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RESEARCH ARTICLE

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Continuity of daily temperature time series in the transition from conventional to automated stations for the Colombian coffee network

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Abstract

The transition from conventional weather stations (CWSs) to automated weather stations (AWSs) of the Colombian coffee network has required testing their performance and adjusting the temperature measurements to ensure the continuity of the historical CWS series. In this study, the mean (T_{mean}), minimum (T_{min}), and maximum temperature (T_{max}) measurements of CWS and AWS operating in parallel at 36 locations between 2014 and 2019 were compared, and the biases of the daily temperature differences (CWS − AWS), the agreement index (d), and the percentage of data within the allowed range (PR05) were calculated. The most consistent method for calculating T_{mean} and T_{max} for CWS was selected for use on the AWS data. With the standard normal homogeneity test and with the metadata, we found that the series of temperature differences between CWS and AWS was not homogeneous, instrument failures and sensor changes being the main causes of the lack of homogeneity. The statistical analyses indicated that the AWS data need to be adjusted to be continuous with the CWS series. To correct the temperature bias, two approaches were applied: quantile mapping and the additive constant. The results suggest that the quantile mapping adjustments improve the average bias at all stations but do not necessarily bring the percentage to within ±0.5°C. In T_{min} and T_{mean}, 12 AWSs can give continuity with the historical series of the CWS, and for the rest of the stations and variables, the series of the AWSs are independent of the CWSs.

KEYWORDS

additive constant, automatic weather stations, conventional weather station, daily temperature, meteorological observation, parallel observations, quantile mapping, temperature bias

1 | INTRODUCTION

In the Colombian Coffee Zone, meteorological monitoring for more than 50 years has been carried out mainly by conventional weather stations (CWSs), whose data have been critical for relating weather to coffee cultivation, its phenology, phytotechnics, pests, and diseases and to support decision-making in crop management. Motivated to improve the monitoring of meteorological factors at a better temporal resolution and to have nearly real-time data in order to improve crop management, an agreement was made between the Ministry of Agriculture and Rural Development of the Colombian government and the National Federation of Coffee Growers of Colombia (FNC) to install automated weather stations (AWSs). The National Coffee Research Center (Cenicafé), administrator of the Coffee Meteorological Network, responded to a suggestion of the World Meteorological Organization (World Meteorological Organization, 2017) to continue measuring in parallel during the transition of stations for 2–5 years at a total of 41 stations according to the variables measured.

In the last 20 years, the government meteorological networks of different countries have made the transition from conventional to automated networks and have evaluated the ability of the AWS observations to give continuity with the historical series of the CWS, by comparing their data, documenting the characteristics and differences between the conventional and automated network series, and adjusting the AWS data (Allard et al., 2016; Almeida, 2013; Karatarakis et al., 2013; Karki, 2010; Kaspar et al., 2016; Matuszko & Nowak, 2018; Ying et al., 2006). Generally, such transitions lead to errors and biases in the measurement (Thorne et al., 2018), or what are commonly known as non-climatic variations, resulting in inaccurate data (Fiebrich & Crawford, 2009; Trewin, 2010; Wu et al., 2005). One of the variables that have been analysed is temperature, since the switch from a liquid in glass thermometer capsule in CWSs to an electronic thermometer in AWSs can lead to different response times (Wendland & Armstrong, 1993). It is necessary that both the location and the measuring instruments be subjected to periodic inspections and verifications. Errors in temperature cannot be avoided, but those caused by the sensors, the effect of the environment or the location can be routinely reduced, staying within a margin of $\pm 0.2°C$ suggested by the World Meteorological Organization (World Meteorological Organization, 2018b), but in other studies (Vincent et al., 2018) and in work by Cenicafé, it was defined as $\pm 0.5°C$, specifically in the coffee network because of the characteristics of the sites (World Meteorological Organization, 2018a) and their being located in tropical mountain conditions (Whiteman, 2000), which increases the error.

Cenicafé (2015, 2017), on the other hand, reviewed the mean, maximum, and minimum temperature variables of the stations that operate in parallel and detected that the automated station data overestimate the data recorded by the conventional station. This led to the development of a quality control procedure for AWSs (Cenicafé, 2018) and to further parallel measurements with the aim of ensuring valid comparisons.

Identifying these differences and non-climatic variations found in parallel measurements through a statistical analysis of homogeneity is essential, as it will allow the identification of the critical points of the series that work in parallel, accompanied by metadata that document the shifts over time (Trewin, 2010). Numerous approaches have been taken to detect discontinuities in climate series, and numerous computer packages can be used to study homogeneity (Easterling & Peterson, 1995; Guijarro, 2018; Wang, 2008; World Meteorological Organization, 2020). The standard normal homogeneity test (SNHT) (Alexandersson, 1986) is one of the better-performing methods and is used for temperature datasets, accurately detecting the date of a changepoint or discontinuity of the series (Dikbas et al., 2010; Ducré-Robitaille et al., 2003; Firat et al., 2012; Lee et al., 2012; Menne & Williams, 2009).

Most studies agree that after detecting that there is non-homogeneity in the series, bias correction techniques should be used when the differences are significant. To preserve the continuity of the historical temperature series with the data from the automated stations, different bias correction methods have been used, such as adjusting the mean value and constant temporal compensation that corrects the daily variability and the discontinuities in month-to-month transitions (Hempel et al., 2013), as well as quantile mapping, which surpasses the simplest bias correction methods, as the latter correct only the mean and variance of the series (Gudmundsson et al., 2012). In a set of data from stations in Canada, Vincent et al. (2012) adjusted the discontinuities using a quantile mapping algorithm (Wang et al., 2010) with the use of a reference series. Similarly, climate researchers from the Science and Technology Branch for Environment and Climate Change of Canada (Milewska & Vincent, 2016; Vincent et al., 2018) used the procedures of seasonal bias, monthly interpolation, multiple regression, and quantile mapping to produce daily adjustments in the parallel observations of temperatures with overlapping periods of up to 5 years. The authors indicated that the quantile mapping adjustments can provide a better estimate than the other methods evaluated.

Few studies have documented the transition from CWSs to AWSs of meteorological networks of agricultural producers. The process that the FNC has carried out over the last 7 years is an important step towards a better temporal resolution, but it would be inappropriate for AWS series to continue from the historical series of the CWS without a bias correction, since it has always been desired to provide quality meteorological data to researchers and coffee producers in Colombia to enable better decision-making about the crop. For this reason, the objective of this study is to determine whether the temperature variable recorded in the AWS requires an adjustment to give continuity to the CWS series or if the two should continue as independent series. The results of this study will be timely to give continuity to historical time series, preserving their homogeneity.

2 | MATERIALS AND METHODS

In the structural organization of the information, the daily data of 36 pairs of conventional and automated stations that share a site were used, located in the Colombian Coffee Zone (Figure 1). For each pair of stations, the mean (T_{mean}), maximum (T_{max}), and minimum temperatures (T_{min}) were considered. They were measured in the conventional stations by Lambrecht thermohygrographs and maximum and minimum glass thermometers, with a measurement range between −40 and 80°C and an accuracy of ±0.3°C, that were housed in a Stevenson wooden screen. In the automated stations, they were measured by Vaisala HMP60 electronic thermistors, with a measurement range between −40 and 60°C and accuracy of ±0.5°C, that were housed in a plastic polycarbonate radiation shield. All instruments were placed at a height of 2 m.

At the conventional stations, three readings of information were made, at 7 AM, 1 PM, and 7 PM, and the

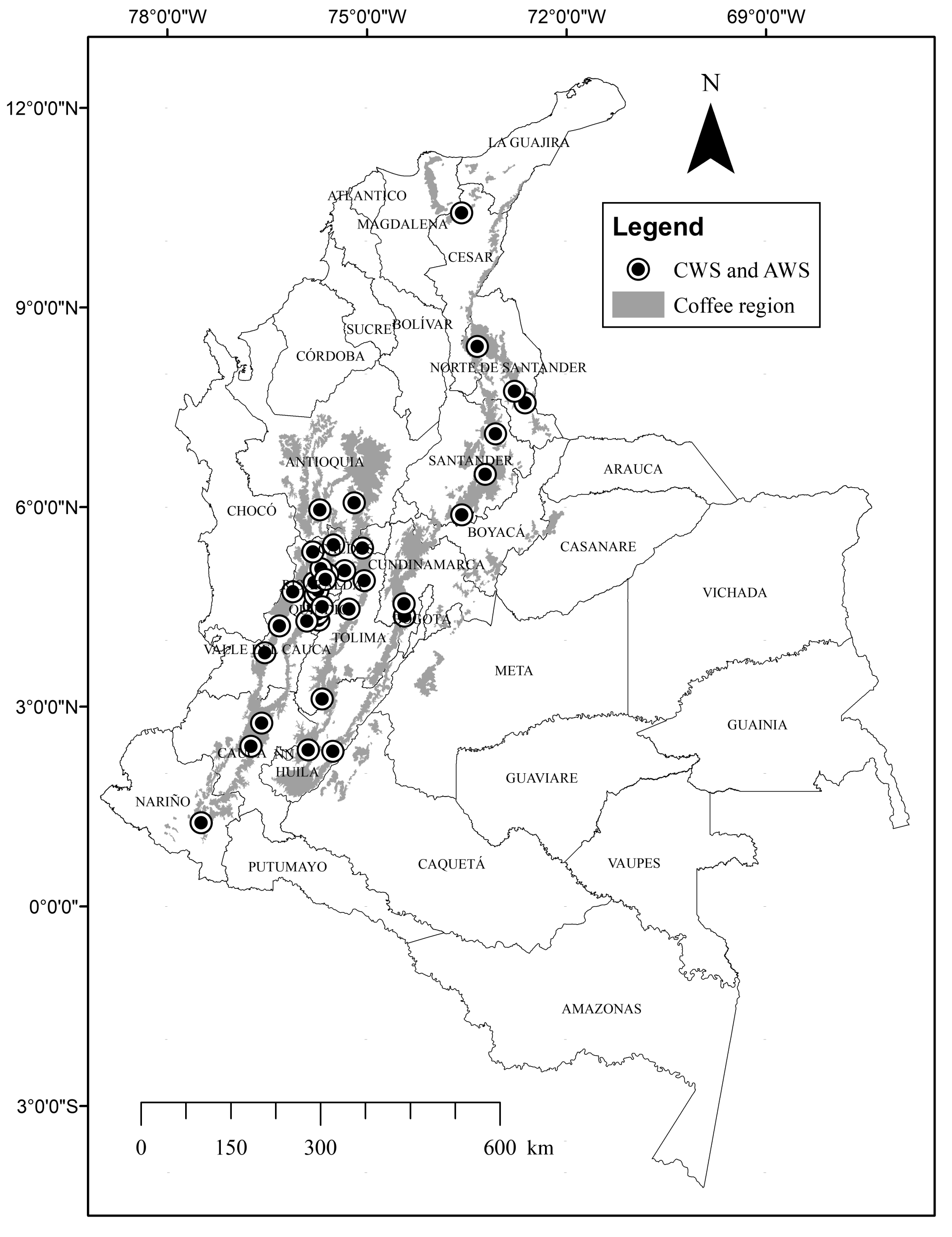

FIGURE 1 Locations of automated and conventional weather stations operating in parallel

automated stations had 288 5-min data readings, each one corresponds to the average of 60 instantaneous readings every 5 s in a period of 5 min.

2.1 | Mean daily temperature

At the conventional stations, temperature was measured at 7 AM, 1 PM, and 7 PM. T_{mean} was calculated with the following equation:

$$T\text{mean}_{\text{CWS}} = \frac{T_{7AM} + T_{1PM} + 2T_{7PM}}{4}. \quad (1)$$

In the automated stations, the data were obtained every 5 min and averaged to obtain the T_{mean}:

$$T\text{mean}_{\text{AWS}} = \frac{T_1 + T_2 + \ldots + T_{288}}{288}. \quad (2)$$

Since the observation times and the calculation of the mean temperature in the automated and conventional stations were different, three more formulas were compared (Equations 3–5) to determine which calculated AWS means best fit the CWS observations (Table 1).

TABLE 1 Calculation methods for mean temperature at the automated stations

Mean temperature calculation for the automated station		Description
Equation 3	$T_{\text{mean}} = \frac{T_{7AM} + T_{1PM} + 2T_{7PM}}{4}$	Mean temperature at 7 AM, 1 PM, and 7 PM, which corresponds to the average of the mean temperature of the last 12 data values comprising each hour
Equation 4	$T_{\text{mean}} = \frac{T_{8AM} + T_{2PM} + 2T_{8PM}}{4}$	Mean temperature at 8 AM, 7 PM, and 8 PM which correspond to the average of the mean temperature of the last 12 data values comprising each hour
Equation 5	$T_{\text{mean}} = \frac{T_{7:05AM} + T_{01:05PM} + 2T_{07:05PM}}{4}$	Temperature at 7:05 AM, 1:05 PM, and 7:05 PM

2.2 | Minimum and maximum temperature (T_{min} and T_{max})

In the conventional stations, the T_{min} and T_{max} data were obtained from the minimum and maximum thermometers. We corroborated them with the thermohygrograph.

In the automated station, T_{min} was obtained from the minimum instantaneous value recorded in a day, and T_{max} was calculated from preliminary studies (Cenicafé, 2015, 2017), where it was the most critical of the temperatures recorded by the AWS. Four formulas were used (Equations 6–9) to obtain the temperature (Table 2) that would be most consistent with the CWS data.

2.3 | Quality control

To ensure the quality of the 5-min information recorded by the automated stations, the number of missing data points was determined, the peaks were filtered, and fixed ranges, temporal consistency tests, and spatial consistency tests were applied.

TABLE 2 Calculation methods for maximum temperature at the automated station

Maximum temperature calculation at an automated station		Description
Equation 6	$T_{\text{max}} = T_{\text{max}}\text{daily}$	Greatest of the 288 data points recorded during the day
Equation 7	$T_{\text{max}} = T_{\text{max}_i} + T_{\text{max}_{i-1}} + \cdots T_{\text{max}_{i-11}}/12$	The maximum temperature was identified in the 288 5-min data, to which the previous 11 data are added and these 12 are averaged
Equation 8	$T_{\text{max}} = T_{\text{max}_i} + T_{\text{max}_{i-1}} + \cdots T_{\text{max}_{i-23}}/24$	The maximum temperature was identified in the 288 5-min data, to which the previous 23 data are added and these 24 are averaged
Equation 9	$T_{\text{max}} = T_{\text{max}_i} + T_{\text{max}_{i-1}} + \cdots T_{\text{max}_{i-35}}/36$	The maximum temperature was identified in the 288 5-min data, to which the previous 35 data are added and these 36 are averaged

Peak filtering: A common problem in the operation of AWSs is the presence of peaks in the records (World Meteorological Organization, 2017). Absolute differences between consecutive data were determined and analysed to detect and mark erroneous values related to sensor failures. If there were differences greater than 5°C in consecutive 5-min data, the data were marked as errors.

Fixed range test: From the historical information of the network of conventional stations, we verified whether the values were within the acceptable range according to the historical climatic conditions of the region and the altitudinal range. We marked the 5-min data that fell outside the maximum and minimum ranges ±3°C as suspect, and we verified whether they corresponded to an extreme value.

Temporal and spatial consistency test: The mean hourly temperature was determined as the average of the 12 5-min records, accepting a missing data rate of 50%. We analysed the differences between the maximum and minimum values during hourly periods throughout the Colombian Coffee Zone, searching for any differences greater than 11°C during 1 h of the day or differences greater than 4°C during the night. If any were found, the hourly data were marked as suspicious and reviewed.

Once the mean daily temperature was calculated using the equations described above for the AWS and CWS, validations were applied at the spatial and temporal scales, taking into account the historical patterns at the regional scale and by altitudinal range. The data outside the historical ranges were reviewed graphically and compared with nearby stations' data.

2.4 | Determination of calibration and validation series

To establish the calibration and validation series of the study, the meteorological observations of the conventional station were compared against the simultaneous observations of the automated station, using the gross bias (Equation 10) and the daily difference series (CWS minus AWS) were created:

$$\text{Bias} = T_{\text{CWS}} - T_{\text{AWS}}. \tag{10}$$

The homogeneity of the series of daily differences was verified using the SNHT as modified by Browning (2015). The metadata suggested by Aguilar et al. (2003) for the parallel operation were collected and graphically analysed together with the series of temperature differences of each station and the changepoints resulting from the SNHT to define the series for calibration and validation of the adjustments. Under the results of the SNHT test, the calibration series had to meet the following conditions: both CWS and AWS had continuous periods of missing data not exceeding 12 days and a minimum of 2 years of information, while the validation series did not have restriction of missing data and its beginning corresponded to the date following the end date of the calibration series.

2.5 | Adjustment of the data of the automated stations

To minimize the difference between the CWS and AWS temperature data of some stations, we took two approaches: correction based on quantiles and bias correction by means of an additive constant. The first approach was applied to the empirical cumulative distribution functions (CDFs) of the conventional and automatic station data calibration series running in parallel using Equation (11). Then, Equation (12) was applied to the validation series to correct for the future values of T:

$$\text{CDF}_P(T_{\text{CWS}}) = F_P(\text{CDF}_P(T_{\text{AWS}})), \tag{11}$$

$$T_{\text{AWSCorrected}} = G_S[T_{\text{AWS}}, F_P(\text{CDF}_S(T_{\text{AWS}}))], \tag{12}$$

where CDF_P is the derived CDF during the time period "*P*" (calibration series, in which CWS and AWS worked in parallel). F_P is the quantile–quantile mapping operator, which transforms the AWS CDF into the CWS CDF at the calibration period.

The fitQmapQUANT function of the qmap package (Gudmundsson et al., 2012) developed in the R language was used to estimate the CDF values of the time series for the conventional and automated stations for quantiles spaced at 0.1 using local linear least squares regression.

We adjusted the AWS data with reference to the CWS data over the 12 months of the year by means of the doQmapQUANT function, which used the estimates of the CDF values to perform quantile mapping for both the calibration series and the validation series. For all values that are not in the quantile, the transformation was estimated by linear interpolation of the fitted values, using the extrapolation suggested by Boé et al. (2007) so that AWS extreme values map correctly. Since the procedure requires complete data in each data series, the ImputeTS package (Moritz & Bartz-Beielstein, 2017) estimated some missing values from a linear interpolation fitting.

The second approach consisted of correcting the bias by means of an additive constant (addition or subtraction). Taking into account the average of the bias values of each station, if the data were located above the bias and the absolute difference between CWS and AWS was greater than 0.5°C, the average bias was subtracted from these data, and if the data were located below the bias and the absolute difference between CWS and AWS was greater than 0.5°C, the average bias was added to these data.

2.6 | Evaluation and validation

The degree of association between the CWS and AWS stations was evaluated on the following data sets: complete series to identify the initial state, uncorrected calibration series to evaluate the effect of eliminating missing periods greater than 12 days, and the series of corrected calibration to assess the effect of adjustment under the two approaches. The precision of the automated station was quantified by calculating the Willmott or agreement index (Willmott et al., 1985) (Equation 13) and the percentage of days on which the difference between daily temperatures was >0.5°C and <−0.5°C (PR05). When the Willmott index was greater than 0.8, it represented good agreement. These indices have been used as performance measures to compare weather stations (Arteaga-Ramírez et al., 2017; Lucas et al., 2010; Sales et al., 2018):

$$d_r = 1 - \left[\frac{\sum_{i=1}^{n} (P_i - O_i)^2}{\left(\sum_{i=1}^{n} \left(|P_i - \overline{O}| + |O_i - \overline{O}| \right)^2 \right)} \right], \tag{13}$$

where d_r corresponds to the Willmott or agreement index, P_i indicates the observations of the conventional stations at time i, O_i are the observations of the automated stations, and $\overline{O}$ is the mean of the automated station observations.

To validate the results of the adjustment, graphs were drawn of the monthly mean values of the temperatures of the CWSs, AWSs, and AWSs corrected with the QM method.

Finally, to define the continuity of the conventional series with the automated series, the criteria according to Table 3 had to be met.

Based on the preliminary results (Cenicafé, 2015, 2017), the maximum temperature is the most critical variable because there were greater differences between the AWS and CWS. For this reason, in expert judgement, we allow a larger percentage of cases or days, in order to give the CWS series the possibility of continuity.

TABLE 3 Criterion to define the continuity of the conventional station series

Variable	Criterion
Mean temperature	The absolute value of the difference between AWS and CWS exceeds 0.5°C in less than 20% of the days
Minimum temperature	The absolute value of the difference between AWS and CWS exceeds 0.5°C in less than 20% of the days
Maximum temperature	The absolute value of the difference between AWS and CWS exceeds 0.5°C in less than 30% of the days

3 | RESULTS AND DISCUSSION

T_{mean} for each of the stations was calculated by the different methods presented in Equations (3–5). The data obtained by Equation (3) are those that best relate to the data measured by the CWS in terms of yielding better values of the index d_r and a higher PR05. For T_{max}, the data obtained by Equation (7) have the smallest differences from the T_{max} data of the CWSs. The above exploration was based on the conclusion of Milewska and Vincent (2016), who stated that it is essential to adjust the daily temperatures of AWSs according to the CWS observation times before applying any general statistical technique for daily adjustments. We decided that Equation (3) for T_{mean} and Equation (7) for T_{max} would be used in subsequent analyses.

A first comparison was made between the complete series of the CWS and AWS, and the homogeneity of the series of daily differences was examined using the SNHT, which detected changepoints with a confidence level of 97.5% for all stations. Abrupt discontinuities were found, which we mainly attribute to changes in the instruments and gradual discontinuities possibly related to the loss of sensitivity of the instrument. Additionally, the categorization or location class of the stations according to how their environment affects temperature measurements (World Meteorological Organization, 2018a) warned us of the quality of the data collected by the instruments, bringing an additional estimated uncertainty of up to 2°C in some stations. However, as the AWSs and CWSs share sites, we did not consider this uncertainty on top of that of the instrument.

The number of discontinuities in the 36 stations analysed is shown in Figure 2a, and the number of changes or failures associated with the temperature variable is shown in Figure 2b. The greatest number of discontinuities in the difference series between CWSs and AWSs occurred mainly in the first semester of 2015 and 2018, related to the replacement of measurement instruments due to previous failures and outdated software. According to Figure 2a, T_{max} and T_{min} have more changepoints, identified as statistically significant discontinuities, than T_{mean}, which implies that these values are more sensitive to instrument changes or failures.

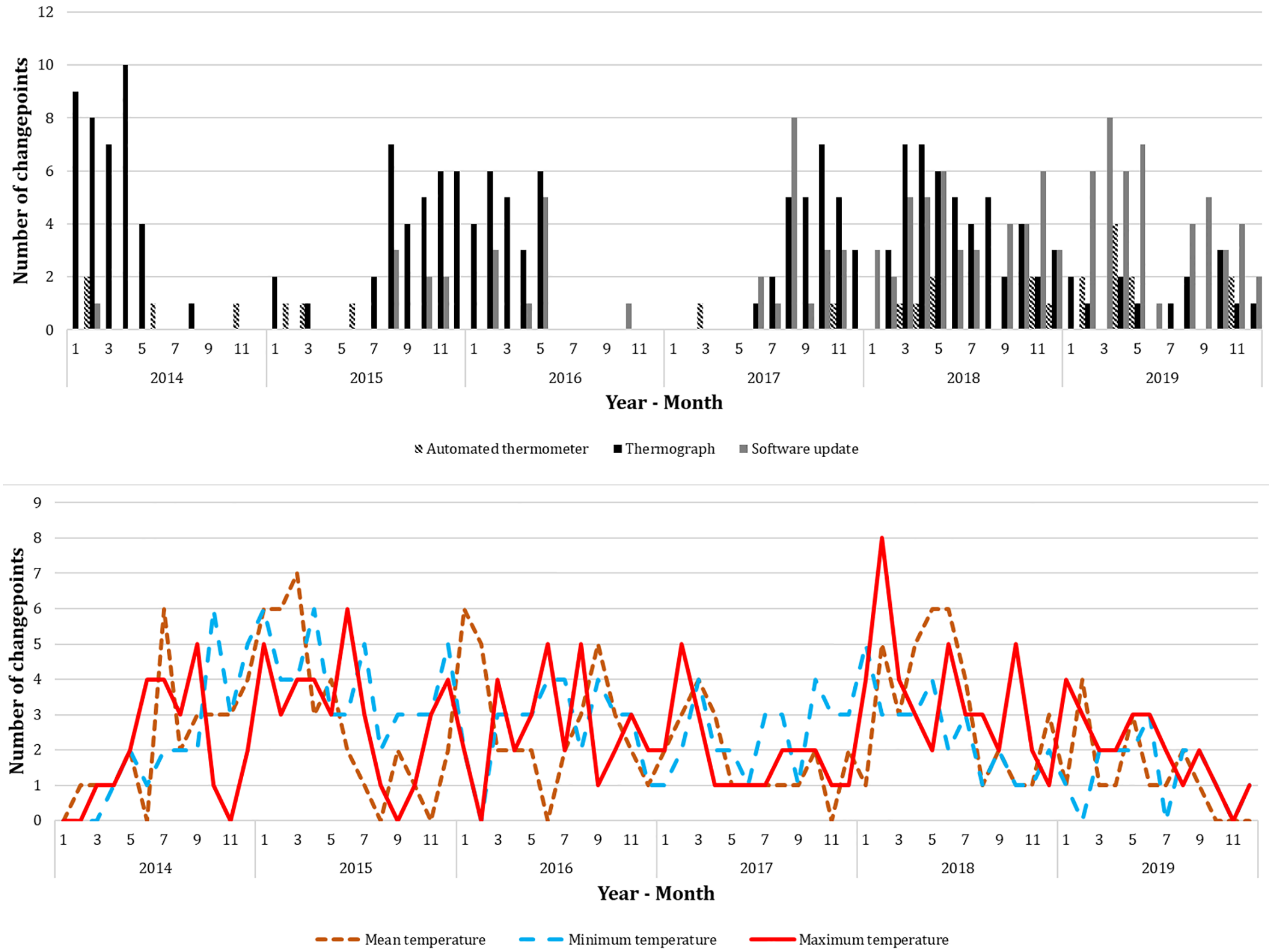

FIGURE 2 (a) Total number of discontinuities or failures found at the 36 stations on a monthly basis. (b) Number of changes or failures at the 36 stations on a monthly basis

The analysis of the graphs of the difference series together with the changepoints and metadata showed three important aspects to address in the analyses. The first is the number of break points in the complete difference series of the stations and their possible cause, the second is the concept of continuing with the adjustments of the AWS series, and the third is to define the dates of the calibration and validation series of each station (Table 4).

From this analysis, we found that 75% of the changepoints are attributed to failures in the conventional or automated instruments, 12.5% of the changepoints are attributed to software updates during visits to the AWSs, and another 12.5% are associated with shifts in the temperature of the climate or perhaps with changes or failures in the AWS temperature sensor that were not reported in the metadata.

As to the continuity of the series, the reason that an AWS was classified as incompatible for series adjustment was related to the many missing data, which interrupted the difference series in several periods.

Keeping in mind that in the results of the SNHT, the changepoints (dates) are repeated because they are run under time windows of 10–220 days, Table 4 presents a synthesis of what is shown in the graphs of the difference series, while Figure 2a shows the total number of discontinuities.

In summary, as seen in Table 4, in the T_{mean} difference series, there are a total of 27 stations with 95 changepoints, in T_{min}, there are a total of 26 stations with 77 changepoints, and in the T_{max} series, there are a total of 29 stations with 91 changepoints.

Thereafter, the analyses were continued with the calibration series limited to the dates shown in Table 4, starting again with the comparison between CWS and AWS temperatures.

Examining the statistics of Table 5 shows that the T_{mean}, T_{min}, and T_{max} values are very similar to those found in the complete series. The bias revealed both positive and negative values due to the different responses of each of the automated sensors and conventional instruments of each station. In fact, the T_{mean} and T_{max} of the

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TABLE 4 Changepoints detected by the SNHT for the mean, minimum, and maximum temperature variables

		Mean temperature						Minimum temperature						Maximum temperature					
Code	Category or class location	Change points	Compatible for adjustment	Initial datemonth–year		Final datemonth–year		Change points	Compatible for adjustment	Initial datemonth–year		Final datemonth–year		Change points	Compatible for adjustment	Initial datemonth–year		Final datemonth–year	
10001	3	3	Yes	10	2014	4	2017	3	Yes	5	2014	4	2017	2	Yes	5	2014	4	2017
10002	4	3	Yes	12	2017	12	2019	3	Yes	12	2017	12	2019	4	Yes	2	2014	12	2015
10003	3	4	Yes	2	2014	3	2019	2	Yes	2	2014	3	2019	4	Yes	2	2014	3	2019
10004	2	2	Yes	6	2015	3	2018	3	Yes	5	2015	3	2018	4	Yes	5	2015	3	2018
10005	3	2	Yes	1	2017	12	2019	3	Yes	1	2014	12	2019	4	Yes	1	2014	7	2016
10006	2	3	Yes	2	2014	10	2018	5	Yes	2	2014	10	2018	5	Yes	2	2014	10	2018
10007	4	2	Yes	7	2016	12	2019	3	Yes	7	2016	12	2019	3	Yes	7	2016	12	2019
10008	3		No						No					1	Yes	3	2017	12	2019
10009	2	5	Yes	2	2014	10	2017	4	Yes	2	2014	10	2017	1	Yes	2	2014	10	2017
10010	3		No						No						No				
10011	3	5	Yes	5	2015	11	2018	2	Yes	5	2015	12	2018	5	Yes	5	2015	12	2018
10012	4	1	Yes	3	2015	9	2018	4	Yes	3	2015	12	2018	3	Yes	3	2015	12	2018
10013	2	4	Yes	2	2014	10	2016	4	Yes	2	2014	1	2017	2	Yes	2	2014	10	2016
10014	3		No						No						No				
10015	3	3	Yes	12	2014	3	2018	2	Yes	12	2014	3	2018	2	Yes	12	2014	3	2018
10026	4	3	Yes	8	2014	7	2017	1	Yes	8	2014	7	2017	1	Yes	8	2014	7	2017
10031	3		No						No						No				
10032	3	4	Yes	1	2014	4	2019		No						No				
10036	3	3	Yes	1	2014	3	2019	3	Yes	1	2014	3	2019	2	Yes	1	2014	3	2019
10037	3	8	Yes	8	2014	12	2019	3	Yes	8	2014	12	2019	5	Yes	8	2014	12	2019
10038	3	4	Yes	7	2016	6	2019	2	Yes	7	2016	6	2019	4	Yes	7	2016	6	2019
10048	3	4	Yes	1	2014	10	2017	2	Yes	1	2014	10	2017	3	Yes	1	2014	10	2017
10049	4	1	Yes	2	2014	5	2016	2	Yes	2	2014	5	2016	2	Yes	2	2014	5	2016
10050	4		No						No						No				
10051	4	3	Yes	2	2014	2	2018	1	Yes	2	2014	2	2018	3	Yes	2	2014	2	2018
10057	3	4	Yes	2	2014	6	2016	5	Yes	2	2014	6	2016	4	Yes	2	2014	6	2016
10064	4	3	Yes	1	2014	5	2018	5	Yes	1	2014	5	2018	2	Yes	1	2014	5	2018
10070	3	4	Yes	1	2014	12	2019	2	Yes	1	2014	12	2019	1	Yes	1	2014	12	2019

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TABLE 4 (Continued)

Code	Category or class location	Mean temperature				Minimum temperature				Maximum temperature			
		Change points	Compatible for adjustment	Initial datemonth-year	Final datemonth-year	Change points	Compatible for adjustment	Initial datemonth-year	Final datemonth-year	Change points	Compatible for adjustment	Initial datemonth-year	Final datemonth-year
10077	2	1	Yes	2 2014	8 2015	1	Yes	9 2015	9 2018	2	Yes	2 2014	8 2015
10078	3	6	Yes	2 2014	12 2019	2	Yes	2 2014	12 2019	3	Yes	2 2014	12 2019
10079	3	7	Yes	12 2015	5 2019	5	Yes	9 2015	12 2018	3	Yes	12 2015	12 2018
10080	3		No				No				No		
10081	3		No				No			6	Yes	10 2014	6 2018
10082	3		No				No				No		
10083	3		No				No			5	Yes	2 2014	1 2017
10101	3	3	Yes	9 2016	6 2019	5	Yes	9 2016	5 2019	5	Yes	9 2016	5 2019
10104	4		No				No				No	3 2015	

AWS are generally higher than those of the CWS. With respect to T_{min}, the CWS data are descriptively higher than the AWS data. The bias found in T_{mean} does not exceed $\pm 1.0^{\circ}$C; in T_{max}, the highest average bias is -1.7°C at the El Pílamo station (Pereira – Risaralda); and in T_{min}, the average bias does not exceed $\pm 0.6^{\circ}$C. In general, there is a different pattern between the biases of the T_{min} and T_{max} values. The magnitude of the differences in T_{min} is notably lower than that for T_{max}.

The differences in T_{max} differ considerably from those reported in the 2017 annual report (Cenicafé, 2017) because we applied quality control at the 5-min and hourly scales to discard data that were outside the limits. Thus, daily data were generated, and the temperatures were adjusted.

From our analyses and experimental observations in the field, we hypothesize that the radiation shield of the AWS temperature sensor used in the coffee network, with only four plates, is what mainly affects the T_{max} variable. It is small, and the material of the screen is not well insulated, so it is more prone to the influence of light scattered on the surface of the plates. T_{min} is not so affected, possibly because shield material during the night and at dawn, when this temperature is recorded, responds well to the influence of radiative cooling. This is supported by the study of Aoshima et al. (2010), in which the shield with the most differences relative to the reference was the smallest one, and by the experiment carried out by the Agroclimatology branch (Cenicafé, 2014), where the AWS temperature sensor presented differences when it was housed inside the Stevenson wooden hut rather than in its original shield.

As for d_r, all stations had values greater than 0.8, indicating good agreement between the CWS and AWS temperatures, with the exception of La Trinidad station (Cauca), which had a value of 0.73 for T_{min}.

According to the T_{mean} criterion for continuity with the CWS series (Table 3), the 11 AWSs that presented a PR05 >80% and a $d_r > 0.8$ would be continuous, but only after the precision of their data is adjusted.

When comparing the T_{max} of the CWSs and AWSs, we found that the PR05 was between 5% and 70%, so none of the AWSs met the continuity criteria to the CWS series. For the proposed assumptions, the adjustment was applied to all the AWSs to improve the PR05 and define the continuity of the T_{max} series.

Regarding T_{min}, 12 stations had a PR05 greater than 80%, a d_r greater than 0.8, and an average bias between 0.35 and -0.02. Thus, this group of AWSs could give continuity to the CWS without affecting the historical series. Even so, they were included in the adjustment analysis to determine if the data improved.

TABLE 5 Results of the analysis of the subseries evaluated by the PR05 statistic, d_r, bias, and total data

		T_{mean} subseries				T_{max} subseries				T_{min} subseries			
Code	Station	PR[a]	d_r[b]	Bias	Total data	PR[a]	d_r	Bias	Total data	PR[a]	d_r	Bias	Total data
10001	Planalto	72	0.98	−0.33	903	14	0.92	−1.18	1048	81	0.97	0.14	1060
10002	Cenicafé	31	0.88	−0.74	753	32	0.94	−0.81	751	47	0.86	−0.54	753
10003	Naranjal	82	0.97	−0.24	1859	27	0.95	−0.76	1831	87	0.96	0.15	1859
10004	La Catalina	82	0.98	0.07	1018	60	0.97	0.02	1013	62	0.90	0.43	1021
10005	Paraguaicito	80	0.97	−0.25	1094	37	0.96	−0.64	1230	80	0.96	−0.02	2190
10006	Bertha	59	0.91	0.12	1688	47	0.95	0.24	1611	74	0.95	0.14	1688
10007	Granja Luker	77	0.96	−0.02	1267	16	0.91	−1.08	1253	42	0.88	0.58	1267
10009	Pueblo Bello	84	0.97	−0.16	1316	54	0.97	−0.37	1305	80	0.98	0.35	1317
10011	El Mirador	77	0.96	−0.17	1290	44	0.97	−0.41	1229	79	0.87	0.14	1320
10012	Blonay	85	0.98	−0.04	1293	62	0.98	0.11	1290	81	0.88	0.27	1384
10013	Gabriel María Barriga	86	0.98	−0.09	967	70	0.98	0.09	952	73	0.91	0.10	1060
10015	El Agrado	70	0.96	−0.22	1197	49	0.97	−0.42	1194	82	0.97	0.07	1199
10026	La Bella	79	0.98	−0.28	1052	61	0.98	−0.24	1070	81	0.96	0.17	1074
10032	Simón Campos	87	0.98	0.00	1946								
10036	Cocorná	92	0.98	−0.06	1916	32	0.94	−0.65	s1910	70	0.91	0.36	1916
10037	El Rosario	90	0.99	−0.11	1973	56	0.98	−0.22	1966	90	0.97	0.11	1973
10038	El Pílamo	13	0.83	−0.96	1068	5	0.84	−1.71	1058	67	0.89	−0.39	1066
10,048	El Jazmín	65	0.96	−0.31	1389	26	0.94	−0.85	1389	66	0.92	0.28	1389
10049	Julio Fernández					49	0.95	0.18	847	62	0.85	−0.19	824
10051	Arturo Gómez	65	0.93	−0.30	1438	55	0.95	−0.05	1434	74	0.91	−0.20	1438
10057	Manuel M. Mallarino	79	0.98	−0.21	839	34	0.95	−0.65	837	83	0.93	0.12	839
10064	La Trinidad	72	0.96	−0.35	1589	32	0.94	−0.69	1584	88	0.96	0.08	1589
10070	El Rubí	71	0.96	−0.21	2190	47	0.96	−0.23	2190	85	0.94	0.11	2190
10077	La Trinidad					54	0.97	−0.28	542	63	0.73	−0.47	1111
10078	Misiones	87	0.98	0.08	2134	54	0.97	0.17	2124	62	0.91	0.47	2134
10079	El Sauce	69	0.90	−0.35	1266	51	0.98	0.36	1087	88	0.96	0.07	1210
10101	La Cristalina	84	0.98	−0.15	1006	52	0.98	−0.33	991				

[a]PR05 is the percentage of days within the range ±0.5°C.
[b]d_r is the Willmott index.

The statistical analyses have clearly indicated that the AWS data require adjustment to preserve the continuity of the CWS series. Therefore, the first procedure to adjust the temperatures was quantile mapping applied to each month. The result corresponds to the correction coefficients calculated from the percentiles of each month, which were applied to both the calibration and validation series. The precision of the QM method was evaluated using the defined statistics (Table 6). The data of the mean, maximum, and minimum temperatures corrected for the AWS of the calibration set indicate a reduction in the bias, which suggests a considerable improvement with the adjustment in most of the stations. The average bias of the corrected temperatures is close to 0 at all stations. d_r at all stations and for each temperature is higher than 0.8, with the exception of the El Sauce station's T_{max}.

For T_{mean}, the adjustments increase PR05 to 71%; however, of the 25 adjusted stations, only nine have an improvement greater than 10% over the uncorrected data. A total of 21 stations, with the corrected T_{mean} data, meet the criteria to preserve the T_{mean} continuity of the historical series of the conventional network.

In T_{max}, all stations, with the exception of the El Sauce station, increase the PR05 to 59%, and 18 stations

TABLE 6 Results of the analysis of the subset corrected by the QM method evaluated by the PR05 statistic, d_r, bias, and total data

		T_{mean} subseries QM corrected				T_{max} subseries QM corrected				T_{min} subseries corrected QM			
Code	**Station**	**PR**[a]	d_r[b]	**Bias**	**Total data**	**PR**	d_r	**Bias**	**Total data**	**PR**[a]	d_r	**Bias**	**Total data**
10001	Planalto	93	0.99	0.00	903	63	0.91	0.00	1084	89	0.97	0.00	1060
10002	Cenicafé	82	0.97	0.00	753	63	0.94	0.00	753	89	0.96	0.00	753
10003	Naranjal	94	0.98	0.00	1859	68	0.95	0.00	1859	89	0.97	0.00	1859
10004	La Catalina	86	0.98	0.00	1018	70	0.97	0.00	1021	93	0.95	0.00	1021
10005	Paraguaicito	92	0.98	0.00	1094	74	0.95	0.00	1244	82	0.96	0.00	2190
10006	Bertha	64	0.92	0.00	1688	59	0.92	0.00	1688	74	0.95	0.00	1688
10007	Granja Luker	79	0.97	0.00	1267	66	0.91	0.00	1267	72	0.95	0.00	1267
10009	Pueblo Bello	92	0.98	0.00	1316	81	0.97	0.00	1317	90	0.99	0.00	1317
10011	El Mirador	80	0.97	0.00	1290	60	0.94	0.00	1320	81	0.94	0.00	1320
10012	Blonay	86	0.98	0.00	1293	63	0.97	0.00	1384	75	0.90	0.00	1384
10013	Gabriel María Barriga	86	0.98	0.00	967	73	0.98	0.00	964	77	0.93	0.00	1060
10015	El Agrado	76	0.97	0.00	1197	71	0.97	0.00	1199	83	0.97	0.00	1199
10026	La Bella	93	0.99	0.00	1052	64	0.97	0.00	1074	91	0.97	0.00	1074
10032	Simón Campos	87	0.98	0.00	1946								
10036	Cocorná	92	0.98	0.00	1916					87	0.95	0.00	1916
10037	El Rosario	93	0.99	0.00	1973	64	0.98	0.00	1916	92	0.97	0.00	1973
10038	El Pílamo	84	0.97	0.00	1068					82	0.95	0.00	1066
10048	El Jazmín	79	0.97	0.00	1389	86	0.89	0.00	1066	78	0.94	0.00	1389
10049	Julio Fernández					88	0.84	0.00	1389	62	0.89	0.00	824
10051	Arturo Gómez	68	0.95	0.00	1438	76	0.91	0.00	904	79	0.93	0.00	1438
10057	Manuel M. Mallarino	92	0.99	0.00	839	79	0.96	0.00	1438	84	0.94	0.00	839
10064	La Trinidad	95	0.99	0.00	1589	68	0.94	0.00	839	90	0.97	0.00	1589
10070	El Rubí	81	0.97	0.00	2190	57	0.95	0.00	1589	87	0.95	0.00	2190
10077	La Trinidad					92	0.97	0.00	2190	65	0.84	0.00	1111
10078	Misiones	90	0.98	0.00	2134	64	0.95	0.00	544	92	0.97	0.00	2134
10079	El Sauce	66	0.93	0.00	1266	42	0.73	0.00	2134	88	0.96	0.00	1210
10101	La Cristalina	88	0.98	0.00	1006								

[a]PR05 is the percentage of days within the range ±0.5°C.
[b]d_r is the Willmott index.

manage to improve their response by more than 10%. For this variable, only nine stations meet the continuity criterion of the historical CWS T_{max} series. Regarding the minimum temperature, seven stations show an improvement in PR05 above 10%–42%, and a total of 17 stations preserve the continuity with the historical series of the conventional network by applying the quantile mapping method.

In general, the results of PR05 are unsatisfactory, in part due to the uncertainty of the locations of the stations, such that the exposure of the instruments in certain periods of the measurement did not have the best conditions, which could have made them fail to achieve a better adjustment at most of the stations.

As an example, the mean monthly temperature values are shown uncorrected and corrected compared with the CWS values for some specific stations (Figures 3–5). The time interval used to average the monthly values corresponds to the calibration series. The graphs clearly show what was revealed through the bias, where T_{mean} and T_{max} of the AWS tend to overestimate the values of the CWS, while in the T_{min}, there are AWSs that overestimate or underestimate the CWS data. After adjusting for bias by the QM method, the corrected AWS data are closer to the CWS data.

The graphs help us understand the results of PR05 when the AWS data are corrected. They show that when the PR05 is lower than the accepted criterion (Table 3) to

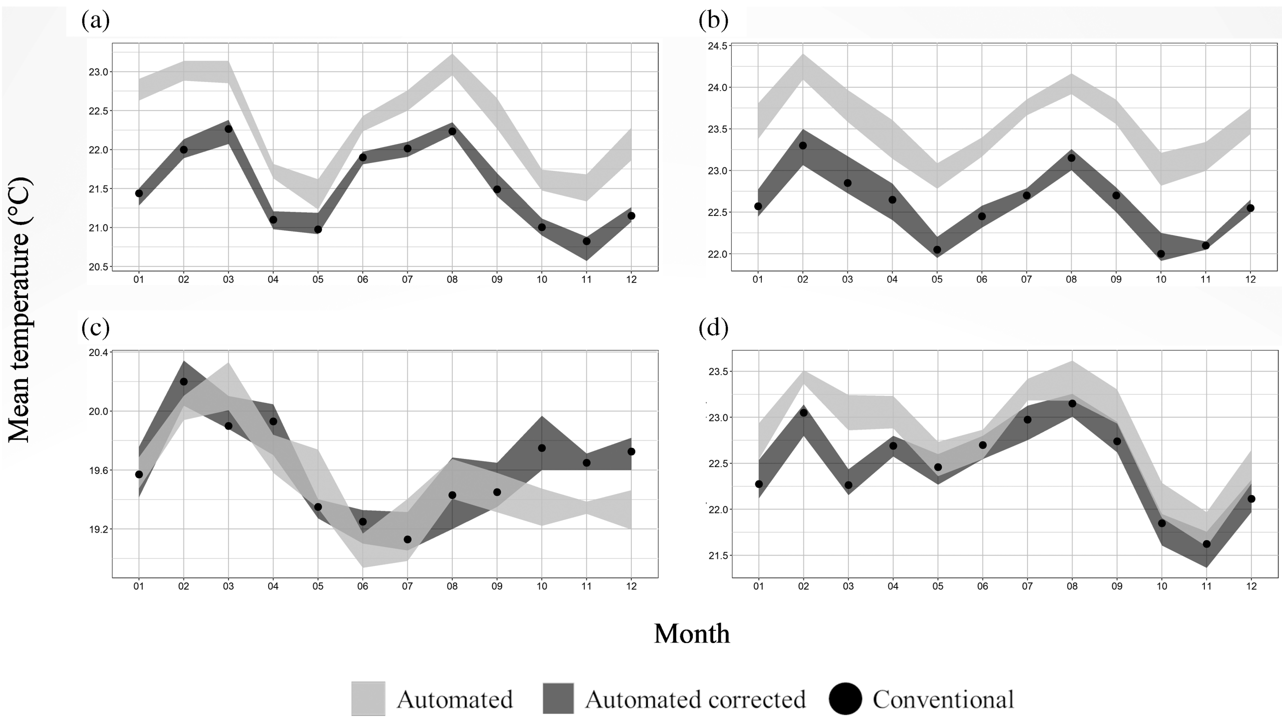

FIGURE 3 Average mean monthly temperature of conventional and automated weather stations before and after bias correction by quantile mapping. The density of the graph corresponds to the error. (a) Cenicafé, (b) El Pílamo, (c) Bertha, (d) Arturo Gómez

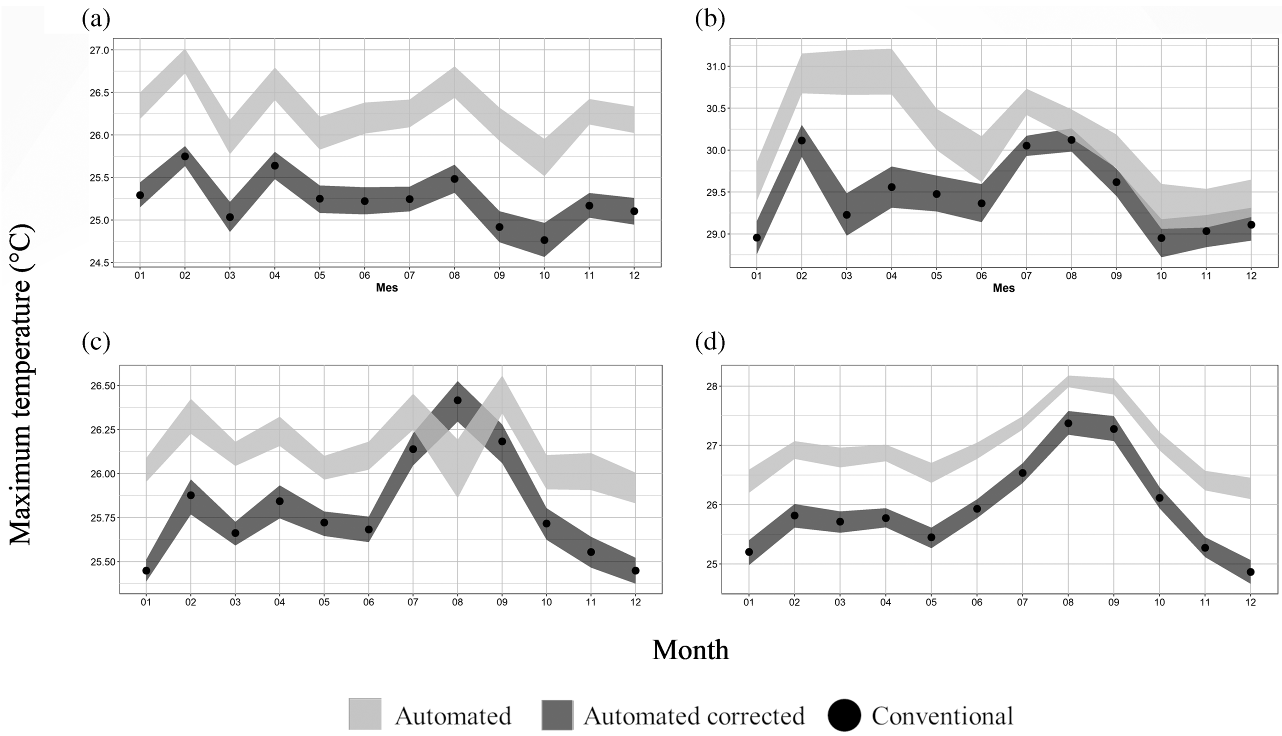

FIGURE 4 Average maximum monthly temperature of conventional and automated weather stations before and after bias correction by quantile mapping. The density of the graph corresponds to the error. (a) El Jazmín, (b) Arturo Gómez, (c) Julio Fernández, (d) El Sauce

preserve the continuity of the historical series, as happened in Bertha and Arturo Gómez (Figure 3c,d, respectively) and La Trinidad and Julio Fernández (Figure 5c,d, respectively), particularly in some months, the uncorrected AWS series coincided to some extent with the CWS data. In short, the error was not systematic. An example of systematic error

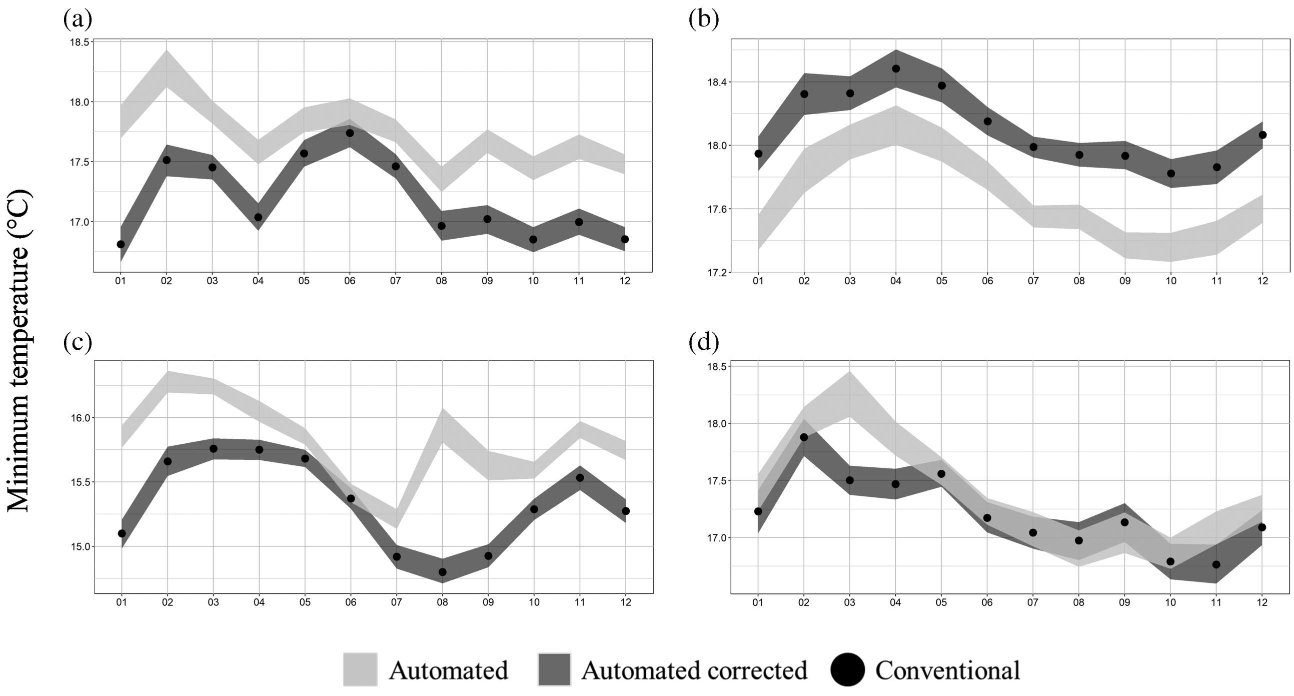

FIGURE 5 Average minimum monthly temperature of conventional and automated weather stations before and after bias correction by quantile mapping. The density of the graph corresponds to the error. (a) Cenicafé, (b) La Catalina, (c) La Trinidad, (d) Julio Fernández

TABLE 7 Results of the analysis of the validation series uncorrected and corrected by the QM method evaluated by the PR05 statistic, d_r, bias, and total data

		T_{mean} validation series uncorrected			T_{mean} validation series QM corrected			
Code	Station	PR[a]	d_r[b]	Bias	PR	d_r	Bias	Total data
10001	Planalto	69	0.95	−0.39	87	0.97	−0.08	852
10003	Naranjal	88	0.95	−0.13	87	0.96	0.10	216
10004	La Catalina	79	0.96	−0.15	76	0.96	−0.22	656
10009	Pueblo Bello	65	0.78	−0.25	66	0.81	−0.05	697
10010	Granja Tibacuy	26	0.37	0.97	23	0.20	1.25	783
10011	El Mirador	13	0.36	−1.15	15	0.45	−0.99	366
10012	Blonay	36	0.75	−0.10	35	0.75	−0.09	426
10013	Gabriel María Barriga	65	0.87	−0.06	61	0.86	0.03	1045
10014	Francisco Romero	31	0.35	−0.39	30	0.33	−0.42	574
10015	El Agrado	25	0.43	0.73	23	0.36	0.94	649
10026	La Bella	87	0.98	−0.16	89	0.98	0.11	727
10036	Cocorná	27	0.41	1.17	24	0.38	1.22	275
10048	El Jazmín	54	0.82	−0.17	53	0.82	0.12	802
10051	Arturo Gómez	49	0.85	−0.51	56	0.89	−0.09	269
10057	Manuel M. Mallarino	62	0.84	−0.10	62	0.84	0.11	1303
10064	La Trinidad	55	0.91	−0.44	84	0.95	−0.08	482

[a]PR05 is the percentage of days within the range ±0.5°C.
[b]d_r is the Willmott index.

was presented in Cenicafé (Figures 3a and 5a), El Pílamo (Figure 3b), La Catalina (Figure 5b), El Jazmín, and Arturo Gómez (Figure 4a,b), where these stations meet the criteria for preserving continuity to the CWS series.

The adjustments derived from the QM were applied to the validation series of 17 stations, which have periods of 189–1303 days. In Table 7, the results for T_{mean} are reported, as this is the uncorrected variable that best fits the CWS data. The Planalto, Pueblo Bello, El Mirador, La Bella, Arturo Gómez, Manuel M. Mallarino, and La Trinidad stations increase their PR05 when applying the adjustment, and nine stations, in turn, have fewer data within the allowable range. The QM adjustment improved the average bias at 14 of 21 stations, but there is no significant achievement to highlight. At six stations, the adjustment worsens the average bias up to 1.25°C. In general, the method performs better at adjusting the calibration series data than the validation series data. This is explained by the findings of Vincent et al. (2012), who found that the QM adjustments have the property of being dependent on the year, since they differ according to where the temperature value is in the probability distribution. This means that the Planalto and La Trinidad stations, for obtaining a PR05 within the criteria

TABLE 8 Results of the analysis of the corrected subset by the additive method evaluated by the PR05 statistic, d_r, bias, and total data

		T_{mean} subseries corrected for additive bias				T_{max} subseries corrected for additive bias				T_{min} subseries Corrected for additive bias			
Code	Station	PR[a]	d_r[b]	Bias	Total data	PR	d_r	Bias	Total data	PR[a]	d_r	Bias	Total data
10001	Planalto	93	0.99	−0.22	903	63	0.98	−0.06	1084	89	0.96	0.16	1060
10002	Cenicafé	82	0.96	−0.34	753	63	0.97	−0.49	753	89	0.94	−0.35	753
10003	Naranjal	94	0.98	−0.21	1859	68	0.99	−0.28	1859	89	0.95	0.16	1859
10004	La Catalina	86	0.98	0.07	1018	70	0.97	0.03	1021	93	0.86	0.53	1021
10005	Paraguaicito	92	0.98	−0.21	1094	74	0.99	−0.24	1244	82	0.96	−0.02	2190
10006	Bertha	64	0.88	0.14	1688	59	0.9	0.26	1688	74	0.94	0.16	1688
10007	Granja Luker	79	0.96	−0.02	1267	66	0.98	−0.29	1267	72	0.71	1.04	1267
10009	Pueblo Bello	92	0.98	−0.14	1316	81	0.98	−0.28	1317	90	0.96	0.41	1317
10011	El Mirador	80	0.97	−0.15	1290	60	0.96	−0.35	1320	81	0.86	0.15	1320
10012	Blonay	86	0.98	−0.04	1293	63	0.97	0.15	1384	75	0.87	0.28	1384
10013	Gabriel María Barriga	86	0.98	−0.09	967	73	0.97	0.1	964	77	0.89	0.11	1060
10015	El Agrado	76	0.97	−0.18	1197	71	0.99	−0.24	1199	83	0.96	0.07	1199
10026	La Bella	93	0.98	−0.23	1052	64	0.98	−0.19	1074	91	0.95	0.19	1074
10032	Simón Campos	87	0.98		1946								
10036	Cocorná	92	0.98	−0.06	1916					87	0.85	0.47	1916
10037	El Rosario	93	0.99	−0.11	1973	64	0.98	−0.13	1916	92	0.96	0.11	1973
10038	El Pílamo	84	0.96	−0.24	1068					82	0.93	−0.29	1066
10048	El Jazmín	79	0.97	−0.24	1389	86	0.97	−0.4	1066	78	0.87	0.36	1391
10049	Julio Fernández					88	0.88	−0.22	1389	62	0.83	−0.21	824
10051	Arturo Gómez	68	0.95	−0.22	1438	76	0.92	−0.53	904	79	0.94	−0.17	1438
10057	Manuel M. Mallarino	92	0.98	−0.18	839	79	0.98	−0.26	1438	84	0.92	0.13	839
10064	La Trinidad	95	0.98	−0.25	1589	68	0.98	−0.19	839	90	0.96	0.08	1591
10070	El Rubí	81	0.97	−0.17	2190	57	0.97	−0.27	1589	87	0.93	0.11	2191
10077	La Trinidad					92	0.97	0.11	2190	65	0.79	−0.39	1111
10078	Misiones	90	0.98	0.08	2134	64	0.94	0.15	544	92	0.83	0.65	2134
10079	El Sauce	66	0.92	−0.31	1266	42	0.69	−1.16	2134	88	0.96	0.06	1210
10101	La Cristalina	88	0.98	−0.13	1006								

[a]PR05 is the percentage of days within the range ±0.5°C.

[b]d_r is the Willmott index.

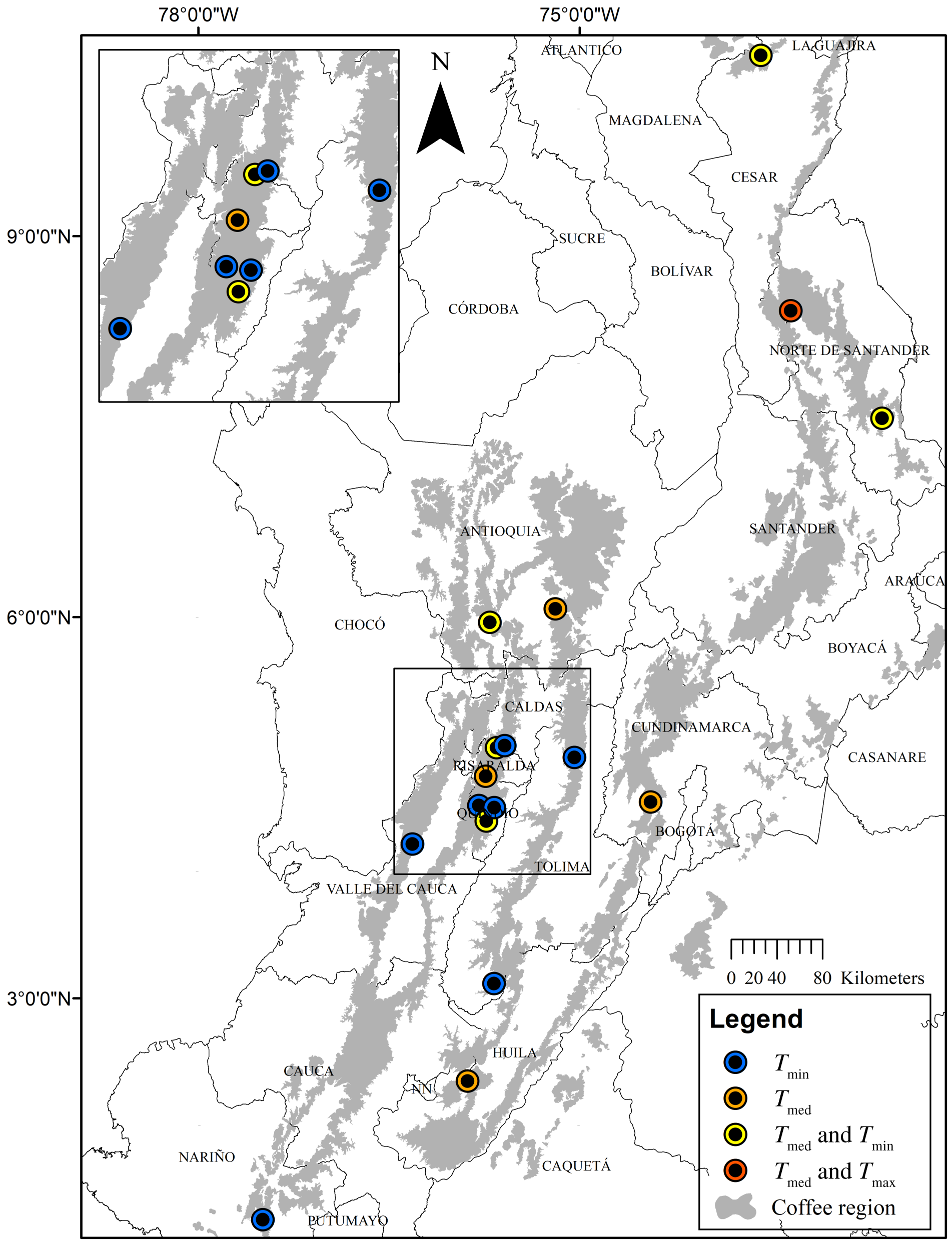

FIGURE 6 Automatic weather stations considered adequate for conventional weather station time series continuity in at least one temperature variable

established to preserve continuity with the CWS series, always had consistent temperature values, while in the rest of the stations the change in instrumentation, updates in the datalogger program, and other things could affect the consistency of the values, making them more difficult to adjust. Applying the QM method, the La Bella station preserves the continuity with the historical series for T_{mean} of the conventional network as long as there are backup sensors in the automated station and a good record of the metadata is kept to correct the changepoints in the series. We suggest treating as independent series those with a PR05 <80% in Table 5.

The second adjustment procedure was the additive constant method, which effectively improved the AWS data, but only in the calibration series, where there is certainty of the values that overestimate or underestimate ±0.5°C compared with those of the CWS, since in the case of validation, only the AWS data are available. In T_{mean} with this method, PR05 is improved at 84% of the stations, in T_{max} at 95% of the stations, and in T_{min} at 80% of the stations (Table 8). Something curious is that the values of PR05 are almost equal to those reported in the correction with the QM method (Table 6). However, the bias in T_{mean} corrected by the additive method improves in 18 of 25 stations, in T_{max} the bias is reduced in 18 of 23 stations, and in T_{min} in 19 of 25 stations. In T_{mean}, all the stations have an average bias between ±0.5°C, while in T_{max} and T_{min}, five stations (Arturo Gómez, El Sauce, La Catalina, Granja Luker, and Misiones) continue to present a higher average bias than acceptable.

4 | CONCLUSIONS

From this work, it can be concluded that:

In our case, the methods to calculate the AWS temperatures that presented the best agreement with respect to those of the CWS are: in T_{mean} using Equation (3), in which 252 of 288 data are discarded, in T_{max} using Equation (7), which applies the average of 12 5-min data from the AWS, and in T_{min} obtained from the minimum value of the 288 5-min readings.

There are differences between the CWS and AWS data; however, some stations present biases within the accepted criteria to preserve continuity. The differences were mainly attributed to failures in the measurement instruments and outdated software.

One of the greatest problems identified was the continuity of the AWS series due to failures in the power supply, the instruments, and their operation, which are not easily solvable. We recommend for AWSs that will continue to operate without the CWSs to use sensors of the same variable to periodically evaluate their operation, record the metadata, and recognize and correct any changepoint in the series quickly.

The CWSs and AWSs should operate at least 2 years in parallel to make comparisons between both technologies and determine the possible continuity of the historical series. This time would allow us to adjust methods for the correct functioning of the AWS when it works as an independent series.

Quantile mapping to correct the AWS temperature data is efficient when the error is systematic.

The bias correction technique with an additive factor meets its objective, but it is only applicable to the calibration series.

It is essential to apply different methods to evaluate the consistency between CWSs and AWSs. In our case, d_r showed good agreement between both series; however, PR05 helped to identify the stations that met the criteria for preserving continuity with the historical series.

In T_{mean}, the Naranjal, La Catalina, Paraguaicito, Pueblo Bello, Blonay, Gabriel María Barriga, Simón Campos, Cocorná, El Rosario, Misiones, and La Cristalina stations can preserve continuity with the historical series of the CWS without the need to adjust the AWS series. The La Bella station can preserve continuity with the historical series if the QM method is applied. The rest of the stations continue as independent series.

The series of T_{max} of the AWSs will function as an independent series, except at the Gabriel María Barriga station, which can preserve continuity with the historical CWS T_{max} series.

In T_{min}, the Planalto, Naranjal, Paraguaicito, Pueblo Bello, Blonay, El Agrado, La Bella, El Rosario, Manuel M. Mallarino, La Trinidad (Tolima), El Rubí, and El Sauce stations can preserve continuity with the historical CWS T_{min} series without needing to adjust the AWS series (Figure 6).

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AUTHOR CONTRIBUTIONS

Carolina Ramírez Carabalí: Conceptualization (equal); data curation (equal); formal analysis (lead); investigation (lead); methodology (equal); project administration (lead); supervision (equal); validation (lead); writing – original draft (lead); writing – review and editing (lead). **Ninibeth Gibelli Sarmiento Herrera:** Data curation (equal); formal analysis (equal); methodology (equal); writing – original draft (equal); writing – review and editing (equal). **Luis Carlos Imbachi Quinchua:** Formal analysis (supporting); writing – review and editing (supporting). **Juan Carlos García López:** Conceptualization (equal); methodology (equal); supervision (equal); writing – original draft (equal); writing – review and editing (equal).

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