Received: 10 April 2021 | Revised: 3 August 2021 | Accepted: 7 August 2021

DOI: 10.1002/wat2.1555

ADVANCED REVIEW

WIREs WATER WILEY

From rain to data: A review of the creation of monthly and daily station-based gridded precipitation datasets

Roberto Serrano-Notivoli[1] | **Ernesto Tejedor**[2]

[1]Department of Geography, Autonomous University of Madrid, Madrid, Spain

[2]Department of Atmospheric and Environmental Sciences, University at Albany (SUNY), Albany, New York, USA

Correspondence
Roberto Serrano-Notivoli, Department of Geography, Autonomous University of Madrid, Madrid, Spain.
Email: roberto.serrano@uam.es

Funding information
National Science Foundation, Grant/Award Numbers: AGS-1702439, OISE-1743738; Government of Aragón

Edited by: Stuart N. Lane, Editor-in-Chief

Abstract

Monthly and daily gridded precipitation datasets are one of the most demanded products in climatology and hydrology. These datasets describe the high spatial and temporal variability of precipitation as a continuous surface and for defined periods. However, due to the complex characteristics of precipitation, it is difficult to obtain accurate estimations. Thus, the creation of a gridded dataset from observations requires the comprehensive and precise application of quality control, reconstruction, and gridding procedures. Yet, despite multiple advances, most of the gridded datasets created and published since the mid-1990s to the present use a wide variety of techniques, methods, and outputs, which can completely change the final representativity of the data. It is, therefore, critical to provide general guidelines for the development of future and more robust gridded datasets based on the data characteristics, geographical factors, and advanced statistical techniques. We identified gaps and challenges for near-future perspectives and provide guidelines for implementing improved approaches based on the performance of 48 products. Finally, we concluded that, despite better spatial and temporal resolutions, data access, and data processing capabilities, observational coverage remains a challenge. Moreover, scientists should adopt tailored strategies to improve the representativity and uncertainty of the estimates.

This article is categorized under:

Science of Water > Hydrological Processes
Science of Water > Water Extremes
Science of Water > Methods

KEYWORDS

grid, interpolation, precipitation, quality control, reconstruction

1 | INTRODUCTION

Precipitation is a climatic variable that has a great influence on human activities (Arnell, 1999; Barnett et al., 2005; Hatfield et al., 2011). Its duration, frequency, and intensity condition the accessibility to water resources and the occurrence of environmental and societal risks derived from floods, droughts, and landslides, among others (Konapala et al., 2020; Serrano-Notivoli et al., 2020). Precipitation critically contributes to the characterization of the climate of the Earth and is also the most measured variable at the thousands of weather stations worldwide (Menne et al., 2012). The great spatial and temporal variability of the data, however, makes it difficult to summarize the characteristics of rainfall at different scales. Therefore, the traditional methods for estimating climatic variables, such as temperature, are not always valid, particularly when working at high-frequency temporal scales (daily or sub-daily). One of the main issues regarding its estimation is that the frequency distribution (FD) of precipitation amounts is not normal and varies according to its temporal aggregation (daily, monthly, seasonal, etc.) and the climate to which it belongs. This relationship between the shape and dispersion of the FD and the climate means explains the occurrence and intensity of extremes (Waggoner, 1989), which is critical in precipitation modeling research. All these components set precipitation as one of the most complex climatic variables to model from a regional to global scale. However, precipitation datasets are popular and necessary for assessing changes in various parts of the climatic system at very different spatial scales, and in recent decades, many initiatives have resulted in the creation of various methods that attempt to profile the behavior of precipitation.

Several of the first gridded precipitation datasets appeared in the early 1990s in parallel with the increasing accessibility to computational resources. Many of those works (e.g., Daly et al., 1994; Frei & Schär, 1998; New et al., 1999; Piper & Stewart, 1996) are the basis of the methods that are still in use nowadays. For example, Daly et al. (1994) created the Precipitation-elevation Regressions on Independent Slopes Model (PRISM) method, which is one of the most popular gridding procedures used nowadays and has not changed much in 25 years. In the following decade, a wide collection of improved global and regional datasets emerged, in which the spatial resolution, number of input data stations, and reconstructed period were increased (e.g., Hijmans et al., 2005; Mitchell & Jones, 2005). The second decade of the 21st century was characterized by an increase in the number of available gridded datasets that were mainly influenced by the higher reproducibility of the methods, the computing power, and the availability of the data, which promoted the current (and unprecedented) ease of data access. Datasets were then developed for most countries globally and included similar methodologies but different spatial and temporal resolutions. At the beginning of the 2020s, the focus was on the creation of datasets that are useful for operational systems. These new products must be updated constantly and are utilized for climate analysis and other purposes (e.g., risk probabilities management, biogeographical modeling, paleoclimatology calibration, etc.). These products compete with other datasets of a different nature, such as reanalysis or data assimilation forecasts, which are better at obtaining extremely high temporal resolution data (sub-daily) but are weaker for long-term analyses due to the small proportion of observations compared with the observational datasets.

In addition to these technical aspects, the temporal resolution revealed climatic properties that must be considered prior to choosing a reconstruction method. For example, most of the datasets are on a monthly (or lesser) scale, which is reasonable for climatic studies that focus on global means and general spatial distributions. However, this is insufficient for other fundamental aspects, such as extreme events analysis, for which a daily temporal scale (even higher) is required (Zhang et al., 2011). The development of high temporal frequency precipitation datasets is less common due to several challenges: (i) the increase in the abundance of data compared to the monthly scale, (ii) the trial of comprehensive quality control methods, and (iii) the great short-term variability of the data, all of which demand considerable efforts in terms of process automation and computing time. These considerations turned daily precipitation into one of the least-addressed variables in climatic reconstruction despite its paramount importance in extreme events analysis (Easterling et al., 2000). The first decades of the 21st century, however, altered the pathway to a more ambitious era of high-resolution gridded datasets. Several studies used the daily precipitation reconstruction as a means to attain other objectives, such as the calculation of climatic means (e.g., Daly et al., 2002; Frei & Schär, 1998; Schneider et al., 2014), the improvement of downscaling methods (e.g., Wong et al., 2014), the creation of station-based and/or gridded global or regional precipitation datasets (a representative sample of these is presented in this review), or the extraction of long-term trends (e.g., Becker et al., 2013; Philandras et al., 2011). Few studies, however, focused on the quality control and reconstruction of daily precipitation as a goal (e.g., Castro et al., 2014; Feng et al., 2004; Simolo et al., 2010; Vicente-Serrano et al., 2010; Serrano-Notivoli, Begueria, et al., 2017). Higher temporal resolutions (sub-daily) are less popular among gridded datasets due to difficulties in handling large amounts of data with extremely diverse temporal and spatial variability. However, several attempts are available for certain regions (e.g., Lewis et al., 2018; Wüest et al., 2010).

Finally, various previous studies explicitly compared gridded precipitation datasets (e.g., Contractor et al., 2015; Schumacher et al., 2020), interpolation methods (e.g., Brunetti et al., 2014; Hofstra et al., 2008; Vicente-Serrano et al., 2003), or reconstruction techniques (e.g., Miró et al., 2017). Nonetheless, a description of the multi-perspective complete methodological process for the creation of gridded datasets, from the initial data processing through the reconstruction process to the final spatial generalization of the results and a measure of their uncertainties, is lacking. For the first time, this review includes a comparison of the most common methods for quality control, missing values reconstruction, and gridding through 48 daily and monthly datasets in a grid format and at different spatial scales. The analysis focused on gridded datasets built from rain gauges. We reviewed the existing techniques for creating gridded precipitation datasets from observations and provide useful guidelines on improved approaches according to the spatio-temporal resolution and coverage.

2 | FROM OBSERVATIONS TO ESTIMATES

The creation of precipitation gridded datasets (also valid for other climatic variables) is based on four main steps that we propose as the general workflow to transform observations into estimates, although there are different methods with slight variations:

1. Quality control:
   a. The original dataset is filtered to remove the anomalous data that lie beyond the natural climatic variability of the location to which the data series belongs. This is created by setting various criteria through statistical tests to search for anomalies (e.g., from out-of-range values to the homogeneity of different parts of the series).
   b. The nature of the observations (temporal frequency, number of observations, length of the series, etc.) will determine the suitability of the various types of criteria.
2. Data series reconstruction: the missing values are reconstructed using a wide variety of statistical techniques to obtain a final serially complete dataset. It is important to note that most of the gridded datasets do not include this step and proceed to the next stage by selecting the data series that have a lower amount of missing data.
3. Gridding: the quality-controlled observations are used to create a model that estimates precipitation amounts at each grid point over the spatial domain. Several factors determine the accuracy of the estimates (the temporal frequency of the data, the spatial resolution of the grid, the spatial density of the observations, the orography of the spatial domain, etc.) that will determine the selection of the model.
4. Uncertainty: is the result of the validation process. The difference between the observations and estimates reflects the accuracy of the gridding process. No method has been established to assess the uncertainty; however, most studies have used common error statistics (e.g., RMSE, BIAS, Pearson correlation coefficient, etc.).

The following sections present a description of the use of these steps in a representative selection of 48 works (Table 1) from the mid-1990s to the present. In the included studies, gridded precipitation datasets were created at very different spatial and temporal resolutions over spatial domains located across the globe. Instead of enumerating the methodological details for each of the studies (which can be reviewed in the original references), they were grouped according to the use of several generic methods, for example, by temporal or geographical checks in Quality control (QC), the use of a reference series in gap-filling, or by interpolation methods at the gridding stage.

3 | QUALITY CONTROL

QC is the first fundamental step required to guarantee the internal consistency of the data (Feng et al., 2004). QC allows for the elimination of nonsystematic errors. These errors jeopardize the validity of individual values due to diverse causes that are frequently related to annotation or digitalization errors, as well as database manipulation (Aguilar et al., 2009). These errors are, in most cases, only detected by comparing the data series with the observatories of the immediate surroundings, which would be expected to retain the same temporal variability. As this variability is substantially more evident in daily data compared with monthly or annual data, the occurrence of extreme values that can be confused with anomalous values (outliers) is also more frequent. Hence, the adoption of methodologies that can detect these types of anomalies, by minimizing the number of false positives (correct values as invalid, also known as *type I* errors) and false negatives (undetected errors, also known as *type II* errors), is of crucial importance and is a challenge.

Most of the QC processes, regardless of the size of the dataset, typically involve the removal of less than 2% of the original data (Llabrés et al., 2019; Serrano-Notivoli, Begueria, et al., 2017; Serrano-Notivoli, de Luis, et al., 2017; Vicente-Serrano et al., 2010). The deletion of the original data, however, is important (Reek et al., 1992) because

TABLE 1 Summary of the characteristics of the selected gridded datasets, sorted by publication year

Source	Denomination	Horizontal resolution	Temporal resolution	Spatial coverage	Maximum period	Quality control	Gap-filling	Gridding method	Uncertainty
Daly et al. (1994)	—	—	M, A	Western CONUS	—	—	—	PRISM	STATS
Piper and Stewart (1996)	—	1°	D	Global	1987	TMP	—	SPH	–
Frei and Schär (1998)	—	25 km	D	Alps	1971–1990	GEO, TMP	–	ADW	VAR
New et al. (1999)	CRU	0.5°	M	Global	1961–1990	TMP	—	TPS	STATS
Shen et al. (2001)	—	10 km	D	Alberta (USA)	1961–1997	PQC, TMP	—	IDW, NS	–
Rubel and Hantel (2001)	BALTEX	0.16°	D	Baltic Sea	1996–1998	—	–	KRG	VAR
Kyriakidis et al. (2001)	—	1 km	D	North California	1981–1982	—	–	KRG	STATS
Chen et al. (2002)	—	2.5°	M	Global	1948–2000	TMP	—	OI	STATS
New et al. (2002)	CRU	10′	M	Global	1961–1990	TMP	—	TPS, ADW	STATS
Hijmans et al. (2005)	—	30″	M	Global	1950–2000	GEO, TMP	–	TPS	STATS
Mitchell and Jones (2005)	CRU TS 2.1	0.5°	M	Global	1901–2002	TMP, HOM	RS	TPS	STATS
Perry and Hollis (2005)	—	5 km	M	UK	1961–2000	TMP	–	LRG, IDW	STATS
Hewitson and Crane (2005)	—	0.1°	D	South Africa	1950–1999	—	—	CI	–
Alexander et al. (2006)	—	2.50°	D	Global	1951–2003	PQC, TMP, HOM	—	ADW	–
Efthymiadis et al. (2006)	HISTALP	10′	M	Alps	1800–2003	TMP, HOM	RS	ADW	STATS
Ninyerola et al. (2007)	—	200 m	M	Spain	1950–1999	—	–	LRG	—
Daly et al. (2008)	PRISM	30″	M	CONUS	1971–2000	GEO, TMP	—	PRISM	LOO, MSE
Di Luzio et al. (2008)	—	2.5′	D	CONUS	1960–2001	GEO, TMP	—	PRISM	STATS
Haylock et al. (2008)	E-OBS	25 km	D	Europe	1950–2006	PQC, TMP	—	TPS, KRG	VAR
Yatagai et al. (2012)	APHRODITE	0.25°	D	Asia	1951–2007	GEO, TMP	—	SPH	–

TABLE 1 (Continued)

Source	Denomination	Horizontal resolution	Temporal resolution	Spatial coverage	Maximum period	Quality control	Gap-filling	Gridding method	Uncertainty
Jones et al. (2009)	—	0.05°	D, M	Australia	1910–2008	PQC	—	TPS	STATS
González-Hidalgo et al. (2011)	MOPREDAS	10 km	M	Spain	1945–2005	GEO, TMP, HOM	RS	ADW	—
Abatzoglou (2011)	—	4 km	D	Western CONUS	1979–2010	GEO, TMP	—	BIL	STATS
Belo-Pereira et al. (2011)	IB02	0.2°	D	Iberian Peninsula	1950–2003	TMP, HOM	—	KRG	TEST
Herrera et al. (2012)	Spain02	0.2°	D	Spain	1950–2003	TMP, HOM	—	KRG	TEST
Jones et al. (2013)	—	0.5°	D	South America	1961–2000	—	—	TPS, KRG	TEST
Becker et al. (2013)	GPCC	0.25°	M	Global	1901–2012	GEO, TMP	—	AAV, ADW	STATS
Rauthe et al. (2013)	HYRAS-PRE	1 km	D	Central Europe, Alps	1951–2006	GEO, TMP, HOM	—	LRG, IDW	LOO
Wu and Gao (2013)	-	0.25°	D	China	1961–2005	—	—	TPS, ADW	—
Schamm et al. (2014)	GPCC	1°	D	Global	2009–2013	TMP	—	KRG	VAR
Isotta et al. (2014)	EURO4M_APGD	5 km	D	Alps	1971–2008	GEO, TMP	—	ADW	LOO
Harris et al. (2014)	CRU TS 3.1	0.5°	M	Global	1901–2009	TMP	—	TPS	STATS
Livneh et al. (2015)	L15	0.0625°	D	North America	1950–2013	TMP	—	ADW	—
Spinoni et al. (2014)	CARPATCLIM	0.1°	D	Carpathians	1961–2010	HOM	RS	KRG	—
Liebmann and Allured (2015)	—	1°	D	South America	1940–2003	TMP	—	AAV	—
Newman et al. (2015)	—	0.125°	D	CONUS	1980–2012	GEO, TMP	—	LRG	RES
Aalto et al. (2016)	FMI_ClimGrid	10 km	D	Finland	1961–2010	PQC	—	KRG	STATS
Fick and Hijmans (2017)	WorldClim	1 km	M*	Global	1970–2000	GEO	—	TPS	TEST
Serrano-Notivoli, Begueria, et al. (2017), Serrano-Notivoli, de Luis, et al. (2017)	SPREAD	5 km	D	Spain	1950–2012	TMP, GEO	RV	RV, LRG	LOO

(Continues)

TABLE 1 (Continued)

Source	Denomination	Horizontal resolution	Temporal resolution	Spatial coverage	Maximum period	Quality control	Gap-filling	Gridding method	Uncertainty
Hiebl and Frei (2017)	—	1 km	D	Austria	1961–2014	PQC, TMP	—	ADW, KRG	TEST
Cornes et al. (2018)	E-OBS	0.25°	D	Europe	1950–2018	PQC, TMP	—	TPS	ENS
Lussana et al. (2018)	seNorge2	1 km	D	Norway	1957–2015	—	—	OI	—
Crespi et al. (2018)	—	30″	M	Italy	1961–1990	PQC, TMP	—	LRG, KRG	—
Aybar et al. (2019)	PISCOp	0.1°	D, M	Peru	1981–2016	GEO, TMP	RS	IDW, KRG	STATS
Hollis et al. (2019)	HadUK-Grid	1 km	D, M	UK	1862–2018	PQC, TMP	—	IDW, LRG	STATS
Gofa et al. (2019)	—	30″	M, A	Greece	1971–2000	GEO, TMP, HOM	—	LRG	—
Contractor et al. (2020)	REGEN	1°	D	Global	1950–2016	GEO, TMP	—	KRG	VAR
Harris et al. (2020)	CRU TS 4	0.5°	M	Global	1901–2018	PQC, TMP	—	ADW	STATS

Note: Temporal resolution: A, annual; D, daily; M, monthly; M*, only monthly means; Quality control: GEO, geographical checks; HOM, homogenization; PQC, previously quality-controlled data; TMP, temporal checks; Gap-filling: RS, reference series; RV, reference values; Gridding methods: AAV, area average; ADW, angular distance weighting; BIL, bilinear interpolation; CI, conditional interpolation; KRG, kriging, all variants; LRG, linear regression; NS, nearest station; OI, optimal interpolation; PRISM, PRISM; RV, reference values; SPH, Spheremap; TPS, thin-plate splines; Uncertainty: ENS, ensembles; LOO, leave-one-out cross-validation; STATS, any of RMSE, SD, MAE, MSE, or BIAS; RES, regression residuals; TEST, training-test data; VAR, kriging variance.

(1) those data represent the most notorious errors that can cause statistical discordances, (2) it discredits the reliability of the dataset, (3) it contributes to misunderstandings in the accuracy of the historical mean and extreme climatic records, and (4) it induces flaws in models and climatic summaries. Considering this, the selection of the criteria for the detection and removal of anomalies will rely on the correct interpretation of the potential sources of error and the use of statistics according to the nature of the data.

3.1 | Sources of error

The recorded data are subject to factors that can distort the measure, such as the location of a station, evaporation or even the wind, which could potentially mean a significant loss in a single event (Buisan et al., 2017). These are the systematic errors, represented by the failure of the rain gauges to measure the complete rainfall of an event, that result in lower total amounts than the actual values. Previous intercomparison studies (Monesi et al., 2009; Sevruk et al., 2009) revealed average losses of 4%–6% to greater than 10%, depending on the device, its location, and whether the observations were manual or automatic (Valik et al., 2020). These errors, which are constant under the same conditions, can be corrected through transfer functions for adjusting the wind bias (Matsuda et al., 2019; Rubel & Hantel, 1999). However, this procedure implies a comprehensive knowledge of the characteristics of the meteorological network, which is not available in most cases, particularly concerning large datasets at a national level or larger regions.

Errors associated with observations and their measurement are generally caused by the observer. Most of the long-term data series contain large portions of data that were recorded using manual rain gauges, which means that the data was recorded daily by a person at the pluviometer. Although these types of data series are reliable, they are also associated with numerous issues that introduce errors that are difficult to evaluate in the final value. Viney and Bates (2004) discovered that, in Australia, the frequency of missing values in data series increased during the weekends which, based on the probability of occurrence, suggested that rainfall may be underestimated by up to 24%. This pattern can potentially be repeated globally during vacation periods or due to unavoidable circumstances such as lock-down situations (Spaccio et al., 2021) and can represent significant incoherencies in seasonal trends and lead to biased results. Conversely, errors can arise in the observation (e.g., erroneous observation, malfunctioning of the measurement instruments, incorrect calibrations, unregistered changes in a station location, etc.) and in the codification process (causing typos, errors in decimal places, duplicated records, errors in dates, etc.). A comprehensive QC process that involves the inspection of individual values and compares them with those of the neighboring stations can partially solve this issue. In the case of the automatic weather stations, the errors are generally associated with malfunctions in the data transfer, mechanical fails, or the partial or total blocking of the pluviometer due to a lack of daily maintenance.

Finally, and common to all types of observations, the location of a station may change. Without a metadata report that includes these changes, precipitation series are prone to suffer variations or unnoticed alterations.

3.2 | QC approaches

Several studies that involved the construction of gridded datasets did not focus on the QC and the initial quality of the data was honored (e.g., Aalto et al., 2016; Jones et al., 2009). Moreover, numerous studies did not notice or apply the QC stage (e.g., Hewitson & Crane, 2005; Ninyerola et al., 2007; Rubel & Hantel, 2001; Yatagai et al., 2008). Other studies applied basic QC methods to the individual data series (e.g., Cornes et al., 2018; Crespi et al., 2018; Haylock et al., 2008; Hollis et al., 2019; Shen et al., 2001) that were mainly based on the finding of anomalous values over predefined thresholds. At this point, the temporal resolution of the data plays a fundamental role in the election of thresholds to detect these anomalies. When considering the statistical differences between monthly and daily data series, the QC methods are also different. In addition to the aforementioned FD of daily precipitation, the probability distributions of this variable are typically biased and have extremely prominent right tails in which there are non-negligible probabilities of observing very high magnitudes in individual episodes, exceeding the mean values by several orders of magnitude. This circumstance creates an issue with setting thresholds to differentiate the outliers from the extreme values.

Next, the number and length of the data series are of key importance in a QC approach because this will ascertain the resources that will be dedicated to a more or less comprehensive analysis. In this regard, most of the methods applied to large precipitation datasets are automatic that is, a collection of tests is applied to the original data all at once or iteratively. The advantage of these tests is that they only require computational efforts, and all the tests are applied equally to all the data series, allowing for complex statistical calculations, even for individual values.

The QC methods can be based on a spatial comparison (geographical checks) or a temporal comparison (temporal checks, also called *internal consistency*; Figure 1). In a spatial comparison, each value is compared with the neighboring data to assess the spatial coherence in the distribution of the variable, albeit the most common methods utilize a comparison between the candidate series (the one to be quality-controlled) and the reference series (the one built from the nearest stations) in all temporal dimensions (i.e., from the beginning to the end of the series; e.g., El-Kenawy et al., 2012; Esteban et al., 2008; Herrera et al., 2012). The methods that are based on a temporal comparison examine each of the data series independently and search for anomalous data in the range of observations (e.g., Abatzoglou, 2011; New et al., 1999; New et al., 2002; Piper & Stewart, 1996).

The selection of the specific criteria to be applied to temporal and/or spatial verifications depends on the type of error to be solved (see Section 3.1). For example, internal coherence is important in every data series (Aguilar, 2013) and duplicated dates, rounding problems, out-of-range values (fixed threshold), quantile-based outliers, inter-day differences, and consecutive values (flat line) must be examined. Several popular global gridded datasets applied some or all these criteria to the original data (Chen et al., 2002; Harris et al., 2014; Mitchell & Jones, 2005; New et al., 1999, 2002; Piper & Stewart, 1996; Schamm et al., 2014). Nonetheless, since the second half of the 2010s, the new datasets began to include improved QC methods and these criteria were combined with those that compared data series to each other, and the data with a low degree of correlation or high dissimilarity to the nearest stations were rejected. In this context, and with further investigation into the statistical structure of the series, several studies applied homogenization methods (e.g., Alexander et al., 2006; Gofa et al., 2019; González-Hidalgo et al., 2011; Herrera et al., 2012; Rauthe et al., 2013) based on tests to assess for non-natural breaks in data series (most of these tests were based on the work conducted by Peterson et al., 1998 who summarized the state-of-the-art about homogenization techniques) or in combination with other QC tests within automatic software. A deeper analysis of the data for the QC stages is less common during the creation of gridded datasets, although there are several exceptions (e.g., Durre et al., 2010; Llabrés et al., 2019; Serrano-Notivoli, de Luis, et al., 2017). For example, Serrano-Notivoli, de Luis, et al. (2017) evaluated all the data series that compared all values, day by day, with their surrounding observations to assess the magnitudes without spatial coherence, the out-of-range values, and the precipitation regarding its probability of occurrence. The advantage of such a method is that all data series, irrespective of the length, can be used.

The choice of the various criteria relies on (1) the user preferences, (2) the global reconstruction method (dependent on the temporal/spatial resolution, the work by timesteps or individual series, etc.), and (3) the available resources (computing, human, data, etc.). The choice of a group of specific criteria does not exclude the issues solved by others, they are generally complementary, that is, the data can be quality controlled in many ways with similar results. Finally, the availability of a metadata compilation that reports the changes in the observatory (changes in the location, measuring instruments, etc.) is extremely useful. Unfortunately, this is not a standard practice in global observation networks,

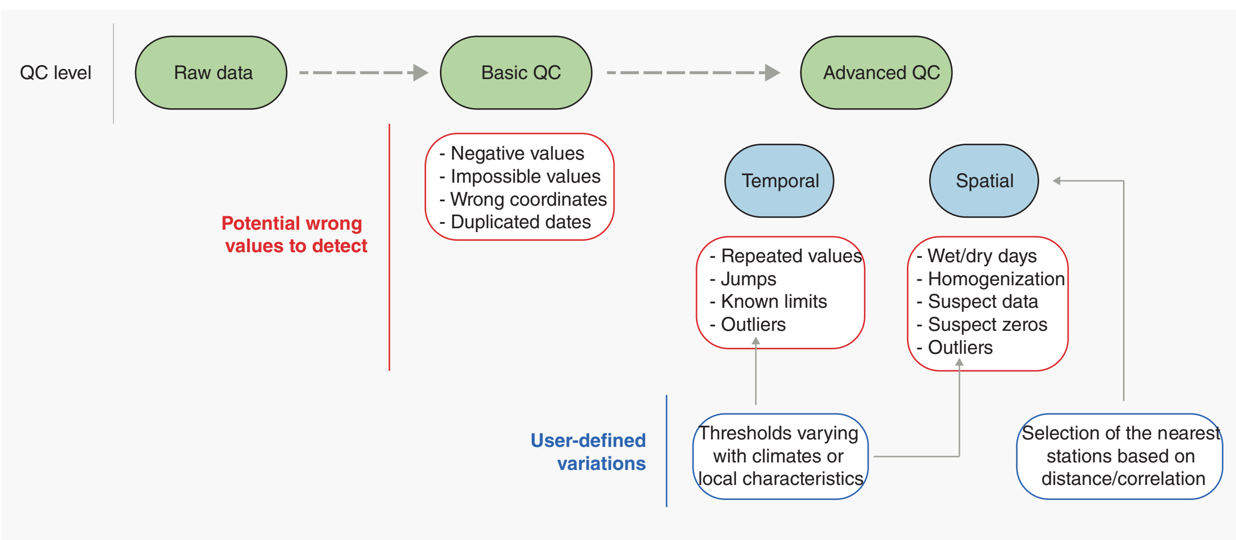

FIGURE 1 Three quality control workflow levels that depend on the comprehensiveness of the approach

although great effort has been made in recent years to annotate each one of the modifications that can produce changes in the climatic records (e.g., Mahmood et al., 2019; Mateus et al., 2020).

4 | DATA SERIES RECONSTRUCTION

The objective of the data series reconstruction process, also known as *gap-filling* or *missing values estimation*, is to obtain complete data series from the initial to final date of the study period. Although this is not common practice (only six of the analyzed works [12%] utilized this method), it has several advantages in the subsequent gridding process. The most important advantage is that the number of observations does not change over time and temporal inconsistencies are avoided. Although several homogenization methods that were applied to a few (8) gridded datasets already included gap-filling processes, only 3 of them explicitly reported that procedure.

The reconstruction process for all climatic variables is generally based on weighted averages or modeling that consists of creating a reference series formed as a weighted model of the data observed at some neighboring stations for each location of interest. The weights featuring the data estimations are generally determined by the correlation or distance between the data series of observations; however, they can also be avoided by including all the observations within a fixed radius (Begueria et al., 2019; Figure 2). These weights are used to estimate the amount of precipitation, which is limited from zero (no precipitation) to a maximum based on the climatic characteristics of the spatial domain. This limitation conditions the statistical modeling to those approaches that prevent out-of-range predictions.

4.1 | Probability of occurrence and magnitude

Several previous works that included precipitation datasets demonstrated that the completion of the reconstruction process using a two-step approach (first estimating the occurrence of the precipitation, then the magnitude) provides improved results compared to a single-step approach. For example, Simolo et al. (2010) calculated the probability of the occurrence of a wet/dry day using the fit of a Gamma distribution of two parameters to all the original series and calculated the magnitude using multivariate logistic regressions (MLR). This is an extremely common methodology that produces suitable results (e.g., Hay et al., 2002; Helsel & Hirsch, 2002; Hwang et al., 2011; Syed et al., 2003). Wong et al. (2014) used logistic models to predict the occurrence of wet days and a combination of probability distributions

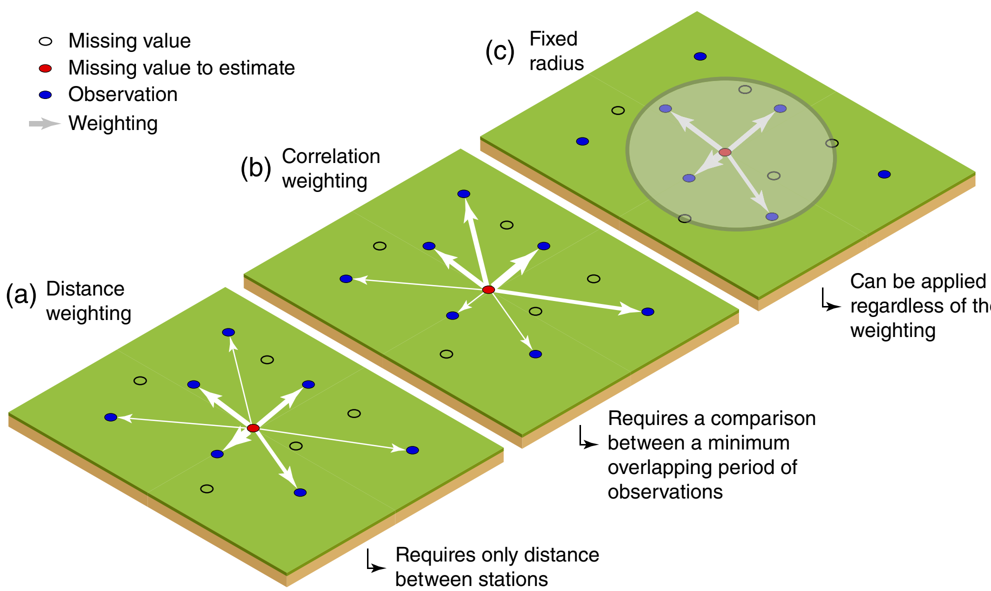

FIGURE 2 Three weighting schemes for the estimation of precipitation at new locations (red dots) from the nearest stations with observations (blue solid dots). The weight of each observation (width of the arrows) varies depending on the geographical distance (a), the correlation (b), or (c) a fixed radius that is set to limit the use of the farthest neighbors

over a complete series of intensities. Conversely, Hwang et al. (2011) used a two-step method with logistic regression to calculate the spatial occurrence of precipitation but used different interpolation methods to estimate magnitudes and also considered the monthly climatologies. Serrano-Notivoli, de Luis et al. (2017) used a binomial prediction, referred to as a wet ($P[X > 0]$) or dry ($P([X = 0)]$) day occurrence probability, and a magnitude prediction to estimate the amount of precipitation ($P([X = x)]$). Furthermore, in the latter case, a quasi-binomial model was used that allowed for upper and lower limits to be set. The commonality of all these approaches is that they are based on the use of the longest series, both in the candidate and neighboring stations, assuming that the relationships do not change over time. Regardless of this assumption, which may not be valid for daily data, all methods require a minimum length and overlapping of the data series for the detection and modeling of the relationships.

4.2 | Reference series and reference values

The reconstruction of missing values can be achieved using two approaches (1) the creation of a new data series from the observations of neighboring stations (reference series [RS]) and then replacing the gaps in the original series or (2) estimating new values (reference values [RV]) by only considering the nearest observations at each timestep.

The construction of an RS requires that the candidate and the neighboring series have a minimum length and overlap during significant periods, which leads to the rejection of small data series and removes valuable information for the reconstruction. Moreover, two hypotheses are assumed during the creation of an RS (1) the data series and their relationships are stationary in the overlapping period and (2) they have a similar temporal structure. These hypotheses are aggravated when working with daily data because the behavior of neighboring stations can be extremely different on a temporal scale. Most of the gridded datasets that reported reconstruction procedures created an RS in various forms: Efthymiadis et al. (2006) used spatial empirical orthogonal functions; Aybar et al. (2019) used the nearest and most similar data series; Spinoni et al. (2014) used the Multiple Analysis of Series for Homogenization (MASH) software; and others used the best-correlated series (e.g., González-Hidalgo et al., 2011; Mitchell & Jones, 2005).

However, considering the high temporal and spatial variability of precipitation, it is desirable not to assume a priori climatic behaviors or stationary relationships between neighboring series; the only way to achieve this is by calculating RV instead of an RS. The RV can be computed using various statistical models; however, previous works (Serrano-Notivoli, Begueria, et al., 2017; Serrano-Notivoli, de Luis, et al., 2017) mostly involved multivariate regression procedures. The covariates concerned can be geographical (e.g., elevation, longitude, and latitude) and/or climatic (e.g., climatic normal, temporal averages, etc.). Nevertheless, topographic factors generally effectively explain the spatial distribution of precipitation and they have been extensively studied during previous attempts of precipitation modeling using linear regressions (Daly et al., 1994, 2008; Di Luzio et al., 2008). The climatic covariables undoubtedly provide important support in precipitation estimations, and they are commonly used in gridding methods (e.g., Haylock et al., 2008; Hofstra et al., 2008; New et al., 2002). However, long-term data series are required to facilitate the calculation of acceptable precipitation normals.

Reconstructions based on RS must use the best quality series and reject the rest (i.e., those that do not fulfill the quality criteria, which are commonly based on correlation thresholds). Although this is the general approach and facilitates the work by reducing the amount of data, it implies a reduction of the variability (bias) and a loss of spatial resolution. Any gridded dataset based on these assumptions also represents the aforementioned simplification. Conversely, the use of RV maintains the original resolution because all the original data series is used (after the QC process). The election of an RS or RV is a key part of the reconstruction process, and the choice will determine the final reliability and representativity of the estimates (Box 1).

5 | GRIDDING

Spatial prediction involves calculating new values of the variable throughout the spatial domain, and the results are typically presented in the form of a map. Prediction can imply interpolation and extrapolation, which is a prediction outside the range of the observations. In other words, extrapolation is the prediction in those locations (or times) where there is not enough statistical evidence to guarantee significant estimates (Hengl, 2009). Precipitation gridding processes include spatial and temporal interpolation and, in general, the extrapolation of observations due to the aforementioned characteristics of its frequency distribution.

BOX 1 A reliable starting point

- All data matters. The longer the data series the better that is, the use of all the available information allows for a better representation of the climatic characteristics.
- A progressive QC from basic verifications to advanced comparisons. This improves the detection of suspect data. Criteria tailored to the target dataset (e.g., type of climate or local characteristics) are helpful.
- Spatial coherence is almost always a guarantee of quality; however, extreme values could fall by the wayside.
- A separated prediction of occurrence and magnitude of precipitation prevents unrealistic near-zero estimates that can potentially bias further indicators (e.g., number of wet/dry days, droughts, etc.).
- An RS is robust in reconstructing missing values but implies the rejection of shorter data series.
- RV are preferred but this requires greater computational resources.

There are numerous interpolation methods for climatic variables, from those that assign the nearest observation (e.g., nearest neighbor, Thiessen polygons, etc.) to those that explicitly consider the synoptic state of the atmosphere at the moment of the observation (e.g., conditional interpolation [CI]). The performance of any method primarily depends on the spatial and temporal scales and the density of the observation network (Hofstra et al., 2008).

Concerning the temporal scale, the use of climatologies (averaged values over a predefined period) as covariates or to set a starting point for the anomalies are general practices as they represent a common climatic signal that can be easily spatialized (coarser temporal aggregations vary less over space). In light of this, methods such as *climatologically aided interpolation* (CAI; Willmott & Robeson, 1995), became extremely popular and are still used nowadays (e.g., Contractor et al., 2020; Hofstra et al., 2008). The use of climatologies imposes certain restrictions on the selected data because a minimum-length data series is required to create a reliable climatic average. This leads to the rejection of important observations, which represents a reduction in the usable information and the representativity of the final estimates. Additionally, the use of climatologies is beneficial for monthly or smaller timescale temporal resolutions; however, they are not always representative of the daily precipitation process, which is characterized by high variability in space and time. This circumstance is also reflected through the election of the interpolation method. For example, geostatistical interpolators generally produce unwanted effects on daily precipitation. The high frequency of low values (low-intensity precipitation) can be increased while high values (corresponding to extreme events) are reduced (Ensor & Robeson, 2008; Robeson & Ensor, 2006).

The spatial scale is also important prior to the interpolation process because it reflects the representativeness of the estimates over the territory. However, there are no rules regarding the spatial resolution of a grid, and the datasets in Table 1 demonstrate this argument and include values from 200 m to almost 300 km (2.5°). The size of the grid box exclusively depends on the researcher's decision. None of the reviewed studies argued more than a compromise between the density of stations and extension of the spatial domain, except for Haylock et al. (2008) who mentioned one station per 25 km^2 grid box as high-resolution. Most of the studies stated a spatial resolution without an explanation for that choice. The setback is that the previously mentioned uneven distribution of observations makes it difficult to select a representative grid box size, and this issue becomes greater with global datasets. Herein, the typical resolution is 0.5°–1°, although great variations exist (from 30″ to 2.5°) without any apparent justification (Figure 3a). A substantiated grid box decision should, therefore, be based on the density of the stations and the temporal resolution (Figure 3b). For this reason, the use of the maximum amount of data available is key to represent the precipitation characteristics in a wide range of environments, which can ultimately aid in the prediction of the variable in similar ungauged locations.

5.1 | Examples of gridding methods

Due to the high number of options available in the literature for precipitation gridding procedures, only several of the most representative examples are summarized in this section. Furthermore, numerous previous works described the performance of several interpolation methods (e.g., Brunetti et al., 2014; Daly, 2006; Dobesch et al., 2007; Henn et al., 2018; Hofstra et al., 2008; Vicente-Serrano et al., 2003) which is not the purpose of this review.

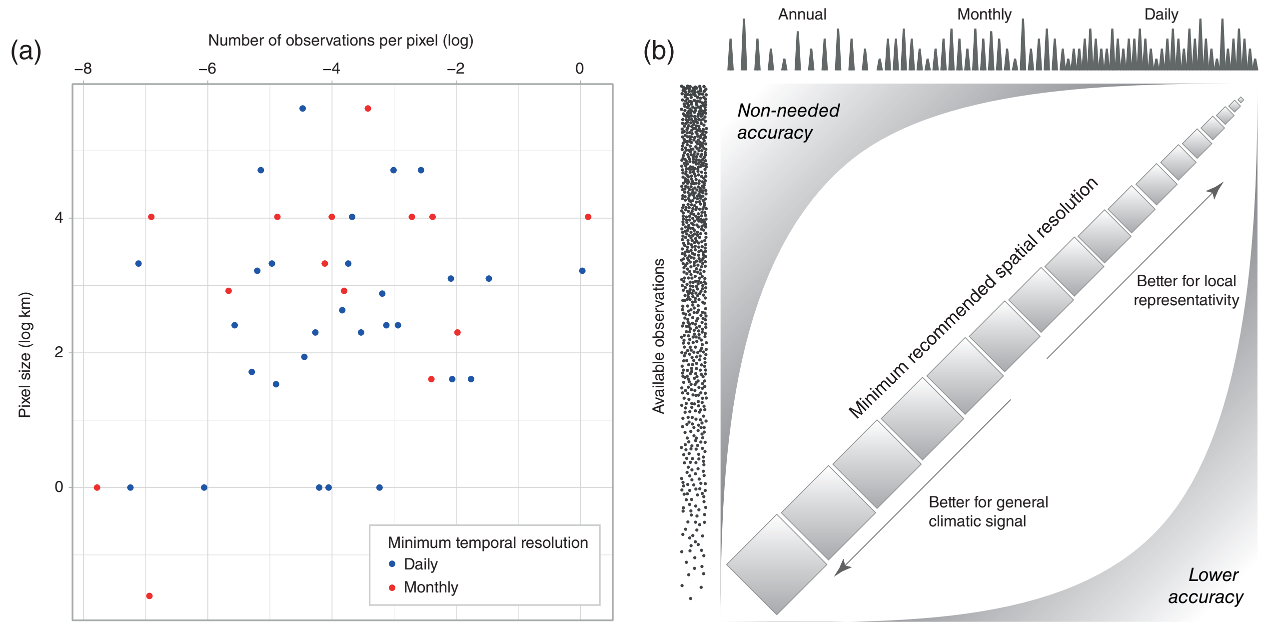

FIGURE 3 The decision-making regarding the spatial resolution of the grid: (a) an empirical depiction of the pixel sizes used in the existing datasets (based on Table 1 references), (b) a theoretical decision of pixel size based on the spatial and temporal resolution of the observations

Most of the datasets created over the past two decades adopted a previously established interpolation method not specifically designed for climatic variables (e.g., Inverse distance weighting [IDW], kriging, TPS, etc.). However, at the very early stage of the grids, the first investigations addressed the issue of creating representative areas of estimates based on meteorological sources. One of the first methods was *Spheremap* (Willmott et al., 1985), which used the angular distance weighting (ADW) algorithm. *Spheremap* was used later in several grids (e.g., Piper & Stewart, 1996; Yatagai et al., 2012) and, although the method did not evolve much further, it generated a foundation for grid creation.

The AWD was originally developed by Shepard (1968) and, since then, it has been widely used for the interpolation of monthly data (e.g., Becker et al., 2013; Efthymiadis et al., 2006; González-Hidalgo et al., 2011; Harris et al., 2020) and daily data (Alexander et al., 2006; Frei & Schär, 1998; Hiebl & Frei, 2017; Isotta et al., 2014; Wu & Gao, 2013). This method is based on the weighting of the nearest stations within a predefined radius (Figure 2c). The weights are based on a distance component that uses the correlation decay distance and an angular component relative to the spatial separation between the candidate and the nearest observations. Shepard (1984) used a modified AWD to create the SYMAP algorithm gridding procedure, which was also widely adopted (e.g., Adam & Lettenmaier, 2003; Efthymiadis et al., 2006; Hiebl & Frei, 2017; Livneh et al., 2015), and González-Hidalgo et al. (2011) used the procedure based on an improved version of Brunetti et al. (2006).

Regressions were widely used to model daily precipitation using various approaches, although they were more frequently used to reconstruct precipitation data series (e.g., Marquínez et al., 2003; Partal et al., 2015; Simolo et al., 2010; Tardivo & Berti, 2014) than for gridding procedures. However, a study of the relationships between precipitation and environmental factors, through multiple linear regressions (MLRs), has been the core of several precipitation grids (e.g., Gofa et al., 2019; Newman et al., 2015; Ninyerola et al., 2007) and, eventually, the MLR were used in combination with other interpolators such as kriging (Crespi et al., 2016) or IDW (e.g., Hollis et al., 2019; Perry & Hollis, 2005; Rauthe et al., 2013). Serrano-Notivoli, Begueria et al. (2017) used MLR as the basis for the creation of RV to compute a grid that separately estimated the probability of the occurrence of a wet or dry day and the amount of precipitation. The authors used latitude, longitude, and altitude as covariates (but many others can be used e.g., aspect, distance to the coast, etc.), similar to several other methods such as PRISM or ANUSPLIN that were previously explored in this type of approach. Despite the contrasting results, there are several issues regarding the use of MLR for precipitation: (1) multicollinearity of dependent variables can provide a noisy signal of the estimates and uncertainty, highlighting the importance of a realistic (not collinear) choice of covariates, (2) certain covariates (such as climatic variables) could have different variability across the precipitation values (heteroscedasticity), leading to biases in the residuals, (3) the relatively high frequency of the occurrence of extremes (particularly on a daily scale) results in outliers that are difficult to predict. While MLR tends to smooth estimates, outliers have a high influence on the data and can produce unwanted extrapolations, (4) depending on the method, underfitting or overfitting issues can occur due to poor training or design of a model. Strategies exist to avoid or minimize these issues (see Serrano-Notivoli, Begueria et al., 2017); however, they are generally reflected in the uncertainty of the estimates (see Section 6).

The PRISM method (Daly, 2006; Daly et al., 1994, 2002, 2008) uses a weighted regression approach to account for complex climate regimes associated with orography, rain shadows, temperature inversions, slope aspects, coastal proximity, and other factors. It adopts the assumption that elevation is the most important factor in the distribution of precipitation and creates a linear relationship between the two variables, which is weighted by various environmental factors such as elevation, coastal proximity, topographic facet, vertical layer, topographic position, and effective terrain. PRISM is one of the most used methods for precipitation gridding, particularly in North America (e.g., Daly et al., 1994, 2008; Di Luzio et al., 2008; Milewska et al., 2005; Xie et al., 2007) due to its effective performance on dense observation networks. This is a common issue for the other gridding procedures: they require dense networks that yield spatial distributions that perfectly represent the orographic effects.

Since the 1990s, thin-plate splines (TPSs) have been widely used to interpolate precipitation (e.g., Hutchinson, 1995). TPS share similar features to kriging; however, they use a different covariance function, which is defined by minimizing the generalized cross-validation error. Thus, the amount of data smoothing can easily be optimized (Hofstra et al., 2008). TPS are appropriate for large heterogeneous areas, and many authors utilized this method to create global datasets, such as the CRU TS (e.g., Harris et al., 2014; Mitchell & Jones, 2005; New et al., 1999, 2002) until they adopted the newest version of AWD (Harris et al., 2020). Furthermore, several other researchers combined TPS with kriging (e.g., Haylock et al., 2008; Jones et al., 2013) or with generalized additive models (Cornes et al., 2018). TPS have also been used as the basis for ANUSPLIN software, developed at the Australian National University. This software has been widely used to create several global gridded precipitation datasets (e.g., Fick & Hijmans, 2017; Hijmans et al., 2005).

IDW or kriging (in any of its variants) are the most used techniques because they are easily implemented in geographic information system (GIS) and because of their contrasted reliability in the spatialization of environmental variables. IDW uses a simple weighting of the neighboring stations based on the distance to the candidate location. The technique has been used in many gridded precipitation datasets, generally in combination with other interpolation schemes but mostly with linear regressions and kriging (e.g., Aybar et al., 2019; Hollis et al., 2019; Perry & Hollis, 2005; Rauthe et al., 2013; Shen et al., 2001). Overall, IDW is not recommended as a single method for precipitation gridding due to its excessive dependence on an observation network that evenly covers the entire spatial domain.

Kriging operates similarly to IDW but considers the spatial variability of the observations. The estimates are a linear combination of the predictors (nearest stations). The interpolated area is, therefore, a local function of the neighboring data but is conditional on the data obeying a particular model of the spatial variability (the variogram; Hofstra et al., 2008). There are diverse variants of kriging; however, two types are most used for precipitation grids. The first is ordinary kriging (OK), which is based on the assumption of an unknown mean. The weights are obtained so that the estimate is unbiased and the variance is minimized. Several datasets have used OK or its variant, block kriging, which allows for an OK performance on areas larger than one pixel (e.g., Aybar et al., 2019; Belo-Pereira et al., 2011; Contractor et al., 2020; Haylock et al., 2008; Herrera et al., 2012; Jones et al., 2013; Rubel & Hantel, 2001; Schamm et al., 2014; Shen et al., 2001). The second variant is regression kriging (RKRG) which is similar to OK because it also considers the trend as not constant on the spatial domain but dependent on the location of the observations. However, RKRG models the relationship between precipitation and other environmental variables at sample locations and applies it to ungauged locations (Hengl et al., 2007). Regression kriging has been widely used in datasets in the past decade (e.g., Aalto et al., 2016; Crespi et al., 2016; Hiebl & Frei, 2017; Spinoni et al., 2014).

Several other gridding methods exist that have been used to estimate precipitation. For example, from simple area averages (e.g., Becker et al., 2013; Liebmann & Allured, 2015) or bilinear interpolation (Abatzoglou, 2011) to more complex procedures such as CI (developed by Hewitson & Crane, 2005) or *optimal interpolation* (OI). The CI approach first defines the characteristics of the synoptic rainfall states in a region surrounding the target grid point, so it can determine the likelihood of a wet or dry day. Precipitation magnitudes are then interpolated using a weighted average of the nearest stations, where the station weights vary as a function of the angular distance and are "conditional" on the synoptic state (Hofstra et al., 2008). OI is a completely different approach that aims to provide the minimum error variance and an unbiased estimate of precipitation by combining prior information (i.e., background) on the grid with in situ observations. This method is not common for precipitation datasets and only two previous studies were obtained (i.e., Chen et al., 2002; Lussana et al., 2018). A method that uses a combination of station data with radar observations has recently been developed and has produced accurate results in overlapping periods of records (Barton et al., 2020; Dumitrescu et al., 2020). While radar data contributes to an accurate representation of the spatial distribution of precipitation, this method is limited to the creation of high temporal resolution grids (sub-daily). The nonlinear translation between the reflectance at the base of a cloud and the precipitation amount, however, requires further investigation, particularly regarding how these factors can impact temporal trends. Additionally, the scarce data coverage in temporal and spatial dimensions in most countries remains a challenge.

Last, it is worth mentioning the potential of the statistical inference (SI) in precipitation gridding, which is the basis of the RV that are developed at the grid nodes (point prediction), as opposed to the customary prediction at the entire grid cell (spatial prediction). Statistical interference allows the induction, from observations provided by a sample (observations), of the behavior of a particular population (precipitation at the spatial domain) with a measurable error margin in terms of probability. Although it is not a method per se (because most of its applications were created through regression methods) but an alternative approach; its consideration is important because it shares several characteristics with other interpolation methods (Serrano-Notivoli, de Luis, et al., 2017). For example, (i) it is a local method (like IDW or kriging) because it considers the nearest observatories, (ii) it is inexact (like any other interpolation method, except IDW) because the values at the rain gauges are not the originals but estimates based on the modeling of the various geographical parameters, (iii) it considers the spatial autocorrelation and rejects the precipitation that occurred far from the target grid point, (iv) it includes independent variables (like the regression methods) and weighting them according to the function of their importance in the observations. Statistical interference allows for the estimation of precipitation at any temporal scale over particular ungauged locations and focuses the climatic reconstruction at specific sites and tailors the spatial resolution to the research objectives, without restrictions.

6 | UNCERTAINTY

Uncertainty is referred to as the error associated with a dataset, either observed or estimated. These errors can have different origins according to the source of the observations or the method used for the estimation. Since the source of observation errors was previously addressed (see Section 3.1), the focus here is on modeling errors.

Errors in modeling are important because they can lead to biased results (Begueria et al., 2015; Fekete et al., 2004; Rowell, 2012; Tsintikidis et al., 2002) and they have been systematically ignored in most of the existing gridded datasets. Ignoring the potential errors in the observed data (most can be detected with a well-designed QC process) and assuming that statistical models have their own error terms, favors the propagation of uncertainties in the final estimates at an unknown magnitude.

6.1 | Sources of uncertainty

Gridded datasets are built from models, and that necessarily produces uncertainty. Several factors control the magnitude of uncertainty; however, in general, the station density and topographic factors are the most influential.

The station density can explain more than 60% of the variance regardless of other factors (e.g., interpolation method, observation representativity, etc.) (Herrera et al., 2019). This is related to the distance-decay relationship between the observations and the surrounding spatial region (Hewitson & Crane, 2005). Moreover, as the density of the stations decreases (an increase in the distance between stations) the uncertainty increases, which is an aspect that can have implications in further climatic analyses and must be carefully considered (Begueria et al., 2015; Merino et al., 2021).

Topographic factors, particularly elevation, are well-known covariates that condition the spatial occurrence of precipitation. Therefore, gridded products over high-elevation areas typically demonstrate poor performance compared to those with a more homogeneous orography. The type of climate also has an impact on the uncertainty due to the irregularity of the occurrence of precipitation. This is characteristic of Mediterranean to arid climates and results in difficulty obtaining an accurate prediction (Figure 4).

Additionally, great spatial and temporal variability and a lower density of observations increase the uncertainty of the estimates (Sharifi et al., 2019). Frei and Isotta (2019) proposed a method to minimize the impact on predictions that used an ensemble of possible fields that were conditional on the observations and dependent on local precipitation. The proposed method, although computationally demanding, was useful for demonstrating the need to focus on the

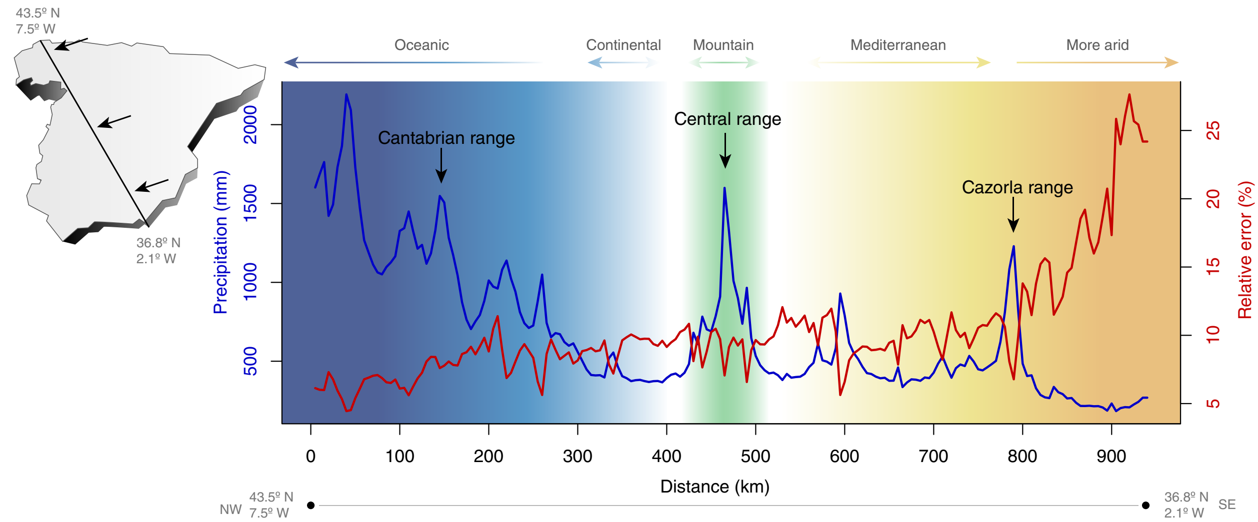

FIGURE 4 A profile graph of precipitation in Spain based on the SPREAD (Serrano-Notivoli, Begueria et al., 2017). The annual precipitation (blue line) is related to the type of climate (background colors), is more regular in oceanic environments and shifts to irregular toward Mediterranean and arid areas. The uncertainty of the precipitation estimates (red line) has the inverse behavior

propagation of uncertainty to precipitation applications (i.e., climate indices). The spatial resolution is also of paramount importance due to the relationships between the grid cells and the surrounding stations, with which precipitation is estimated. Merino et al. (2021) highlighted that an increase in the spatial resolution does not improve the reduction of uncertainty as much as the density of the observations; however, it becomes relevant in areas with strong altitudinal gradients due to the improved representativity of the estimates. Serrano-Notivoli, de Luis et al. (2017) demonstrated that precipitation-altitude interactions have a great influence at high elevations. The authors showed that grid cells at low elevations used stations at the same elevation range (usually below 1000 m a.s.l.), although cells that were located at higher elevations still used the low-elevation stations (Figure 5). This situation indicated that the number of stations at high elevations was not enough to equate precipitation reconstruction with lower elevations. Although the authors conducted the study in Spain (and included 12,848 stations), the altitudinal distribution of the observations was similar to that obtained in other countries. This confirmed a common issue in climatology: a lack of representativity at high elevations. The absence of observations in these areas leads to nonrealistic extrapolations in the predictions, particularly when using linear relationships (Daly et al., 1994; Daly et al., 2008), which is an issue regarding the study of the spatial distribution of any climatic variable (e.g., Chimani et al., 2013; Hwang et al., 2011; Marquínez et al., 2003).

Finally, the meteorological conditions at the moment of the observation, or the type of climate, also have a great impact on the reliability of the estimates. For example, low amounts of precipitation generally occur in dry seasons (zero values are common depending on the climate zone) and the events are typical of a small spatial extent, leading to higher uncertainty of the estimates, thus, producing low values of fit between observed and estimated precipitation.

6.2 | Measuring the uncertainty

Uncertainty provides quantitative information about the reliability of the estimated data in a way that can be translated to further calculations, such as precipitation indices or temporal aggregations. Uncertainty is directly related to the validation of the estimates. Most of the gridded datasets only compare observations and estimates and provide several error statistics, which may be enough to account for the global accuracy of the dataset; however, it does not provide sufficient information about the reliability of the data.

The estimation of uncertainty depends on the gridding method, so it varies spatially and from one-time step to the next, reflecting the changes in the conditions that affect the estimates. No established method exists to measure uncertainty, but it is always derived from the validation process of the model. Certain interpolation methods, such as OK, provide the variance of the predictions for the entire spatial domain, which has been demonstrated as a reliable measure of prediction errors (Heuvelink & Pebesma, 2002), and several gridded datasets used that as uncertainty

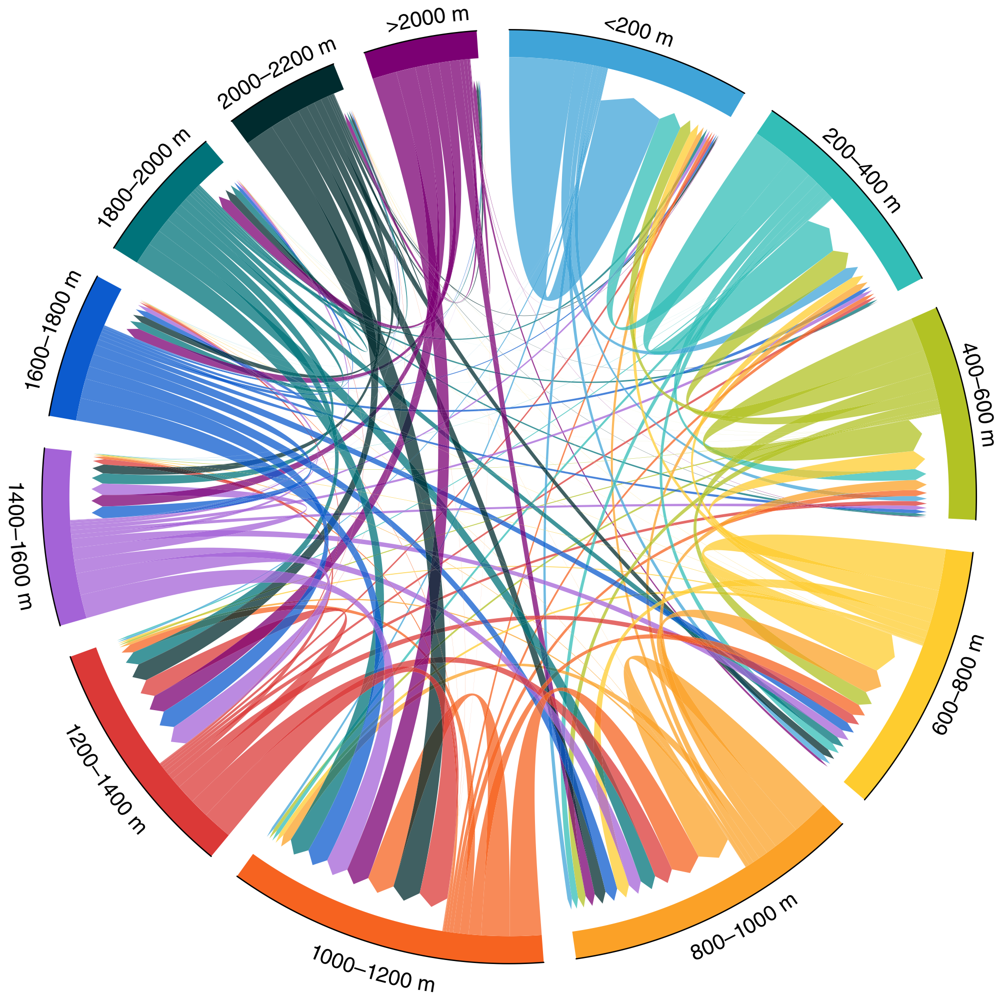

FIGURE 5 Altitudinal relationships in the SPREAD dataset (Serrano-Notivoli, de Luis, et al., 2017) between the grid points and the nearest 10 observatories. The labels show the elevation ranges (ER), which are represented by the colors. In each of them, the outgoing (incoming) arrows represent the proportion of grid points in that (other) ER using the nearest stations from the same or different ER

(Contractor et al., 2020; Frei & Schär, 1998; Haylock et al., 2008; Rubel & Hantel, 2001; Schamm et al., 2014). However, most of the existing datasets, particularly up to the 2000s, did not provide an explicit value of uncertainty (29%) or they included simpler expressions of the differences between the observations and predictions in the validation process (40%). These were regularly expressed using the RMSE, SD, MAE, MSE, BIAS, or correlation coefficients (codified as STATS in Table 1). The use of these error statistics can result in a misleading interpretation of the reliability of the dataset because they are representative of variables with a normal FD, which is not the case concerning precipitation (see Section 3.2). The correct approach for validating precipitation should include statistical tests that account for heavy-tailed FD or separate analyses of the goodness-of-fit (GOF) by percentile ranges. Also, as precipitation is greatly dependent on altitude (see Section 6.1), the GOF analysis by elevation ranges facilitates an understanding of how reliable the estimates are depending on their location.

Several other datasets applied a cross-validation process at the gridding stage based on a leave-one-out procedure (Daly et al., 2008; Isotta et al., 2014; Rauthe et al., 2013; Serrano-Notivoli, de Luis, et al., 2017) or a significant proportion of the original observations were reserved as a test dataset to validate the estimates that were built with the rest of the data (Belo-Pereira et al., 2011; Fick & Hijmans, 2017; Herrera et al., 2012; Hiebl & Frei, 2017; Jones et al., 2013). Finally, Cornes et al. (2018) used an alternative approach, based on a stochastic simulation, to produce an ensemble of realizations of each daily field, which is more typical of climate projections. The ensemble spread, used as a measure of the uncertainty, was calculated as the difference between the 95th and 5th percentiles from the 100 members at each grid box.

In addition to a statistical comparison of the estimates and observations, hydrological modeling is also used in the validation of gridded datasets (Beck et al., 2017; Lussana et al., 2018). This involves an indirect evaluation that compares runoff measures (or water balance) with precipitation amounts in the same period, generally using a distributed hydrological model. This is a useful practice in areas with scarce meteorological networks. The procedure, however, adds additional uncertainties. For example, due to differences in soil properties, vegetation, or type of precipitation (rain or snow), all catchments do not respond equally in space and time to the incident precipitation. Furthermore, changes in land cover over time can produce variations in runoff that are not attributable to precipitation. All these compounded uncertainties can largely affect the evaluation of precipitation, particularly at higher temporal resolutions (daily and sub-daily; Box 2).

7 | CONCLUSIONS: ADVANCES, GAPS, AND THE CHALLENGES OF GRID CREATION

This review of 48 studies that constructed gridded precipitation datasets revealed a wide range of data treatments for QC and spatial and temporal resolutions, but less so regarding gridding (interpolation) methods (Figure 6). Moreover, most of the datasets bypassed the intermediate step of reconstructing a quality-controlled data series to maintain temporal homogeneity, and many also failed to provide a measure of uncertainty.

Considering the techniques used in recent decades, gridded datasets have evolved to more complex approaches that provide higher accuracy and improved representations of the occurrence of precipitation over large areas. This evolution occurred in parallel with:

1. Advances in spatial analysis. Although the methods did not undergo dramatic changes or improvements (ADW, TPS and kriging are still the most used spatialization strategies), several new perspectives (e.g., based on the use of all the available information or different approaches for the representation of uncertainty) have fulfilled the need for high-resolution datasets.
2. Computational capacity, which has allowed for increases in the spatial and temporal resolution of the data and the inclusion of a higher number of observations and environmental variables that explain the precipitation variability.

BOX 2 A reliable gridding

- Most of the interpolation methods tend to smooth the extreme values and increase the lower ones. This issue is aggravated by (1) low density or uneven observations, (2) high temporal scales (daily and longer), and (3) arid climates with extremely low frequency of precipitation.
- The size of the grid box is significant over complex orography areas; however, it mainly depends on the density of observations.
- The amount of data is the most decisive factor in gridding: lower densities dramatically reduce the accuracy.
- What works for missing values reconstruction also works for gridding: decoupling the occurrence and magnitude improves the accuracy of wet or dry situations.
- MLR in any of its variants is the most accurate method when choosing the appropriate covariates. It is computationally expensive.
- TPS are appropriate for large heterogeneous areas, such as global and low resolutions (monthly to annual).
- AWD is advantageous as a weighting method but must be complemented with other climate-sensitive methods (considering the FD).
- Kriging methods yield effective results in larger areas, and covariates are recommended for local scales.
- A measure of error arising from the statistical model must be provided for each estimate. It provides information regarding reliability and aids in drawing the climatic characteristics.
- Validation cannot be addressed through statistics based on normal distributions. Datasets should be split by quantiles or elevation.

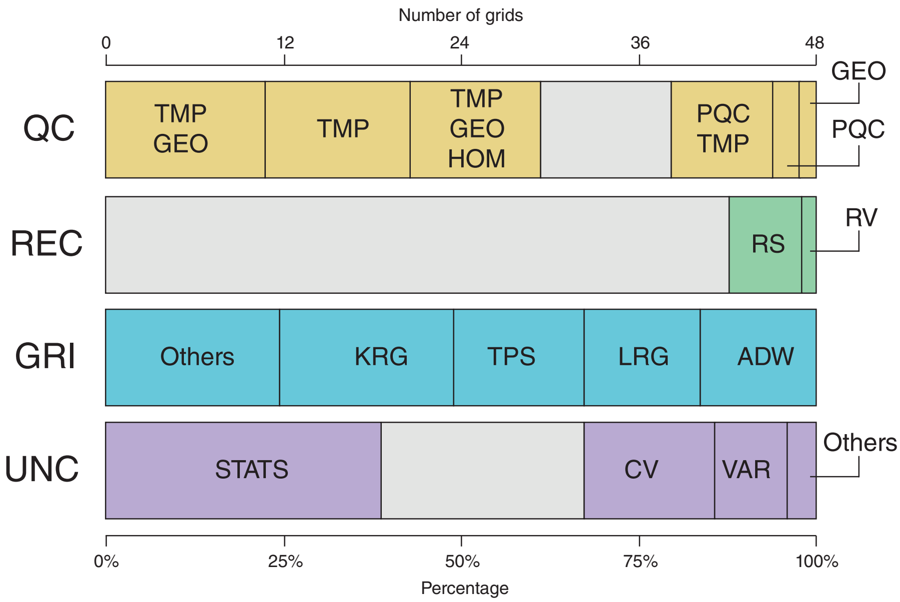

FIGURE 6 Percentage of the datasets (48 in total) that used the various techniques at each of the four stages: Quality control (QC), reconstruction (REC), gridding (GRI), and uncertainty (UNC). See Table 1 for a definition of the acronyms. The gray shaded boxes represent the absence of methods. KRG, LRG, and ADW also include combinations with other methods. LRG includes PRISM, and ADW includes Spheremap

3. Data availability. An increase in the number of instrumental locations in recent decades has been accompanied by unprecedented ease of access to these data, which has greatly contributed to the creation of new representations of precipitation, not only on a global scale but also for other regions of interest.
4. These three factors have dramatically improved the creation of gridded precipitation datasets, yet challenges and gaps remain that must be resolved to fulfill the new demands. In this regard, the new generation of grids will most likely encounter a new demand of representativity for the datasets in near real-time conditions. Thus, there are two potential challenges to be solved:

- First, most of the grids rely on the known average climate to obtain spatially coherent surfaces and a general climatic signal for the entire spatial domain. This is useful for certain purposes; however, it often fails to provide reliable estimates. There are several areas in the world, such as high-elevation mountains or remote areas (e.g., large tropical forests, deserts), for which the models do not accurately reproduce the behavior of the precipitation. This is due to uneven locations and the inaccessibility of rain gauges, and also the use of all-purpose models that do not reflect the local conditions of such a high-scattered variable as precipitation.
- Second, most of the gridding (and reconstruction) methods require relatively long data series, which avoids the optimal use of available information. If short data series are rejected, precious precipitation representativity is lost. This is also associated with an aspect that is dependent on the administrations and not the researchers: most of the climatic information remains unavailable due to administrative restrictions, resulting in extreme difficulty in creating an intercomparison between countries.

The main limitation of observational gridded datasets is that observational coverage is scarce. Consequently, an accurate estimate of precipitation at the same level for all regions of the world is extremely difficult when using large-scale observations. However, spatial gaps could be complemented with other sources of observations such as satellite information or radar-based data. Despite their different nature, several processes can be applied to fit satellite or radar-based data in a single dataset, as has been performed in several studies (e.g., Ashouri et al., 2015; Joyce et al., 2004). In this regard, *data assimilation* approaches have already been applied in climatic forecasting (Penny & Hamill, 2017; Xie et al., 2003) and the first attempts involved observational gridded datasets (e.g., Abatzoglou, 2011). This would help to keep the grids updated and reliable; however, these types of implementations require great computational resources. An intercomparison with other datasets could also help to quantify uncertainties in grids in specific locations, types of climate, or precipitation regimes that are difficult to estimate using only station-based observations. Reanalysis products, which are built in a completely different manner but with a higher spatial and temporal resolution, can provide complementary information to evaluate the uncertainty of precipitation.

New opportunities based on several technical advances will aid in solving previous issues (which should be addressed) and improve the reliability of the gridded datasets. For example, machine learning techniques (e.g., convolutional neural networks, deep learning, etc.) that have been applied to detect patterns in climate models (e.g., Chen et al., 2020; Weber et al., 2020; Yu et al., 2020) could greatly aid in the estimation of precipitation at ungauged locations. Accordingly, the use of *high-performance computing* (HPC) is essential for extensive, expected amounts of data. Managing multi-dimensional datasets (commonly used for gridded datasets) requires an optimum working strategy to extract the most effective outcomes at a scientific and computational level. Consequently, highly efficient workflows must be designed and implemented in advance to benefit from the computational advantages of working with HPC architectures. For example, strategies based on the dynamical splitting of raw data (Hoyer & Hamman, 2017; Manubens et al., 2018) can be utilized to take advantage of distributed computer architectures.

Finally, accurate, versatile, and computationally efficient methods are highly valued. The new challenge is, therefore, to obtain a balance between reliability at high spatial and temporal resolutions and present-day information, without losing the long-term perspective that climate studies deserve.

ACKNOWLEDGMENTS

This work was supported by the Government of Aragón through the "Program of research groups" (group H09_20R, "Climate, Water, Global Change, and Natural Systems"). Ernesto Tejedor is partially funded by the NSF-PIRE (OISE-1743738).

CONFLICT OF INTEREST

The authors have declared no conflicts of interest for this article.

AUTHOR CONTRIBUTIONS

Roberto Serrano-Notivoli: Conceptualization (equal); formal analysis (equal); investigation (equal); methodology (equal); writing—original draft (equal); writing—review and editing (equal). **Ernesto Tejedor**: Conceptualization (equal); formal analysis (equal); investigation (equal); methodology (equal); writing—original draft (equal); writing—review and editing (equal).

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

ORCID

Roberto Serrano-Notivoli https://orcid.org/0000-0001-7663-1202
Ernesto Tejedor https://orcid.org/0000-0001-6825-3870

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How to cite this article: Serrano-Notivoli, R., & Tejedor, E. (2021). From rain to data: A review of the creation of monthly and daily station-based gridded precipitation datasets. *Wiley Interdisciplinary Reviews: Water*, *8*(6), e1555. https://doi.org/10.1002/wat2.1555