Data Article

High-resolution gridded hourly precipitation dataset for Peru (PISCOp_h)

Adrian Huerta*, Waldo Lavado-Casimiro, Oscar Felipe-Obando

Servicio Nacional de Meteorología e Hidrología (SENAHMI), Calle Cahuide 785, 11, Jesús María, Lima, Perú

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A B S T R A C T

This article introduces a high-resolution (0.1°) gridded dataset of hourly precipitation across Peru for the period 2015–2020, called PISCOp_h. The product was developed using a temporal disaggregation technique based on the gridded daily precipitation dataset PISCOp and additional data from 309 automatic weather stations and three satellite precipitation products (IMERG-Early, PERSIANN-CCS, and GSMaP_NRT). The workflow of PISCOp_h involved the spatial interpolation of hourly precipitation and a bias correction of the diurnal rainfall cycle. Based on a technical validation, we demonstrated that PISCOp_h provides moderate to high efficiency in characterizing the frequency, intensity, and temporal coherence of hourly precipitation, particularly in central and southern Peru. PISCOp_h represents an important advance to construct gridded hourly precipitation products under challenging environmental conditions in, e.g., mountain regions with complex terrain. This new dataset provides a useful baseline for future studies in hydrology, climatology, and meteorology. The data collection described is available on figshare: https://doi.org/10.6084/m9.figshare.c.5743166.

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* Corresponding author.
E-mail address: adruerta@gmail.com (A. Huerta).

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Specifications Table

| Subject                        | Earth and Planetary Sciences        |
|-------------------------------|-------------------------------------|
| Specific subject area         | Hydrology, Meteorology, Climatology |
| Type of data                  | Geolocated gridded files            |
| How the data were acquired    | Automatic weather stations and PISCOp (daily gridded product) were obtained from the National Service of Meteorology and Hydrology of Peru. Non-gauge-corrected satellite-based precipitation products (IMERG-Early, PERSIANN-CCS, and GSMaP_NRT) were downloaded from their websites. The gridded data was constructed and performed using R (v3.6.3.) and Python (v3.8.5) environments. All codes are available at https://github.com/adrHuerta/PISCOp_tdisaggregation |
| Data format                   | Data are in .nc (NetCDF files)      |
| Description of data collection| The final dataset consists of a collection of four gridded products of hourly precipitation for the period 2015–2020 at 0.1° spatial resolution. |
| Data source location          | Institution: Servicio Nacional de Meteorología e Hidrología |
|                               | Country: Peru                        |
|                               | Latitude and longitude for collected data: 0.95°N-18.75°S, 81.25°W-68.05°W |
| Data accessibility            | Repository name: Figshare            |
|                               | Direct URL to data: https://doi.org/10.6084/m9.figshare.c.5743166 |

Value of the Data

- This article provides the development of a high-resolution gridded hourly precipitation dataset called PISCOp_h. This new product represents the first hourly gridded dataset in Peru based on a temporal disaggregation technique using the gridded daily precipitation dataset PISCOp and additional data from 309 automatic weather stations and three satellite precipitation products.
- This dataset provides an important baseline for hydrological modelling, such as the calibration and validation of hydrological models at different spatial scales in Peru.
- PISCOp_h is of great value for the assessment of impacts and risks of extreme precipitation in Peru. For the first time, the spatio-temporal characteristics of this dataset allows modelling at high resolution in Peru.
- This dataset is made up of multiple NetCDF files using the CF convention, sharing similar time coordinates. This format guarantees easy data processing, use and sharing.

1. Data Description

1.1. Gridded Files

The dataset comprises four gridded products covering the Peruvian area at 0.1°x0.1° spatial resolution and hourly temporal resolution for precipitation (millimeters) from 2015 to 2020. Each product is the result of the applied methodology (see next section for details), including different precipitation sources such as the gridded daily precipitation dataset PISCOp [1], automatic weather stations (AWSs) and three satellite-based precipitation products (SPPs). All products can be found on figshare [2] as follows:

- **SAT**: hourly precipitation based on a linear average of three non-gauge-corrected SPPs (IMERG-Early [3], PERSIANN-CCS [4] and GSMaP_NRT [5]).
- **SATc**: hourly precipitation based on a linear average of three non-gauge-corrected SPPs with a diurnal bias correction using AWSs
- **PISCOp_h_non-DBC**: hourly precipitation based on the temporal disaggregation of PISCOp using SAT.
- **PISCOp_h**: hourly precipitation based on the temporal disaggregation of PISCOp using SATc.

Gridded files are provided in NetCDF (extension .nc), a self-describing file format that can be read using scripting languages (Python, Matlab, R, etc.) and graphical user interfaces (GIS,
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Fig. 1. Spatial distribution of the hour with the maximum value (at local time) and amplitude of the diurnal cycle during austral summer for the period 2015–2020 for the gridded products (PISCOp\textsubscript{h} and PISCOp\textsubscript{h\_non-DBC}) and automatic weather stations (AWSs).

Panoply, etc.). Each file is defined by three dimensions (time, latitude, longitude) and one variable (\(p\) - hourly precipitation). Each day in the temporal dimension begins at 00 h until 23 h, corresponding to the 08 h (at local time) until 07 h of the next day (at local time), respectively. The simple accumulation at a daily scale (of PISCOp or PISCOp\textsubscript{h\_non-DBC}) using the predetermined temporal dimension provides the daily value of PISCOp, which is the same as in the conventional stations. It should be mentioned that a temporal shift of eight (+8) times should be done to obtain the temporal dimension as in the original AWSs.

Although PISCOp\textsubscript{h} and PISCOp\textsubscript{h\_non-DBC} are the main output of this article, we also provide SATc and SAT. The intention of sharing these data is based on the fact that they can be used for other applications in conjunction with other variables already established in Peru, such as reference evapotranspiration [6] and air temperature [7]. Finally, it should be mentioned that PISCOp\textsubscript{h} will be updated according to the availability of PISCOp.

1.2. Gridded Files Illustration

This article introduces the first gridded hourly precipitation dataset that merges PISCOp, AWSs and SPPs in Peru. Thus, it offers a diversity of potential applications to assess precipi-
tation variability at a sub–daily scale. Here we illustrate a brief analysis at climatological scale of PISCOp_h (PISCOp_h_non-DBC) by characterizing the diurnal cycle (2015–2020).

Fig. 1 depicts two key parameters of the diurnal cycle: the time of the maximum value (at local time) and the amplitude (maximum minus minimum value during the day) for austral summer using the disaggregated dataset and AWSs. Maximum precipitation tends to oscillate between 16–22 h and 4–10 h in the entire study area. It can be observed that higher spatial variability is present in mountain regions, particularly in the centre/southwestern Andes, where different peaks of maximum rainfall can be found. The amplitude parameter exhibits a more complex spatial variability, where the maximum values are located in the Andes and Amazon. Interestingly, the maximum values outline the complex topographic limits of the Andes-Amazon and Pacific Coast-Andes regions.

Finally, the bias correction effect can be noticed in the amplitude of the diurnal cycle which tends to be overestimated by PISCOp_h_non-DBC. On the other hand, PISCOp_h and AWSs are more similar in magnitude. Similarly, during the hour of maximum precipitation, we found that the bias correction modified the values in the southern, central (Andes), and northern (Pacific Coast) areas.

2. Experimental Design, Materials and Methods

2.1. Overview

We applied a temporal disaggregation technique of 24 h accumulated gridded product (PISCOp) with merged SPPs and AWSs data to produce hourly precipitation fields (PISCOp_h). The development of PISCOp_h presented four stages (Fig. 2): (i) First, we established the auxiliary precipitation product SAT, built through a linear average of three SPPs. (ii) Second, AWSs were spatially interpolated using Inverse Distance Weighting (IDW). (iii) Third, the daily precipitation cycle in SAT is corrected with the spatially interpolated AWSs using a diurnal bias correction (DBC) procedure; the corrected SAT is called SATc. (iv) Finally, SATc is employed for the temporal disaggregation of PISCOp to obtain PISCOp_h. In addition, PISCOp_h_non-DBC was produced, following the same workflow but omitting the DBC procedure. This additional product was made...
to examine the added value of DBC in PISCOp_h. The used data sources and applied processes are presented in the following subsections.

2.2. Data Collection

2.2.1. Automatic Weather Stations

The observed hourly precipitation data were provided by SENAMHI which maintains a network of 323 AWSs within Peru (Fig. 3). AWSs have been available since 2000, however, only recently since about 2015 the number of stations has substantially increased. In this work, we used AWSs that present at least 5% of data for the period 2015–2020, comprising 309 AWSs. The spatial distribution of AWSs is uneven with less (more) AWSs in the Amazon (Pacific Coast and Andes) area (Fig. 3), and substantially varying distance between AWSs.

By convention, the daily totals correspond to the accumulated value reported at 07:00 and 07:00 (UTC-5) of the next day. All precipitation data underwent automatic quality control.

2.2.2. Satellite-Based Precipitation Products

This study employed three SPPs to develop PISCOp_h, i.e., IMERG-Early, –PERSIANN-CCS, and GSMaP_NRT (for more details see Table 1). Although non-gauge-corrected SPPs typically perform poorer compared with post-processing SPPs, they have the advantage of reduced latency, which is vital for hydrological forecasting. The selected SPPs were downloaded and processed for the period 2015–2020 at hourly scale.

Any missing values in the PERSIANN-CCS dataset were filled by linear temporal interpolation. Furthermore, the temporal coordinate of the SPPs was shifted twice to match the local
time and the total daily values of precipitation. Finally, the three SPPs were merged through a linear average to obtain SAT at 0.1° spatial resolution. Unlike using a single product, it is more representative to use the average of all SPPs, since there would not be a single best-performing product across the entire territory.

2.2.3. **PISCOp**

In this study, PISCOp (version 2.1) represents the reference dataset for temporal disaggregation of daily precipitation. PISCOp 2.1 has been available since 1981 at 0.1° spatial resolution and can be freely accessed (http://iridl.ldeo.columbia.edu/SOURCES/SNAMHHL/HSR/PISCO/Prec/). This dataset is a blended precipitation product of three sources: quality-controlled and gap-filled station observations, satellite-derived observations from TRMM 2A25, and from the gridded CHIRP (Climate Hazards Group InfraRed Precipitation) dataset. Its development involves a climatological CHIRP correction on monthly scales using TRMM and station values. This product provides the basis for merged daily and monthly precipitation using Kriging and IDW interpolation techniques, respectively. Likewise, a monthly correction factor is added to provide a higher spatial consistency to the daily estimates and ensure that the monthly aggregation of the daily product matches the monthly product. An independent validation and a comparison of the respective water balance show that PISCOp 2.1 performs reasonably well with highest efficiency over the Pacific Coast and western Andes (Fig. 3).

2.3. **Generation of PISCOp_h**

2.3.1. **IDW Interpolation**

IDW is a deterministic interpolation method where the predicted value is a spatially weighted average of the sample values within a search radius. We used this approach to obtain gridded hourly precipitation values from AWSs (used for the DBC in SAT). The hourly rainfall was calculated as:

\[
\hat{Z}(s_0) = \sum_{i=1}^{N} \omega_i Z(s_i)
\]

Where: \(s_0\) is the location of the prediction grid; \(s_i\) are the locations of the AWSs within the search radius; \(\hat{Z}(s_0)\) is the predicted hourly precipitation; \(N\) is the number of AWSs; \(\omega_i\) are the weights assigned to each AWSs; and, \(Z(s_i)\) are the hourly precipitation values from AWSs. The weights were determined as:

\[
\omega_i = \left( \frac{1}{d_{i0}^\rho} \right) / \sum_{i=1}^{N} \left( \frac{1}{d_{i0}^\rho} \right)
\]

Where: \(d_{i0}\) are the Euclidean distances between the prediction grid and sample AWSs; and, \(\rho\) is the user-defined power or distance exponent value (\(\rho = 2\)).

2.3.2. **Diurnal Bias Correction**

The SPPs (SAT) in this study were used for the temporal disaggregation of daily precipitation. Although SPPs provide an estimation of the diurnal cycle over the entire territory, they may

| Product       | Timespan      | Version | Spatial coverage | Temporal resolution | Spatial resolution |
|---------------|---------------|---------|------------------|---------------------|-------------------|
| IMERG-Early   | 2000/06 - Present | 6B      | 60°N-60°S       | Half-hourly         | 0.1° x 0.1°       |
| PERSIANN-CCS  | 2003/01 - Present | 1       | 60°N-60°S       | Hourly              | 0.04° x 0.04°     |
| GSMaP_NRT     | 2000/03 - Present | 6       | 60°N-60°S       | Hourly              | 0.1° x 0.1°       |
exhibit several limitations, specifically in mountain regions with complex terrain. Therefore, a diurnal cycle bias correction was conducted in SAT to improve the overall confidence of the final dataset. Recent work has demonstrated that diurnal cycle correction allows hydrological simulations to represent the diurnal streamflow cycle in small catchments accurately [8].

Quantile mapping bias correction algorithms are commonly used to correct systematic distributional biases in precipitation outputs from climate models, and they are effective at removing historical biases relative to observations. We applied this approach to SAT correction, using the DBC variant that recognizes that raw model biases are not constant throughout the diurnal cycle (e.g. daylight biases may differ from nighttime biases). Bias corrections were computed for each hour, using a three-hour moving window to pool all hourly values within a given month before applying the quantile delta mapping algorithm [9]. The transfer function was, thus, set as:

$$\hat{x}_{s,c} = x_{s,c} \frac{F_{\tau,c}^{-1}[\tau_{s,c}]}{F_{\tau,c}[\tau_{s,c}]}$$

$$\tau_{s,c} = F_{\tau,c}[x_{s,c}], \quad \tau_{s,c} \in \{0, 1\}$$

Where: $\hat{x}$ is the corrected hourly precipitation; $x$ is the raw hourly precipitation; $F$ is the cumulative distribution function (CDF); $F^{-1}$ is the inverse CDF; $\tau$ is the nonexceedance probability associated with the value; the subscripts $s$ and $o$ equates to the satellite (SAT) and observed (AWSs) data, respectively; the subscript $c$ corresponds to the sample value for each time step (8760 steps from January to December), while $c$ to the full-time sample (three hours range). The bias correction of SAT leads to SATc.

2.3.3. Disaggregation

A temporal disaggregation [10] of the daily precipitation based on the evolution of rainfall seen by the SPPs was performed. This procedure combines the advantages of PISCOp (accuracy at the daily timescale) with that of the SPPs (diurnal cycle estimation). The disaggregation was carried out as follows:

$$R(s_0, t_i) = \frac{E(s_0, t_i)}{\Sigma_i E(s_0, t_i)} R_d(s_0, t_i); \quad 0 \ll t_i \ll 23$$

Where: $R(s_0, t_i)$ is the disaggregated hourly precipitation at grid $s_0$ and time $t_i$ (hour); $E$ is the hourly precipitation value from the SPPs and $R_d$ is the daily precipitation (PISCOp). The construction of PISCOp_h (PISCOp_h_non-DBC) sets $E$ as SATc (SAT). This approach distributes the daily total into hourly slices, but preserves the daily precipitation totals.

In some cases, PISCOp and SATc (SAT) presented inconsistencies and the following rules have been applied to overcome missing or contradicting observations:

- PISCOp captured precipitation while SATc (SAT) did not: the hourly disaggregated values were processed equally into 24 hourly parts (1/24).
- SATc (SAT) captured the precipitation while PISCOp did not: the hourly disaggregated values were all set to zero to meet the ground truth observations.

2.4. Technical Validation

Evaluation of the disaggregated dataset was based on the temporal variability of precipitation at local scales. For that purpose, the gridded products were compared with the point-pixel approach. Although a time series at a grid point is not fully comparable to an AWS due to the spatial resolution, we aimed to test the reliability of the datasets concerning variations in the time that are obtained from the SPPs. The selected metrics evaluate aspects of the frequency and intensity distribution to systematic measures of temporal correlation [10], as follows:

- Frequency ratio (Fr):

$$\frac{F_D}{F_S}$$
Fig. 4. Spatial distribution of the frequency (a) and intensity (b) ratio for the period 2015–2020 between the gridded products (PISCOp_h and PISCOp_h_non-DBC) and automatic weather stations (AWSs) for austral summer (months 12, 01 and 02) and winter (months 06, 07 and 08).

Where: $F_D$ is the frequency of hourly precipitation (equal to or larger than 0.1 mm) in the disaggregated dataset (PISCOp_h or PISCOp_h_non-DBC) and $F_S$ is the frequency in AWSs.

- Intensity ratio (Ir):

$$\frac{I_D/I_S}{M_D/M_S}$$

Where: $M_D$ and $M_S$ equal the mean precipitation of the disaggregated dataset (PISCOp_h or PISCOp_h_non-DBC) and the co-located AWS, respectively. $I_D$ and $I_S$ are the precipitation intensities, i.e., the average precipitation rate during wet hours (equal to or larger than 0.1 mm).

- Standardized mean absolute difference (MAD):

$$\frac{1}{n} \sum_{i=1}^{n} \left| \frac{r_{D_i}}{I_D} - \frac{r_{S_i}}{I_S} \right|$$

Where: $r_{D_i}$ and $r_{S_i}$ correspond to the hourly time series (with $n$ samples) of the disaggregated dataset and target AWS, respectively. The scaling of hourly precipitation rates by the respective climatological precipitation intensity is performed to, (1) make this metric less sensitive to systematic biases, and to (2) make MAD comparable between AWSs with different average intensities.

The metrics were only applied in AWSs that (at least) presented 50% of data for the period 2015–2020. This lead to a total of 214 AWSs.

2.4.1. Frequency and Intensity of Precipitation

Fig. 4 illustrates the frequency (Fr) and intensity (Ir) ratio for two seasons (austral summer and winter) from 2015 to 2020. The central and southern Andes show good performance (green points) for both metrics, particularly in the wet season (austral summer). Conversely, the precipitation frequency (intensity) tends to be underestimated (overestimated) in the northern parts (Pacific Coast and Amazon) mostly during austral winter.
A bias in frequency follows the bias of the intensity ratio. More rainfall during short periods (e.g., a day) leads to a lower intensity in the hourly precipitation. This situation might be related to the fact that SPPs tend to characterize more precipitation peaks in those areas. This can positively influence the austral summer due to shorter rainfall events; the opposite can be found for the austral winter when rainfall events are limited. In addition, we did not find any efficiency effect based on elevation; however, a bias correction (DBC) influence was evident. PISCOp_h provides a better coherence with the AWSs rather than PISCOp_h-non-DBC. PISCOp_h, shows a ratio range of 0.75–1.25 (green symbols, Fig. 4), notably during austral summer.

In general, PISCOp_h can exhibit dissimilarities in the mean frequency and intensity in the northern areas of Peru (Pacific Coast and Amazon). However, the results were acceptable over the Andes, particularly in the central and south regions. Here, the metrics (Fr and Ir) were within ±25% of the observed values (austral summer).

### 2.4.2. Temporal Evolution

The temporal alignment of precipitation peaks between the disaggregated dataset (PISCOp_h and PISCOp_h_non-DBC) and AWSs was quantified using the standardized MAD metric. Fig. 5 exhibits MAD values for two seasons (austral summer and winter) from 2015 to 2020. There is a noticeable difference between the seasons; lower (higher) values are found in austral winter (summer) varying from 0 to 0.1 (0.2 to more), particularly in the western Andes. Additionally, MAD values tend to be less than 0.25 for entire Peru, suggesting that the disaggregated products are within 25% of the AWS value after systematic bias correction.

The more considerable disparity in the western Andes (in austral summer) could be attributed to the limited representation of PISCOp (conventional stations only) and the AWSs mea-
surements. It should be mentioned that PISCOp was built using gauge stations rather than AWSs. Therefore, considerable differences for both types of stations can be expected [11]. Although there is no substantial difference in the DBC application, PISCOp_h presents a slight improvement over PISCOp_h_non-DBC (higher number of red points, Fig. 5).

The dissimilarity between PISCOp_h and AWSs seems related to the methodological approach, the data used, and the perspective of random errors. Locations of higher errors can be taken as regions where the disaggregated products are less reliable.

Ethics Statements

Not applicable

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

High-resolution gridded hourly precipitation dataset for Peru (PISCOp_h) (Original data) (figshare).

CRediT Author Statement

Adrian Huerta: Conceptualization, Methodology, Data curation, Writing – original draft; Waldo Lavado-Casimiro: Writing – review & editing; Oscar Felipe-Obando: Writing – review & editing.

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