

Improving the measurement quality of surface meteorological observations through routine physical maintenance and shield cleaning practices

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Abstract

Automatic Weather Stations (AWS) are increasingly relied upon to supplement or replace manual observation networks, yet sensor degradation can compromise data quality over time. This study evaluated the effect of a routine cleaning and maintenance intervention on AWS data quality by comparing co-located AWS and Manual Weather Station (MWS) observations of daily maximum temperature and relative humidity over a 40-day period, split into 20 days before and 20 days after maintenance. Agreement was assessed using Pearson's correlation coefficient, Root Mean Square Error (RMSE), Mean Bias Error (MBE), and Percentage Bias (PBIAS). Maximum temperature showed strong agreement in both periods, with the correlation coefficient improving from 0.992 to 0.999 and PBIAS narrowing from -2.85% to -0.83% after maintenance. Relative humidity showed weaker agreement overall but a more pronounced improvement, with the correlation coefficient rising from 0.740 to 0.876 and PBIAS decreasing from -20.13% to -6.91% . In both periods, the AWS systematically underestimated values relative to the manual reference station, though this bias was substantially reduced following maintenance, particularly for relative humidity. These findings indicate that routine physical maintenance measurably improves AWS data quality, emphasising the importance of regular AWS servicing schedules for networks supporting operational meteorological and early warning applications, where undetected sensor drift could otherwise propagate into downstream products.

Introduction

Maintaining high-quality measurements requires well-calibrated instruments, systematic preventive maintenance, and rigorous quality management practices [1, 2]. In many meteorological stations, particularly in regions exposed to harsh environmental conditions such as dust, high temperatures, and seasonal variability, sustaining measurement accuracy presents ongoing challenges [3, 4]. While National Meteorological and Hydrological Services (NMHS) across Southern Africa and the broader continent are rapidly upgrading to modern Automated Weather Stations (AWS) to improve climate monitoring and service delivery [5, 6], keeping these systems accurate remains a major challenge. Unlike traditional wooden Stevenson screens, small plastic AWS radiation shields easily trap solar heat on calm, sunny days, which causes daytime temperature readings to run much warmer than the true ambient air [7]. In semi-arid and dust prone regions such as Zimbabwe, this problem is severely worsened because wind-blown dirt cakes onto the white plastic shields, thereby lowering their ability to reflect sunlight and blocking natural ventilation [3, 7]. Many countries in the developing world lack the specialised calibration laboratories, technical training, and financial budgets required to perform formal instrument calibrations [2]. Because of these constraints, installed sensors are often left in the field for years without any technical validation, violating standard guidelines for data quality and sensor upkeep prescribed by the World Meteorological Organisation (WMO) [8].

While it is well-known that unmaintained instruments lose accuracy over time, we still know very little about how much we can improve data accuracy in these resource limited regions by using simple, low-cost physical cleaning as another dimension of formal maintenance and calibration [9, 10]. To address

this gap, this study quantifies trends in daily maximum temperature (Tmax) and relative humidity (RH) errors attributable to dust accumulation, and evaluates the extent to which a simple, physical cleaning routine restores sensor accuracy. This is assessed through analysis of a targeted 40-day period, comprising twenty days before and twenty days after maintenance at Chisumbanje weather station in Zimbabwe.

Materials and methods

Study area

The study was carried out at one of the meteorological weather stations operated by the Zimbabwe Meteorological Services Department in Chisumbanje. The station is located at 32.23° longitude and – 20.80° latitude, at an altitude of approximately 401 m above sea level in the southern part of Manicaland province. The local climate is semi-arid and typical of the lowveld region, experiencing high daytime heat and significant wind-blown dust from nearby commercial agricultural activities [11]. This environment causes thick layers of red dust to settle on the weather instruments, which blocks natural airflow thereby interfering with how the sensor radiation shields handle heat [7].

Datasets

Two variables, maximum temperature (Tmax) and relative humidity (RH) were selected for validation based on having no missing values during the analysis period. For each variable, paired daily values from the AWS and MWS were compiled across both the pre- and post-maintenance windows. To evaluate the biases of measurements, data were collected simultaneously from two collocated observing setups within the same standard station site[6]. The MWS, serving as the control, uses standard liquid-in-glass maximum thermometers exposed inside a traditional, double roofed and louvred wooden Stevenson screen [8]. The AWS has electronic sensors, specifically PT100 resistance and capacitive relative humidity sensors enclosed within a compact, naturally ventilated multi-plate plastic radiation shield [7].

Maintenance design

This study isolated instrument drift by tracking a routine field maintenance intervention. The physical maintenance intervention was executed on August 20, 2025, at the Chisumbanje weather station. In lowveld operational environments like Chisumbanje, August represents a critical exposure window due to high seasonal wind speeds coupled with low soil moisture and agricultural tillage. High wind gusts act as a dynamic driver, forcing wind-blown dust deep into the louvered inter-plate spaces of compact multi-plate shields and against sensor protective membranes. This wind-driven impaction accelerates particulate caking, simultaneously degrading the reflective white surface albedo and physically constricting natural convective airflow paths during subsequent low-wind, high-insolation hours. The field intervention involved a thorough physical cleaning of the AWS multi-plate plastic shields with

distilled water to remove dust layers, alongside clearing particulate blockages from the relative humidity sensor's protective mesh cap [12]. To isolate the statistical impact of this cleaning, a forty-day data period was established around the intervention date. The pre-maintenance period ran from 31 July to 19 August 2025, representing the maximum environmental dust contamination phase and post-maintenance period ran from 21 August to 09 September 2025 capturing data from the newly cleaned sensor environment.

Statistical analysis

Agreement between the AWS and MWS was assessed using four complementary statistical metrics, calculated separately for the pre-maintenance and post-maintenance periods. All statistical computations were performed on paired daily observations. Scatterplots of AWS versus MWS readings, overlaid with the 1:1 line of perfect agreement, were generated for each variable to visually assess agreement and any systematic deviation. Timeseries plots of both instruments across the forty-day observation window were also produced to visualise temporal patterns in agreement and to clearly delineate the maintenance intervention date. The strength of the linear relationship between the two systems was evaluated using the Pearson correlation coefficient (R), calculated following standard statistical procedures [13, 14]. Values of R range from +1 to -1 and values from 0.90 to 1.00 indicate a very strong correlation, 0.70 to 0.89 a strong correlation, 0.40 to 0.69 a moderate correlation, 0.10 to 0.39 a weak correlation, and 0.00 to 0.10 a very weak correlation [13].

The Root Mean Square Error (RMSE) was also used and it expresses the magnitude of typical deviation between paired AWS and manual observations in the native units of each variable [1, 15]. Low RMSE values indicate smaller sensor drift, while higher values indicate severe drift. Mean Bias Error (MBE) was also used. This metric indicates the average direction and magnitude of systematic offset between the AWS and the MWS reference [15], with negative values showing an AWS underestimation, while positive values show an overestimation relative to the manual station. Percentage Bias (PBIAS), expressing the MBE as a proportion of the mean observed MWS value was also used. This metric transforms the relative magnitude of bias to be compared across variables with different measurement scales such as relative humidity and maximum temperature in this study [16].

Altogether these metrics allowed the quantification of the magnitude of sensor error caused by environmental dust buildup on instruments. The formulas for R , RMSE, MBE and PBIAS were implemented programmatically using formulas demonstrated in the works of [1, 13–15].

Results

Summary validation statistics for both variables and observation periods are presented in Table 1. Across both maximum temperature and relative humidity, agreement between the AWS and the MWS reference station improved following the maintenance intervention, though the magnitude of improvement differed substantially between the two variables.

Table 1
Summary of validation statistics.

Variable	Maintenance period	R	RMSE	MBE	PBIAS (%)
Tmax (°C)	Pre	0.992	0.863	-0.797	-2.850
Tmax (°C)	Post	0.999	0.305	-0.282	-0.830
RH (%)	Pre	0.740	5.015	-4.790	-20.130
RH (%)	Post	0.876	1.949	-1.759	-6.910

Validation statistics comparing automatic and manual station daily maximum temperature (Tmax) and relative humidity (RH) observations, before and after automatic station maintenance.

Maximum temperature

For maximum temperature, the AWS showed strong agreement with the manual station even prior to maintenance, with a Pearson correlation coefficient of 0.992, an RMSE of 0.863°C, an MBE of -0.797°C, and a PBIAS of -2.85%. Following maintenance, agreement improved further, with the correlation coefficient rising to 0.999, RMSE declining to 0.305°C, MBE narrowing to -0.282°C, and PBIAS reducing to -0.83%. This pattern is illustrated in Fig. 2, in which both the pre-maintenance (blue circles) and post-maintenance (red triangles) observations cluster closely around the 1:1 line across the full range of recorded values (approximately 23°C to 37°C), with the post-maintenance points showing visibly tighter clustering and reduced scatter relative to the pre-maintenance points, particularly in the 26°C to 30°C range.

The corresponding time series in Fig. 3 shows close tracking between the MWS and AWS temperature records throughout the full observation window, with the AWS consistently registering slightly lower maximum temperatures than the manual station across both periods, consistent with the negative MBE.

Relative humidity

Relative humidity showed comparatively weaker agreement in both periods, though it improved after the maintenance intervention. In the pre-maintenance period, the correlation coefficient was 0.740, with an RMSE of 5.015%, an MBE of -4.790%, and a PBIAS of -20.13%. Following maintenance, the correlation coefficient increased to 0.876, RMSE declined to 1.949%, MBE reduced to -1.759%, and PBIAS decreased to -6.91%. Figure 4 shows that pre-maintenance observations (blue circles) fall predominantly below the 1:1 line, indicating that the AWS under-recorded relative humidity relative to the manual station across most of the observed range (approximately 14% to 28%). Post-maintenance observations (red triangles) show a comparatively tighter distribution around the 1:1 line, although a degree of scatter and continued underestimation persists, particularly at higher humidity values above 24%.

The time series in Fig. 5 shows a pronounced divergence between the MWS and AWS relative humidity records during the pre-maintenance period, with the AWS trace consistently positioned below the manual station trace, followed by a visible narrowing of this gap after the maintenance date, though the two records do not fully converge for the remainder of the observation window.

Across both variables, the direction of bias was consistent: the AWS underestimated values relative to the manual station in both the pre- and post-maintenance periods, as reflected in the uniformly negative MBE and PBIAS values in Table 1. However, the relative magnitude of this bias, and the associated improvement following maintenance, was substantially larger for relative humidity than for maximum temperature, with the pre-maintenance PBIAS for relative humidity (-20.13%) representing roughly seven times the magnitude observed for maximum temperature (-2.85%).

Discussion

This study evaluated the operational performance of the Chisumbanje Automatic Weather Station (AWS) relative to co-located manual observations across a 40-day period. Prior to servicing, environmental dust accumulation was associated with systematic bias, with negative biases reaching -0.80°C for maximum temperature (T max) and -4.79% for relative humidity (RH). The scheduled maintenance intervention on 20 August produced an immediate improvement in agreement, reducing MBE magnitude by 65% for T max (from -0.80°C to -0.28°C) and by 63% for RH (from -4.79% to -1.76%). While dust accumulation typically causes temperature readings to run higher due to reduced shield albedo, the AWS consistently displayed negative biases, underscoring an uncorrected sensor calibration drift. The baseline negative offset of -0.28°C remaining after maintenance confirms this downward calibration shift. Before servicing, heavy dust build-up superimposed a further -0.52°C ventilation error onto this offset. Cleaning the multi-plate shield eliminated the physical airflow block, recovering the thermal response while clearly exposing the underlying calibration drift. These results indicate that routine physical cleaning of sensor housings and radiation shields is an effective, low-cost intervention for restoring AWS data quality, and reinforce the value of dust and debris removal as a standalone component of preventive maintenance in dust-prone operational settings [1, 3].

Despite similar proportional MBE reductions, post-maintenance recovery differed in absolute quality between variables. Maximum temperature approached near-perfect agreement ($R = 0.999$, $\text{RMSE} = 0.305^{\circ}\text{C}$), fully satisfying standard WMO accuracy tolerances (WMO)[8]. In contrast, relative humidity remained partially degraded ($R = 0.876$, $\text{PBIAS} = -6.91\%$). This asymmetry indicates that capacitive relative humidity sensors are naturally more vulnerable to in-service drift caused by fine particulate contamination of the protective sensing membrane. Cleaning only the multi-plate radiation shield is insufficient for full relative humidity recovery because particulate dust also accumulates on the sensor's protective mesh cap and filter mesh. As fine dust lodges within this porous cap, it restricts water vapor diffusion and creates a micro-climate around the sensing element itself. Because field wiping cannot completely remove these microscopic contaminants from inside the protective mesh without damaging the underlying polymer, internal sensor drift remains uncorrected. Consequently, simple field wiping and

distilled water rinsing, while highly beneficial for shield ventilation, cannot completely reverse sensor element drift, pointing to a required combination of field cleaning and periodic laboratory recalibration [2, 12, 17].

These performance discrepancies carry significant operational implications for regional climate services and hydrological applications [4, 5]. Because relative humidity is an essential variable for derived products such as reference evapotranspiration, heat indices, and wildfire risk assessment, a persistent negative bias of approximately 7% can propagate systematic errors into downstream decision-support and early warning models [9, 10]. Maintaining routine field cleaning schedules is therefore essential for sustaining model integrity and dataset quality across regional observation networks [3, 6].

Conclusion

National Meteorological and Hydrological Services (NMHS) should enforce strict compliance with WMO guidelines requiring physical inspection and cleaning of all operational instruments during routine check readings so that any anomalies are corrected as soon as they occur, thereby preventing degradation of data[8]. Beyond routine cleaning, operational stations should execute comprehensive regular servicing, including instrument sanity checks and field cross validation against calibrated reference standards, to catch early sensor drift and ensure long-term data stability [2, 10]. NMHS data management centres should integrate automated threshold flags within central ingest systems to trigger immediate field maintenance alerts whenever daily relative humidity or temperature deviations exceed acceptable operational tolerances [1].

These findings are best read within the scope of this study. The 40-day window and single station design offered a controlled before- and -after comparison, but they represent one station's conditions at one point in time. The results may not directly transfer to Zimbabwe's broader AWS network, where dust exposure and local microclimate differ [3, 11]. Extending this comparison across multiple stations, longer time frames, and repeated maintenance cycles would help establish whether the recovery magnitudes observed here hold more generally across the network [4–6].

Declarations

Acknowledgement

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Figures



Legend

- Chisumbanje station
- + Stations
- Zimbabwe
- Provinces
- Elevation (m)**
 - ≤ 441
 - 441 - 721
 - 721 - 1000
 - 1000 - 1280
 - 1280 - 1559
 - 1559 - 1838
 - 1838 - 2118
 - > 2118

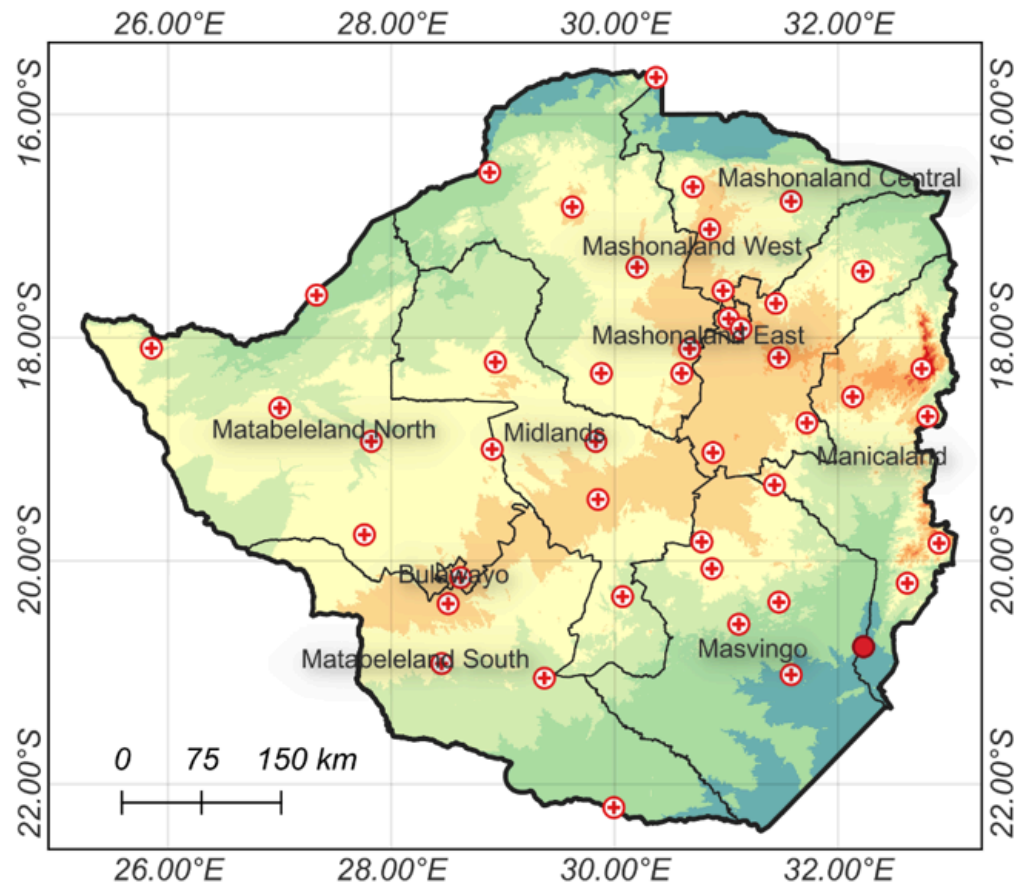


Figure 1

Location of Chisumbanje weather station relative to the other weather stations in Zimbabwe.

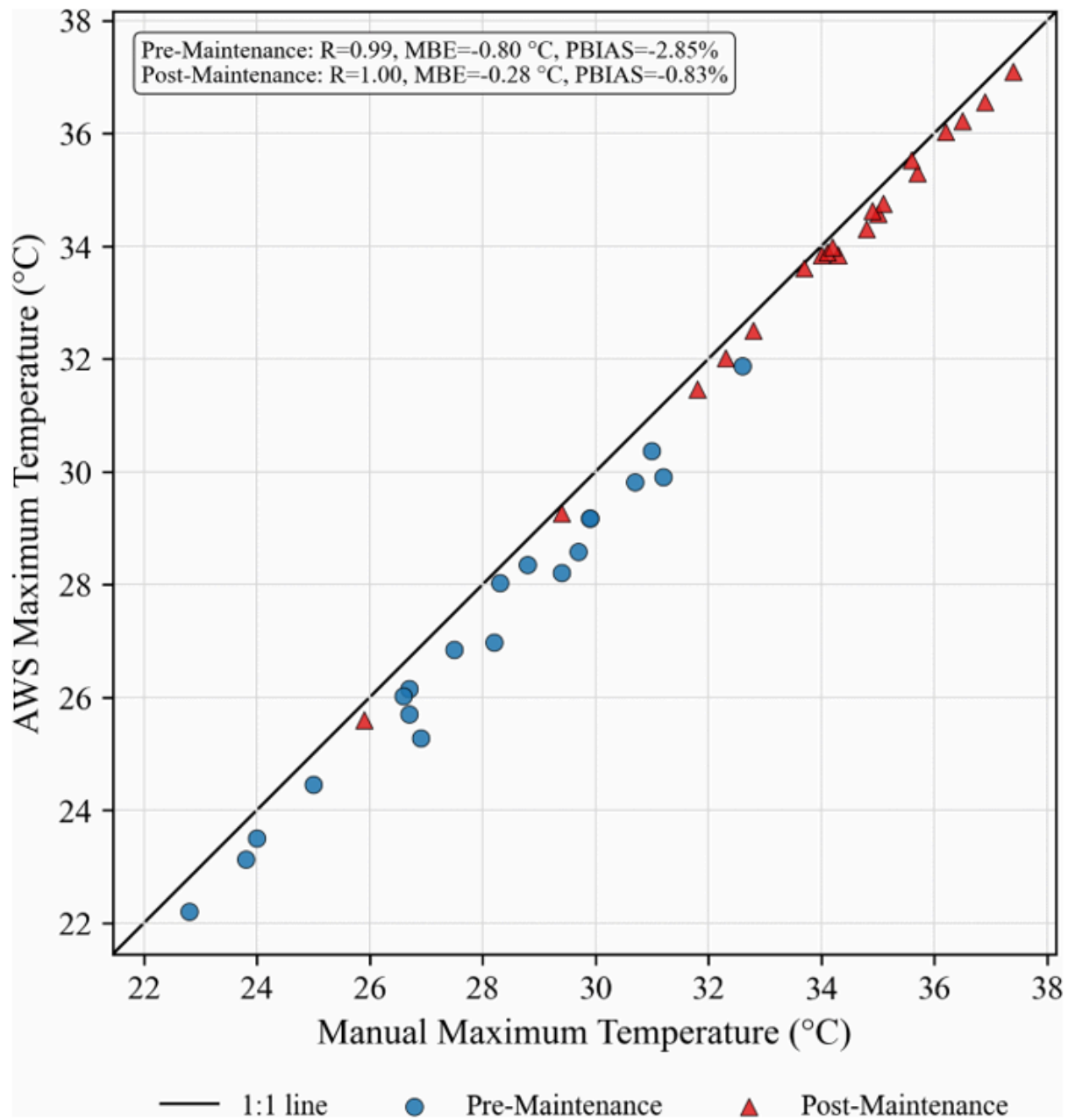


Figure 2

Agreement between automatic and manual station daily maximum temperature readings. Data shown before (blue circles) and after (red triangles) AWS maintenance. The solid diagonal line represents the 1:1 line of perfect agreement.

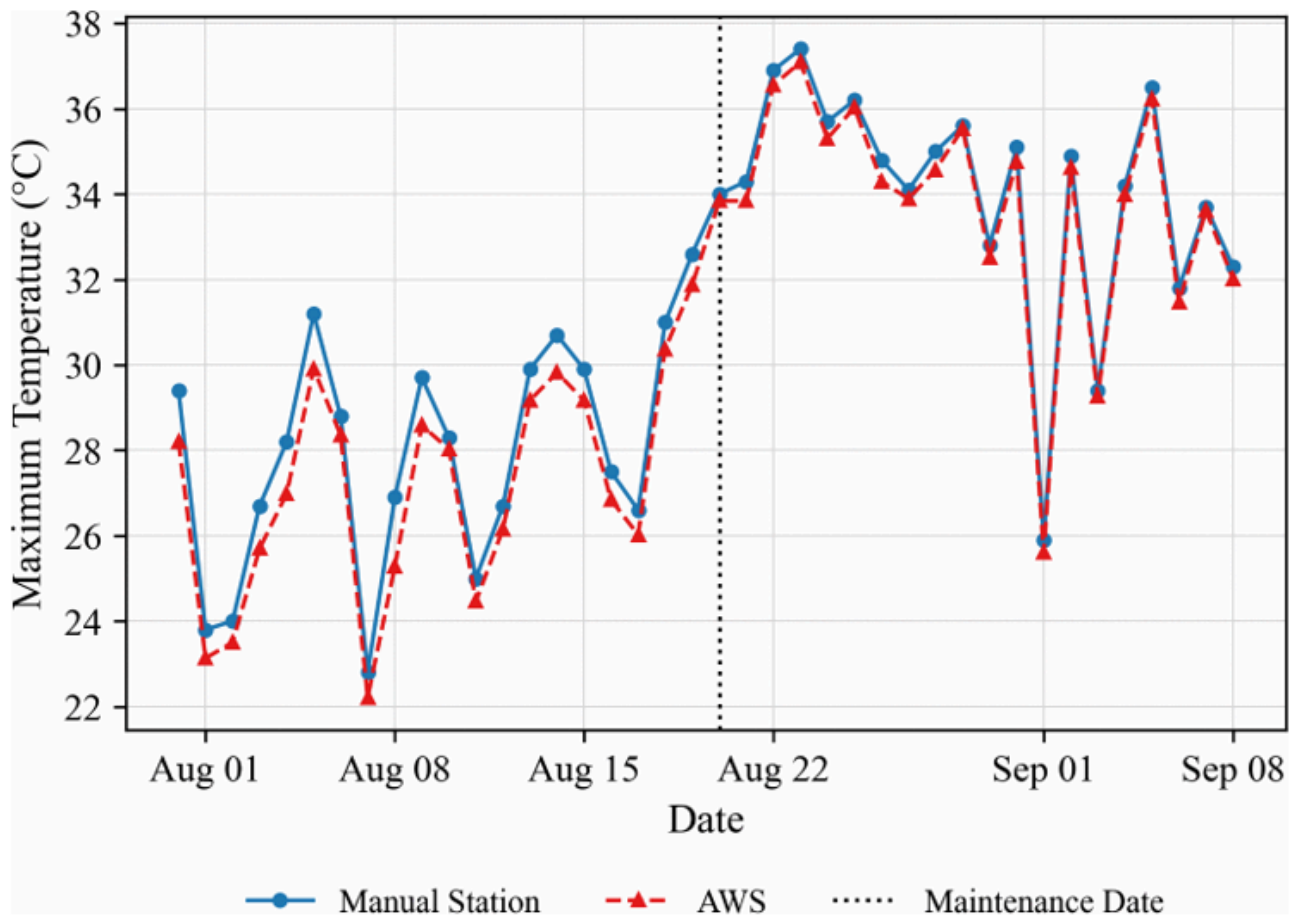


Figure 3

Daily maximum temperature time series. Data from the manual station (solid blue line, circles) and Automatic Weather Station (dashed red line, triangles) from 1 August to 8 September 2025. The vertical dotted line marks the date of AWS maintenance.

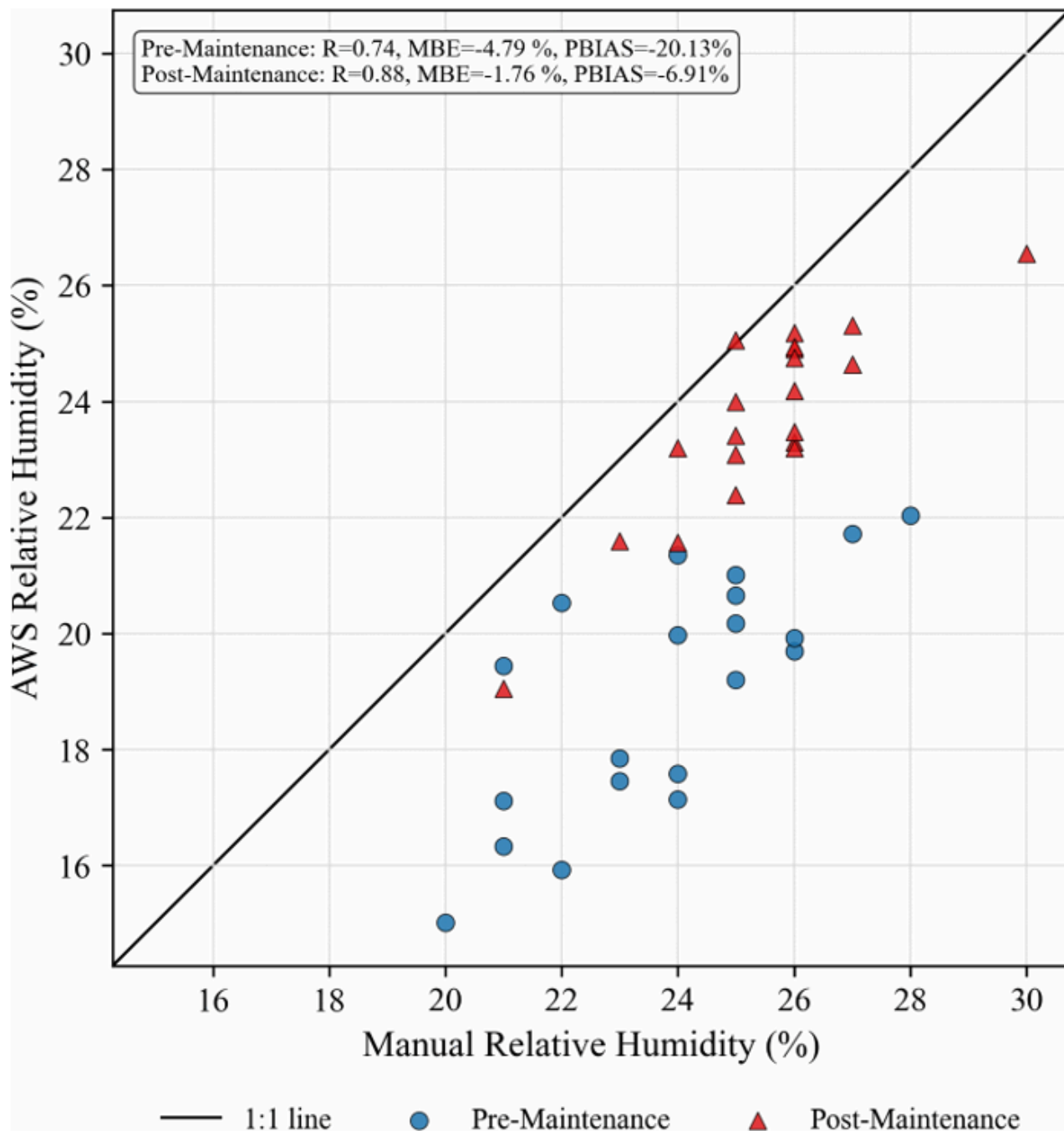


Figure 4

Agreement between automatic and manual station daily relative humidity readings. Data shown before (blue circles) and after (red triangles) AWS maintenance. The solid diagonal line represents the 1:1 line of perfect agreement.

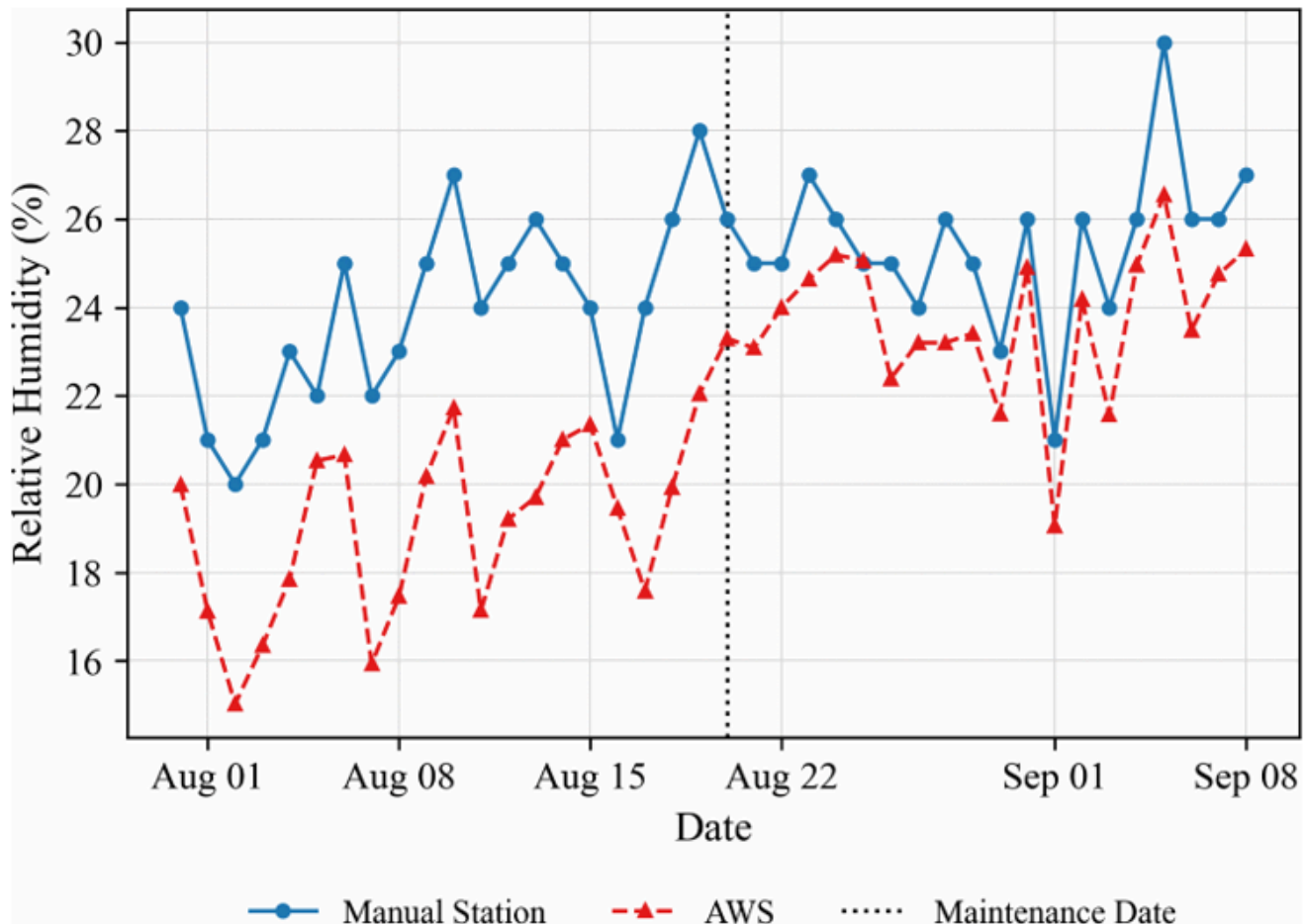


Figure 5

Daily relative humidity time series. Data from the manual station (solid blue line, circles) and Automatic Weather Station (dashed red line, triangles) from 1 August to 8 September 2025. The vertical dotted line marks the date of AWS maintenance.