtual (CHIRPS) annual maximum daily precipitation (pdMa) for the Córdoba Observatory station. On the left, the direct correspondence (year by year). On the right, that of the ordered series. The continuous line is the identity; the dashed line is the regression line through the origin.

The comparisons presented on the right of Figure 7 (for all stations) and Figure 8 (at an example station) were made considering the ordered series. In the bias correction model given by Equation (3), a significant increase in the linear correlation can be observed and, therefore, the notable reduction in residuals.

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Bias correction map

According to Figure 7 (right) it can be concluded that, in general terms, CHIRPS underestimates pdMa; however, looking at individual values of the bias correction coefficient *r* shows underestimates and overestimates, depending on geographic location. Based on this, the bias correction factor was considered as a continuous spatial variable. To obtain the associated field, the bilinear spline interpolation described above was performed, obtaining the map in Figure 9.

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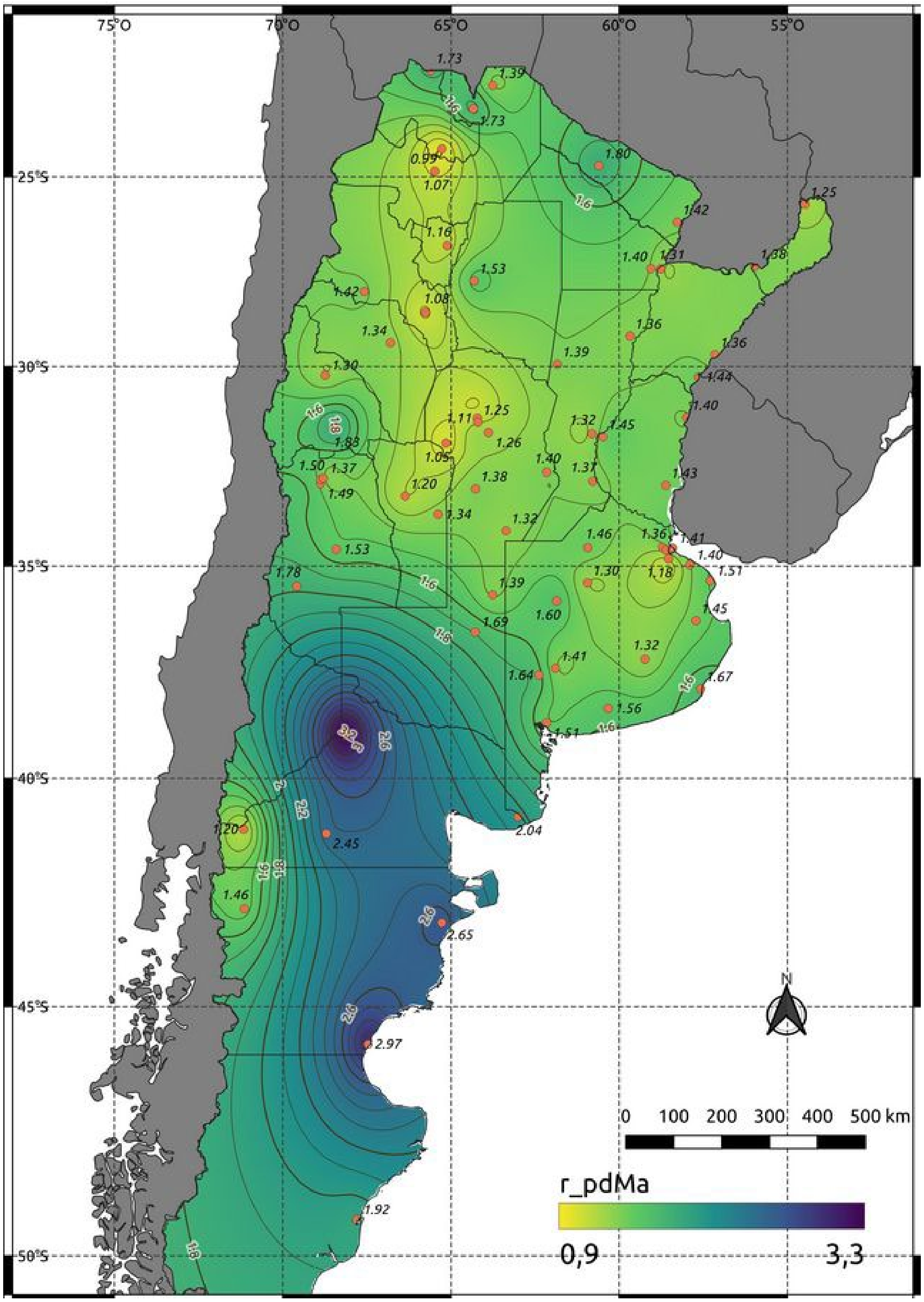

Figure 9. Spatial distribution of the parameter *r* of the linear regression $pdMa_r = r \cdot pdMa_v$. Ordered series.

Design rainfall maps

From the optimal distributions found (and their parameters), the rainfall depths corresponding to return periods of 2, 5, 10, 20, 25, 50 and 100 years, for each pixel, were estimated. With this, the corresponding design rainfall maps were built, which were visualized and post-processed in the QGIS geographic information system. Figure 10, Figure 11, Figure 12, Figure 13, Figure 14, Figure 15 and Figure 16 show the maps obtained.

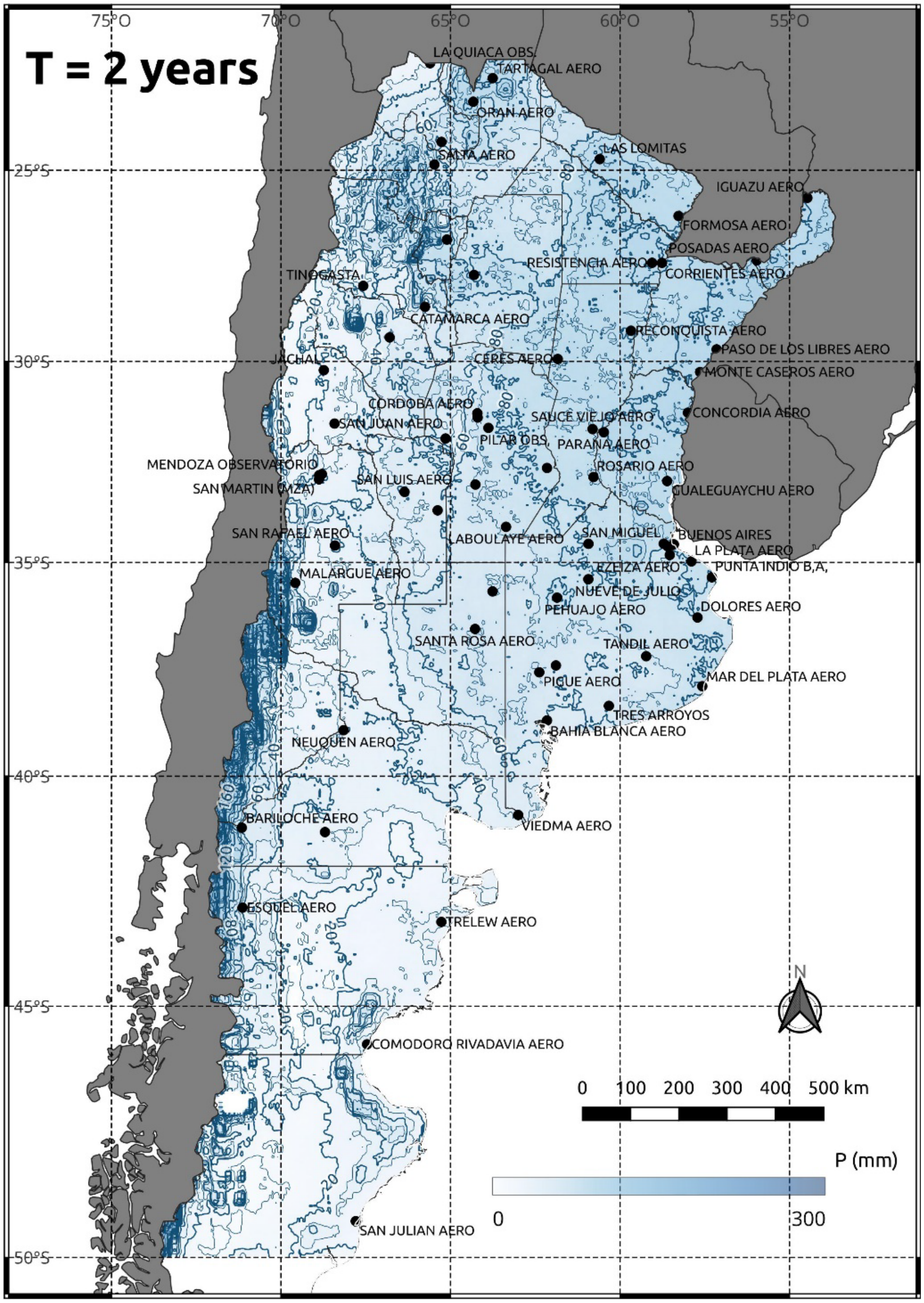

Figure 10. Estimated design rainfall for a 2-year return period. Equidistance: 10 mm.

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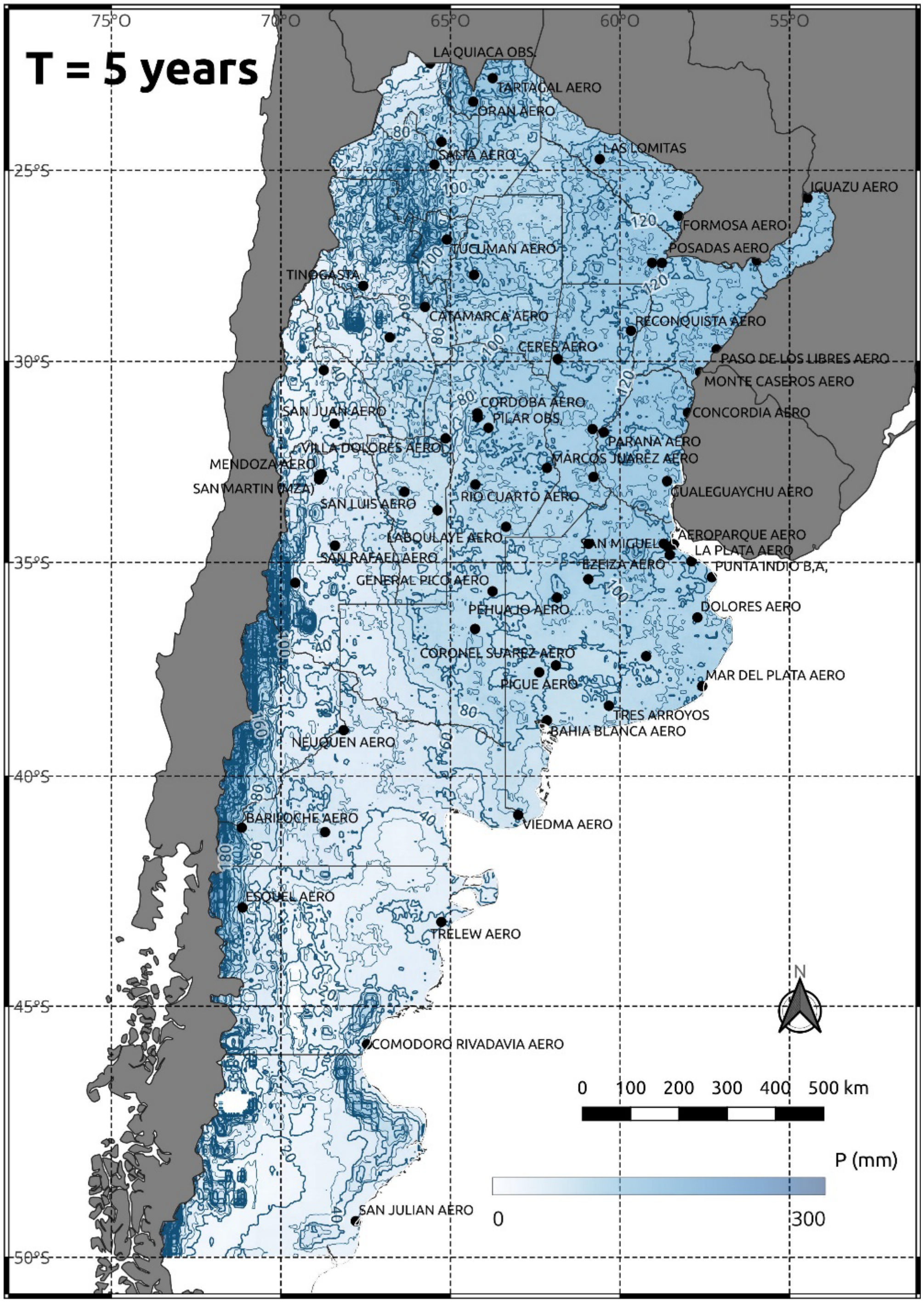

Figure 11. Estimated design rainfall for a 5-year return period. Equidistance: 10 mm.

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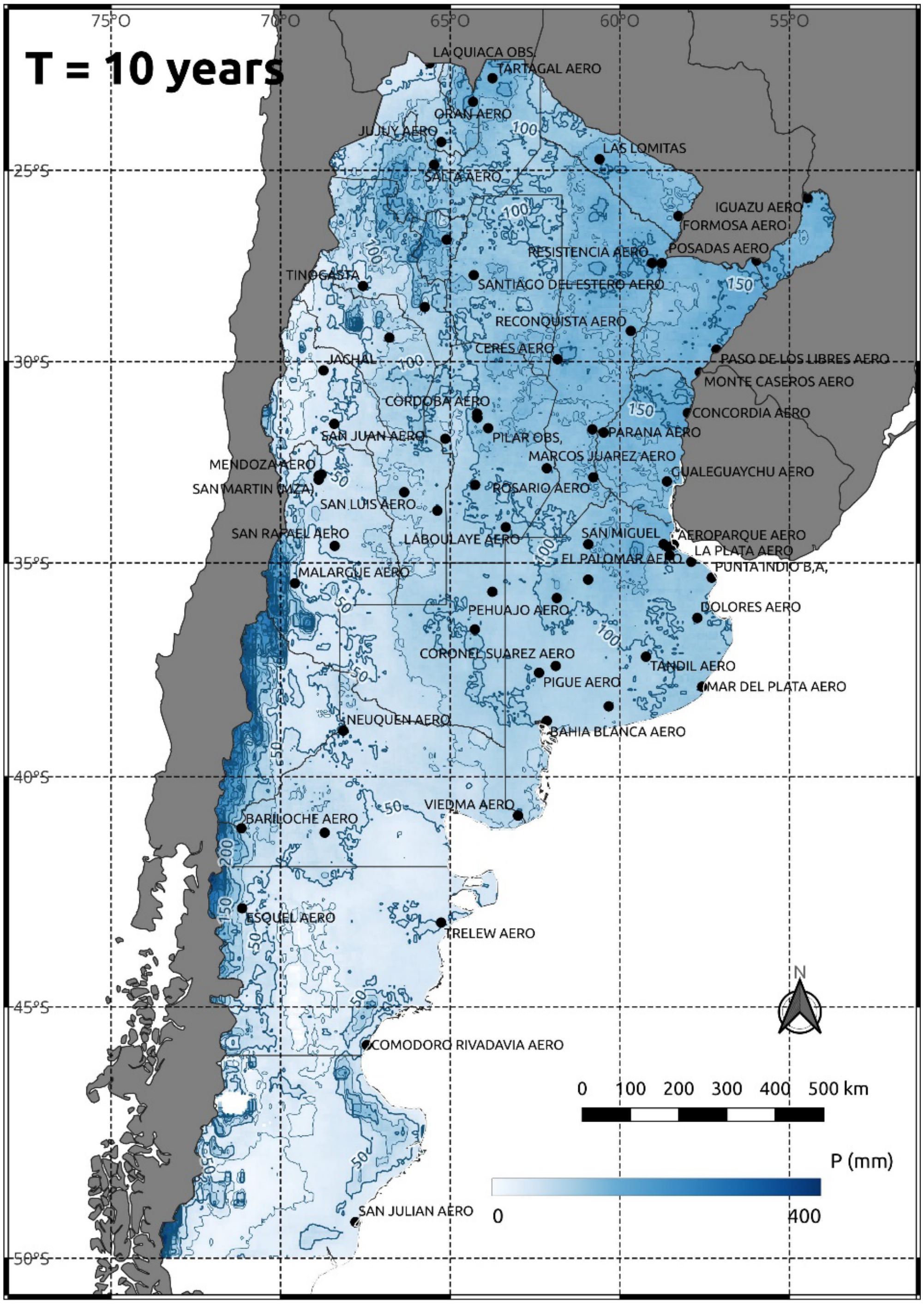

Figure 12. Estimated design rainfall for a 10-year return period.

Equidistance: 25 mm.

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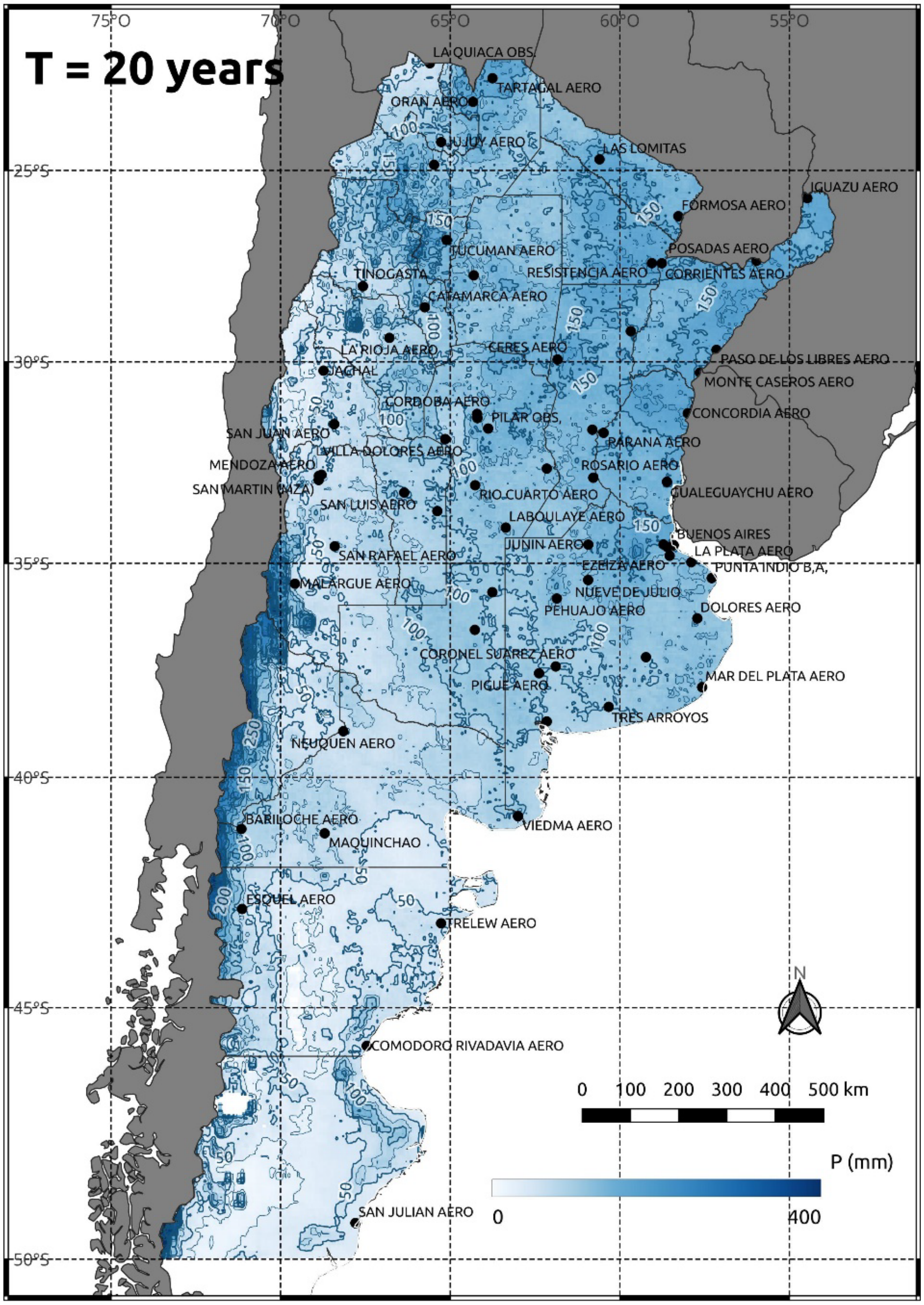

Figure 13. Estimated design rainfall for a 20-year return period. Equidistance: 25 mm.

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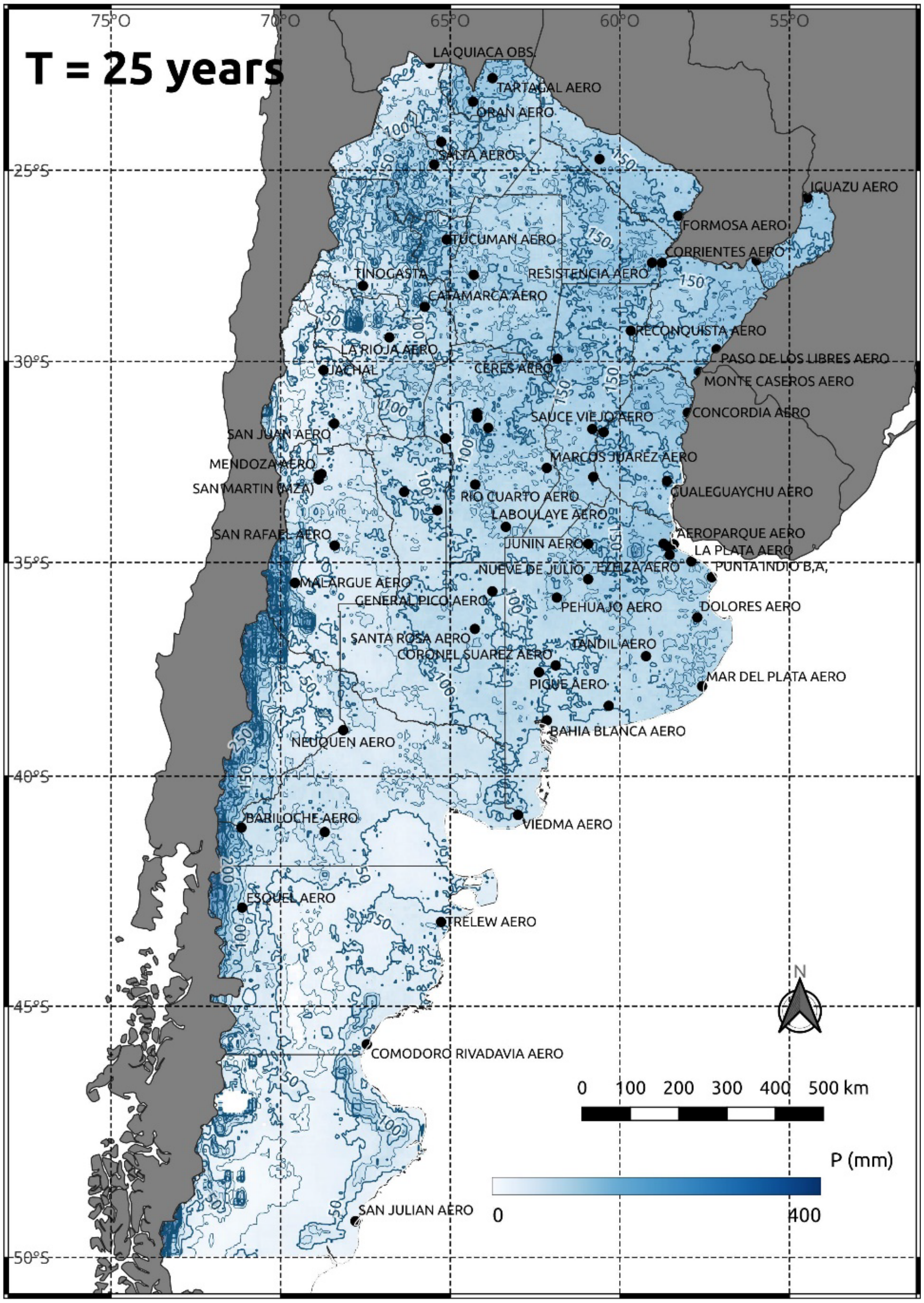

Figure 14. Estimated design rainfall for a 25-year return period. Equidistance: 25 mm.

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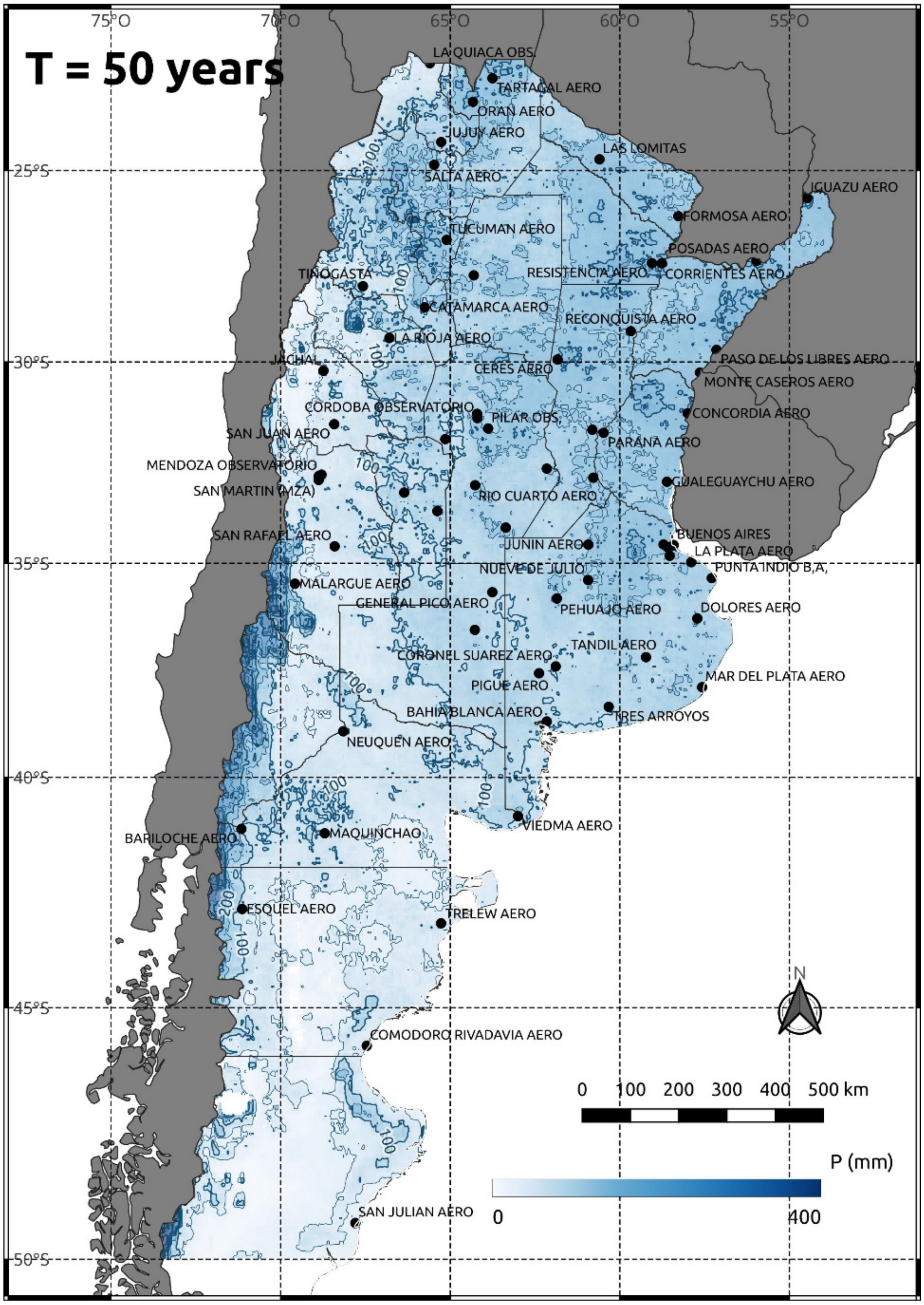

Figure 15. Estimated design rainfall for a 50-year return period. Equidistance: 50 mm.

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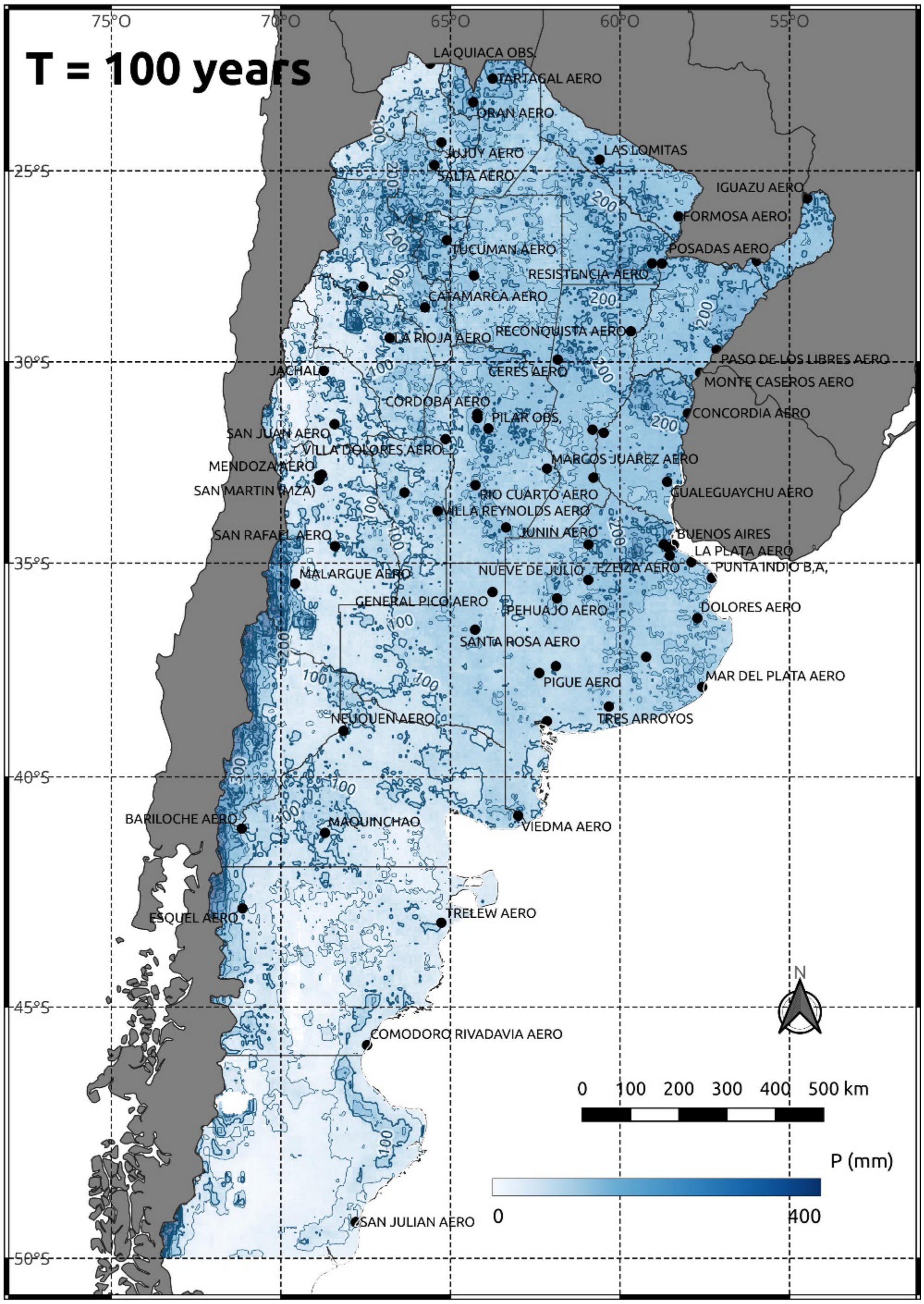

Figure 16. Estimated design rainfall for a 100-year return period. Equidistance: 50 mm.

Validation results

Design rainfall depths obtained at the 30 rain gauge stations set aside for validation were compared with those extracted from synthetic maps generated from virtual rainfall. Figure 17 shows, as an example, the real (pluviometric series) and virtual (CHIRPS) design rainfall depths, as a function of the return period; adding to the real design rainfall depth the confidence interval obtained for a confidence level of 90 %, for four of the 30 stations. Estimates of these design rains obtained by the Devoto's method are also added.

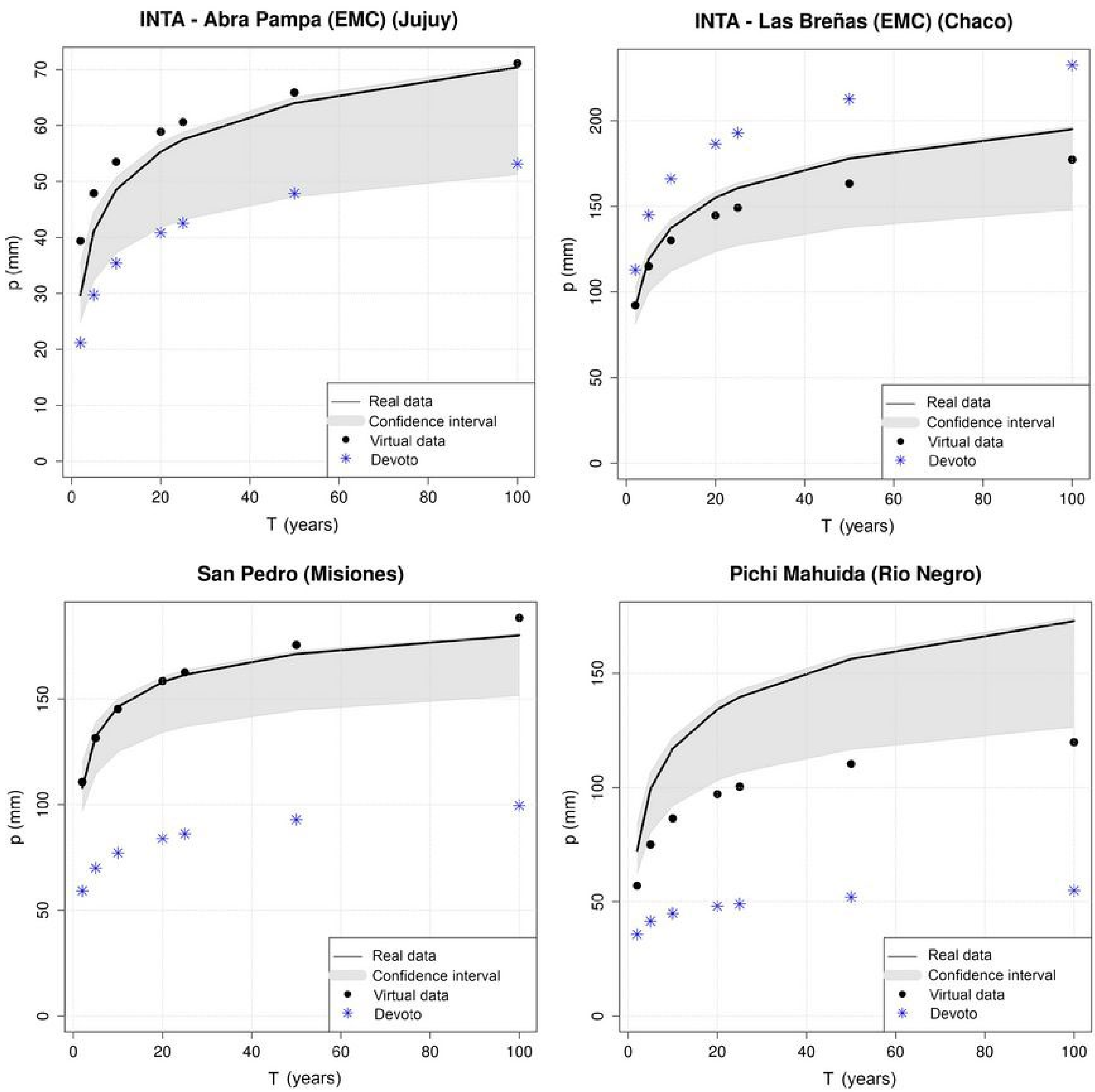

Figure 17. Design rainfall depth validation estimated from pluviometric data (real data), together with its 90 % confidence interval, and from satellite-derived rainfall data (virtual data). Abra Pampa (Jujuy), Las Breñas (Chaco), San Pedro (Misiones) and Pichi Mahuida (Río Negro) stations.

Figure 18 shows, as an example, some correlation graphs between the design rainfall depths obtained from real and virtual data, for the 30 validation stations, for the 10- and 25-year return periods, together with the error bars associated with 90 % confidence interval; the values estimated by the Devoto's method (also plotted on the horizontal axis) also overlap with the real values.

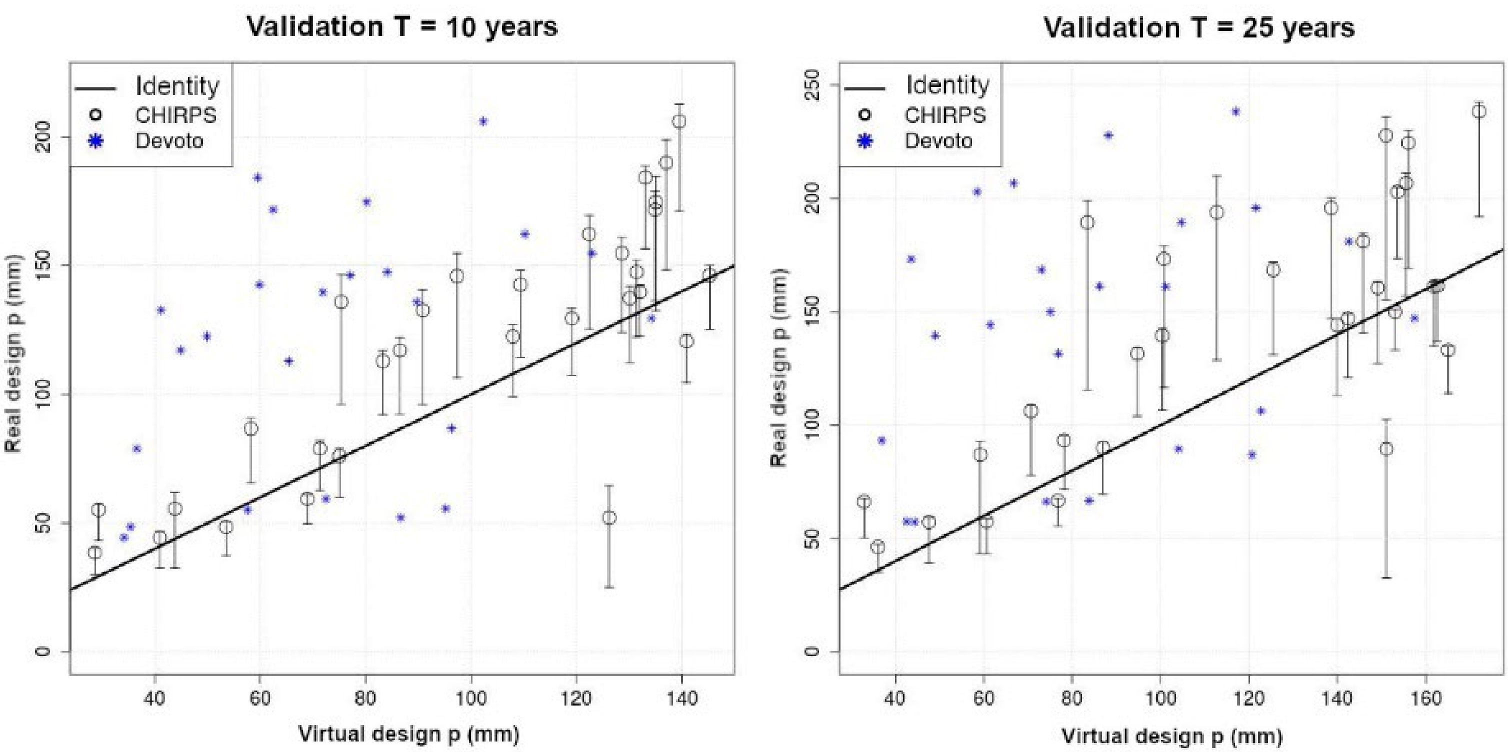

Figure 18. Virtual *versus* real design rainfall depths (with its confidence interval) in the 30 validation stations, for the 10 years (left) and 25 years (right) return periods. Results from the Devoto's method are included.

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Figure 19 (left) shows a correlation graph between design rainfall depths obtained from real and virtual data, at the 30 validation stations, for all considered return periods, along with error bars, associated with the 90 % confidence interval; on the right, the percentage relative error between both estimates is observed, both those obtained from the CHIRPS product and those obtained from the Devoto's method.

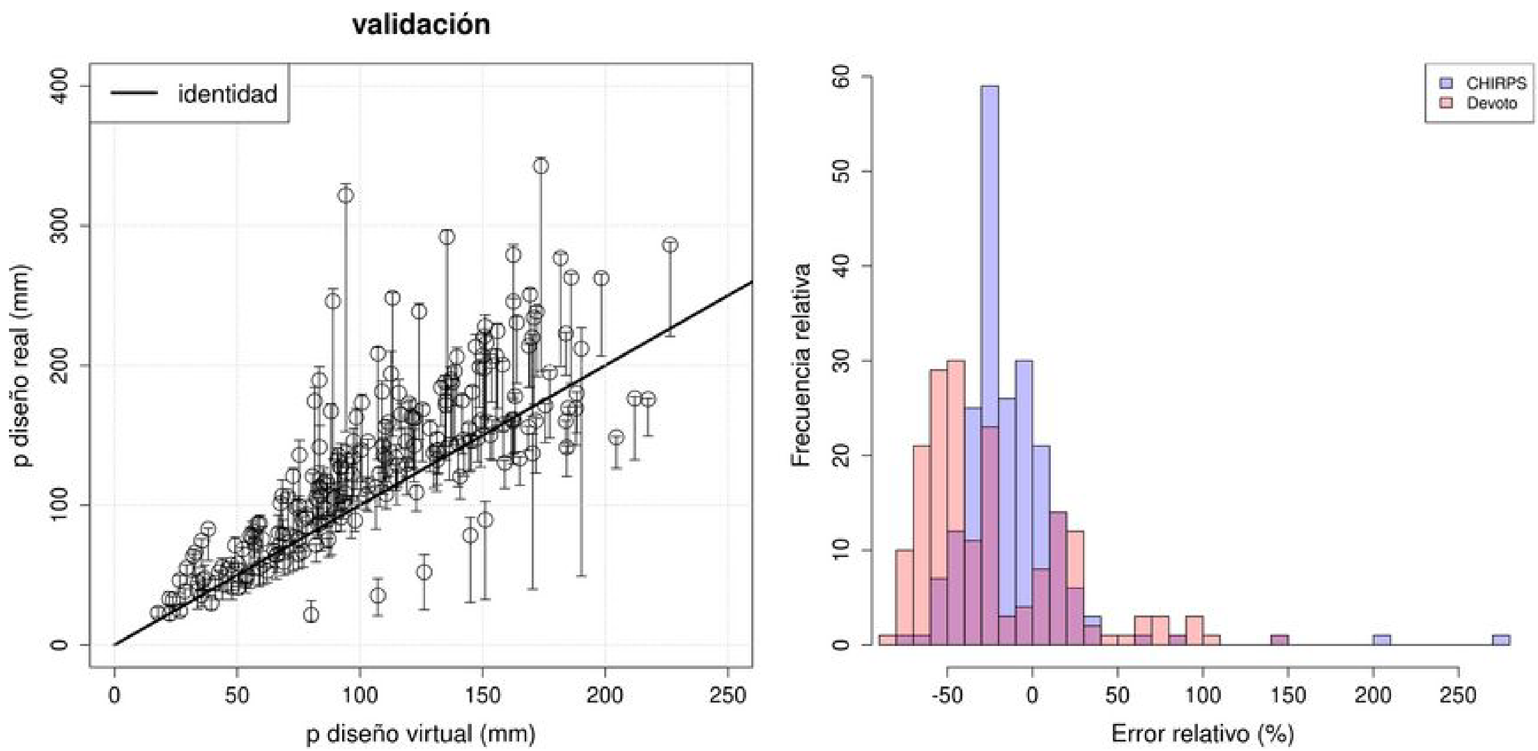

Figure 19. On the left: virtual *versus* real design rainfall (with its confidence interval) at the 30 validation stations. On the right: histogram of relative frequencies of the percentage relative errors between the virtual and real design rainfall depths.

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Discussion

Estimations of the design daily rainfall depths, based on the CHIRPS product, present relative errors smaller than those given by the Devoto's method, in correspondence with the 30 validation stations considered. This can be observed globally in the error histograms of Figure 19 (right), and in particular and as an example for two return periods in Figure 18. More specifically, of the 30 validation stations considered, the Devoto's method presents a lesser error in the description of the design rainfall depths as a function of the return period, in four seasons; in two of them it presents results similar to those obtained with CHIRPS; while in the remaining 24 stations, the function p(T) is better approximated from the satellite data (Figure 17).

The design rainfall depth maps, depending on the return period considered (Figure 10, Figure 11, Figure 12, Figure 13, Figure 14, Figure 15, Figure 16), show a great spatial variability, greater than that obtained by applying the Devoto's method. Figure 20 shows the spatial distribution of the relation R, for the return period of 25 years: defining *R* as the relation between the design rainfall depths obtained from CHIRPS and the corresponding ones given by the Devoto's method. It should be noted that only the northern sector of the country is presented, because the Devoto's method yields inconsistent design rainfall values for the central and western sector of Patagonia: this is probably due to the fact that for the construction of the maps of the method, this author did not have stations in that region, so it is assumed that the published isolines arise by extrapolation (Figure 1). It should be noted that the spatial distribution reported in Figure 20 is similar for other recurrences. In this Figure, *R* values less than 1 (cool tones) represent areas where the Devoto's method overestimates the satellite results, while *R* values greater than 1 (warm tones) correspond to areas where the satellite estimates exceed the given values by the Devoto's method and, therefore, the precipitation (and other results derived from hydrological modelling, such as flowrates) provided by this method could be underestimated.

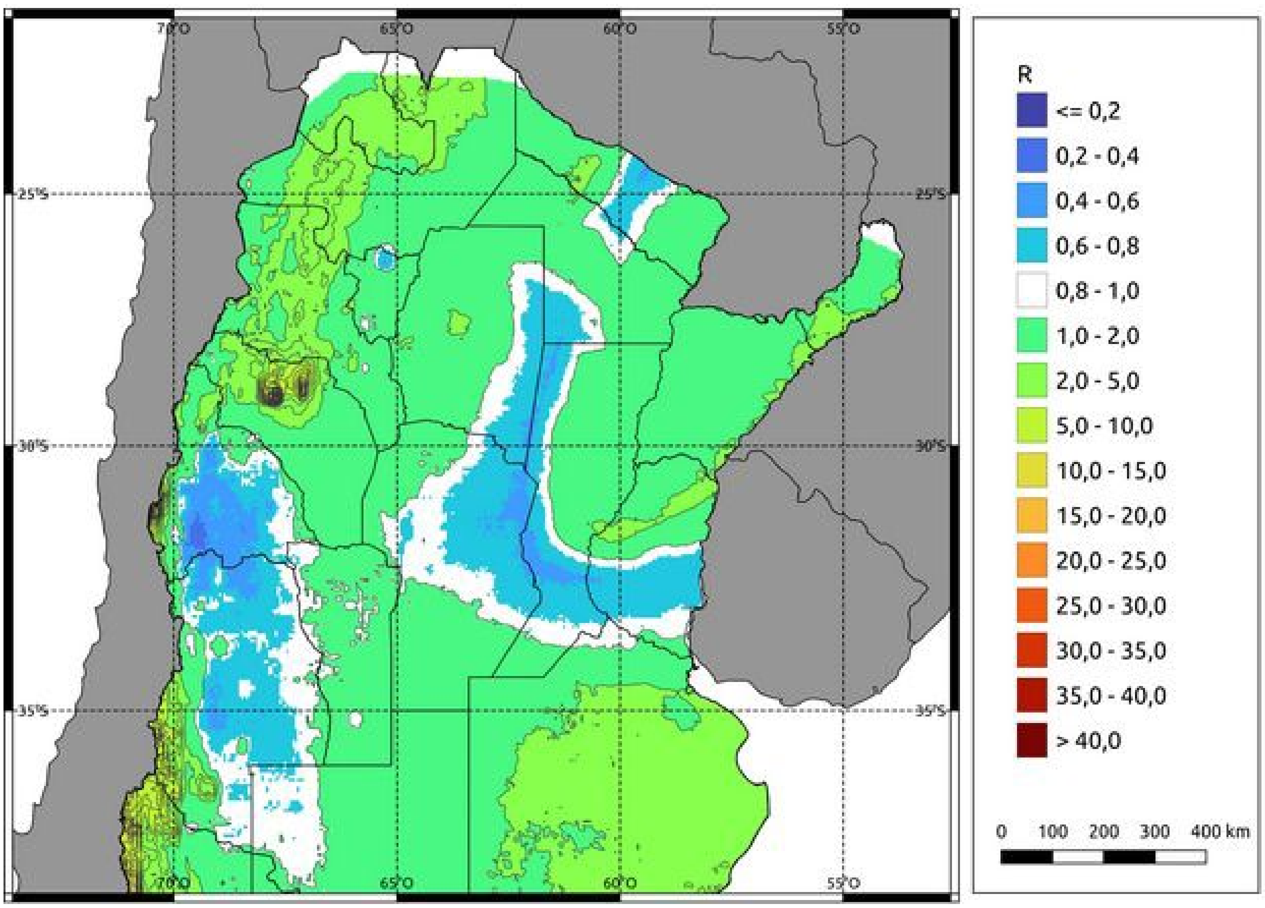

Figure 20. Spatial distribution of the relationship *R* between the daily design rainfall depths (T = 25 years) estimated based on the Satellite Derived Precipitation Data and according to the Devoto's method.

The spatial distribution of the daily design rainfall depths reported in Figure 10, Figure 11, Figure 12, Figure 13, Figure 14, Figure 15, Figure 16 presents a spatial pattern that accompanies the climatic variability of the country. In fact, for all the return periods considered, high-value cores are systematically observed over the Patagonian Andean region, which, given the rainfall pattern indicated in Figure 5 (winter wet season), are mostly snowy. Likewise, relatively high values are presented in the northern, central and coastal regions of the country, although of lesser magnitude than the aforementioned Patagonian mountain ranges. Both sectors are separated by a wide region with low design precipitation values, in correspondence with the Semi-arid Diagonal that climatically divides the territory. Although Devoto's method generally accompanies this spatial variability induced by orography and climate, it does not capture local conditions with the detail that CHIRPS estimates do. Figure 21 (left) shows, as an example, four transects that cross region with great climatic and orographic variability in the country. For each of these transects, the altimetric distribution (topographic profile) is shown together with the distribution, as an example, of the daily design rainfall depths estimated with CHIRPS and by the Devoto's method, for 25-year return period. It can be seen that the satellital estimations show a correspondence with the topography (in phase or counter phase, depending on the local climatic conditions) that the Devoto's method fails to identify in detail. These patterns are replicated for other transects and other return periods.

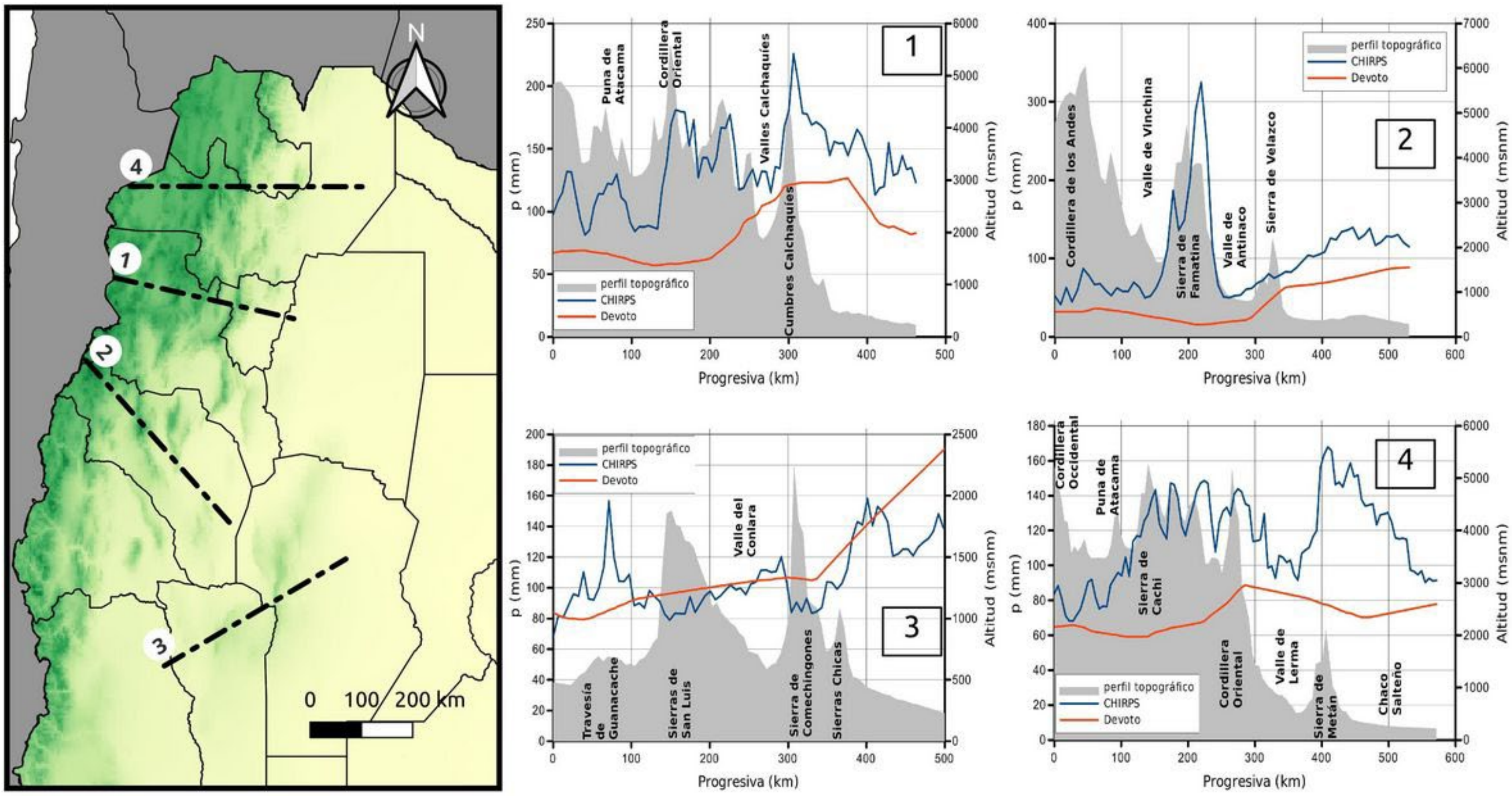

Figure 21. Spatial distribution of estimated daily design rainfall (T = 25 years) based on Satellite Derived Precipitation Data and according to the Devoto's method, together with the topographic profile, for four transects. Local names, as a geographic references, are included in the figures to the right.

Conclusions

It was possible to develop a methodology to estimate the daily design rainfall depths for Argentina, based on the use of the precipitation data set derived from the CHIRPS satellite. For this, computational tools were developed that allowed the automatic acquisition and analysis of precipitation data derived from satellites, in general, and from the CHIRPS product in particular.

It was possible to statistically characterize the series of annual daily maximum rainfall (pdMa) obtained from satellite-derived rainfall data, by processing (through specially developed computer codes) the acquired raster information.

Direct comparison between the Satellite Derived Precipitation Data (DPDS) and the precipitation recorded in a set of 64 pluviometric stations of the National Meteorological Service, day by day, shows a very low or null correlation. This discourages its use for hydrological modeling of historical events, particularly for small and medium-sized watersheds. Even the comparison of the virtual annual daily maximum precipitation (DPDS) and real (pluviometric) does not show a good correlation either (Figure 7 and Figure 8, left); therefore, these pdMa virtual series would also not be useful for time series analysis (time autocorrelation, for example). However, the necessary ordering of these series (required for the assignment of non-exceedance empirical probabilities, according to their plot position) significantly improves this correlation (Figure 7 and

Figure 8, right) and, consequently, enables their use for the design rainfall depth estimations.

From the CHIRPS Satellite Derived Precipitation Data, it has been possible to generate Daily design precipitation maps, for 2-to-100-year return periods, for most of the Argentine continental territory. The generated maps, with a 5 km spatial resolution, alllows us to describe the spatial distribution of this variable in large regions of the country where rainfall series of sufficient duration and quality are not available to implement a classical statistical hydrological analysis. It is considered that the results obtained are superior in quality to those reported by the method proposed by Devoto (2002), also of national scope. Likewise, it is considered that these maps describe more adequately the spatial variability of the design rainfall considering the orographic and climatic effects in the wide territorial extension of Argentina, in relation to the previous Devoto's method (Figure 21).

These results can be useful for several hydrological design applications, particularly in regions with absence of mentioned above information.

The described procedure may be updated in the future, with certain frequency, as the DPDS extends their temporary coverage; this will reduce the associated confidence intervals and increase the return periods of the design rainfall depths to be obtained.

Satellite Derived Precipitation Data, through systematic error correction from field station data, are considered useful for the generation of design daily precipitation fields in Argentina. It is also considered that the described procedure can be useful for other regions with absence of pluviometric information.

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