

Article

Long-Term Evaluation of AIRS Precipitable Water Vapor over China (2005–2025): Moisture-State-Dependent Bias and Temporal Consistency

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Highlights

What are the main findings?

- AIRS Version 7 closely reproduces monthly PWV variability, but AIRS–IGRA differences become increasingly negative under anomalously moist conditions even after station and seasonal controls.
- The monthly correlation remains high while the annual bias drifts and station-scale trend agreement remains only moderate; the ascending–descending differences are largest in summer.

What are the implications of the main findings?

- Satellite climate records should be evaluated for long-term consistency as well as monthly agreement.
- For monthly PWV climatology and broad variability over China, AIRS provides useful information; small long-term trends require independent constraints, stable sampling, and homogeneous reference records.

Abstract

Long-term satellite precipitable water vapor (PWV) records are widely used in climate studies, but excellent monthly agreement does not necessarily imply equivalent long-term climate-record consistency. We evaluated Atmospheric Infrared Sounder (AIRS) Version 7 Level-3 monthly PWV against Integrated Global Radiosonde Archive Version 2 (IGRA2) observations at 76 Chinese stations during 2005–2025, using 19,053 matched station-months. The overall agreement was high ($R = 0.984$, bias = -1.34 mm, RMSE = 3.36 mm). Nevertheless, station-by-calendar-month leave-one-year-out anomalies showed a robust moisture-state dependence of AIRS–IGRA differences (Spearman $\rho = -0.722$; 95% CI -0.741 to -0.704). The AIRS-on-IGRA OLS anomaly-response slope was 0.473; equal-variance Deming regression increased it to 0.560 (95% CI 0.519–0.596), still below unity. The ascending-minus-descending monthly PWV averaged +0.561 mm and was largest in summer. The network annual bias became more negative at -0.141 mm yr^{−1}, compared with -0.138 mm yr^{−1} for a strict 73-station fixed network, while the annual R had no



Academic Editor: Manuel Antón

Received: 15 September 2026

Revised: 13 October 2026

Accepted: 18 October 2026

Published: 22 October 2026

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significant trend. The station-scale trend consistency was moderate (Pearson $r = 0.545$; sign agreement 65.8%). An independent BJFS GNSS comparison supported an AIRS contribution to local divergence, but did not establish nationwide attribution. These findings support monthly PWV climatology and broad variability applications over China while showing that small long-term trends require independent constraints, reference-record homogenization, and explicit attention to sampling stability.

Keywords: precipitable water vapor; radiosonde; moisture-state dependence; validation; temporal consistency

1. Introduction

Atmospheric water vapor is a key component of Earth's climate system and hydrological cycle. It influences longwave radiative transfer, cloud and precipitation formation, latent heat exchange, and atmospheric circulation, and it provides one of the strongest positive feedbacks in a warming climate [1–3]. Precipitable water vapor (PWV), the vertically integrated amount of water vapor in an atmospheric column, provides a compact measure of total-column moisture and is widely used to study moisture transport, precipitation processes, climate variability, and long-term hydroclimatic change. Long radiosonde and satellite records reveal pronounced spatiotemporal variability in the atmospheric moisture, while also showing that trend estimates can be affected by changes in observing systems and data-processing procedures [2,3].

China spans strong gradients in climate, elevation, land surface, and monsoon influence, making it a useful natural laboratory for testing the environmental dependence of satellite PWV products. Radiosonde observations show a pronounced PWV climatological gradient, from humid southeastern China toward the arid northwest and the Tibetan Plateau, together with a strong annual cycle characterized by high summer and low winter values [4–8]. Elevation contributes to this large-scale moisture pattern, while atmospheric circulation and the East Asian monsoon introduce additional regional and interannual variability. Satellite PWV accuracy therefore cannot be assumed to be spatially or seasonally uniform across China.

Radiosondes, Global Navigation Satellite System (GNSS) observations, reanalyses, and satellite retrievals have been widely used for multi-source PWV validation over China [7,9–15]. These studies show that a product can reproduce the broad PWV climatology while still exhibiting substantial regional or seasonal errors. Evaluations of MODIS, VIIRS, FY-4A, and ERA5 PWV, for example, have all reported performance variations with region and/or season [11–14]. National-scale correlation coefficients and RMSE values alone can therefore mask retrieval differences with a coherent environmental structure.

The Atmospheric Infrared Sounder (AIRS), launched aboard NASA's Aqua satellite in 2002, provides near-global hyperspectral infrared observations of atmospheric temperature and water vapor [16–19]. AIRS and its retrieval system were designed to improve the atmospheric sounding capabilities relative to earlier satellite sensors. Over more than two decades, AIRS observations have been used extensively in weather analysis, studies of atmospheric processes, model evaluation, and climate research [18–23]. Validation against radiosondes and other reference observations has shown that AIRS captures humidity variability well, although the retrieval performance can depend on cloud conditions, surface properties, atmospheric state, and sampling [20,22,24–28].

This environmental dependence is particularly relevant to PWV retrievals. Yue et al. [24] showed that the sampling characteristics of AIRS temperature and humidity

retrievals depend strongly on cloud state. Hearty et al. [25] separated AIRS sampling errors into temporal- and instrument-sampling components, and showed that the cloud-related selection of valid retrievals can generate appreciable dry biases under some meteorological conditions. A global assessment by Roman et al. [26] likewise found that AIRS PWV errors vary systematically across the PWV range, with negative bias becoming especially evident at high PWV. More recent studies have also identified the cloud amount and other environmental variables as important factors associated with the AIRS infrared PWV performance [29,30].

AIRS water-vapor products have also been evaluated over China. Using high-resolution observations from 113 radiosonde stations, Zeng et al. [31] found pronounced spatial variability in AIRS water-vapor retrievals, including stronger underestimation in southeastern China, where cloud amounts are relatively high. That study, however, focused mainly on June 2013 and June 2014. It therefore characterized short-term regional retrieval behavior but did not establish whether the environmental dependence persists through the seasonal cycle or evolves over a multi-decadal satellite record.

As AIRS is increasingly used in climate applications, retrieval agreement must be distinguished from long-term temporal consistency. AIRS Version 7 products have been used to examine the atmospheric change over approximately two decades [32], whereas recent analyses of long-term AIRS observations have shown that trends from operational retrieval products do not necessarily agree with trends obtained using methods designed specifically to exploit long-term radiance stability [33]. AIRS climatologies can also be influenced jointly by retrieval availability and time-dependent sampling [23–25,34,35]. Strong agreement with a reference record at monthly time scales therefore does not, by itself, demonstrate suitability for detecting small long-term trends.

Long-term comparisons must also account for uncertainty in the radiosonde reference. IGRA is among the most comprehensive quality-controlled global upper-air archives [36–38], but quality control is not equivalent to homogenization. Instrument changes, observing-practice adjustments, station relocations, and changes in humidity-sensor characteristics can introduce non-climatic discontinuities into long radiosonde records. This issue is particularly relevant in China, where homogenization studies and independent GNSS comparisons have shown that radiosonde-system transitions can materially affect apparent humidity and PWV trends [6,9]. Accordingly, we evaluate the trend consistency between AIRS and IGRA rather than treating either dataset as an error-free representation of the true climate trend.

The contribution of this study is not the first identification of AIRS moisture-dependent differences. Cloud-state sampling, high-PWV dry biases, and regional validation differences are already documented [20,24–31]. Here, we connect those established concerns to a 21-year assessment of monthly and long-term record consistency over China. Specifically, we (1) distinguish excellent monthly agreement from network-scale bias evolution and station-scale trend consistency; (2) test moisture-state dependence after station and seasonal controls, explicit covariate adjustment, and errors-in-variables regression; and (3) evaluate the stability of the conclusions under stricter radiosonde coverage, fixed-network and spatial-sampling tests, early-2020s segmented models, and a targeted independent GNSS comparison. The central question is whether high monthly AIRS–IGRA agreement implies equivalent consistency for small long-term climate signals.

2. Materials and Methods

2.1. Radiosonde Observations

Radiosonde observations were obtained from the Integrated Global Radiosonde Archive Version 2 (IGRA2) [36–38]. We selected stations in China with sufficient tem-

poral coverage during 2005–2025. The profiles contain pressure, temperature, and relative humidity at multiple vertical levels. For relative humidity, the calculated humidity field was used preferentially when physically reasonable, with the reported humidity field used as a fallback when required.

Profile quality control required pressures of 10–1100 hPa, temperatures of 180–330 K, and relative humidities of 0–110%. Each profile was required to contain at least six valid pressure levels spanning more than 300 hPa, and derived PWV values outside 0–100 mm were excluded. PWV was integrated only over the observed valid pressure range, with no extrapolation above the highest or below the lowest valid level. These requirements provide minimum coverage rather than full-column closure. At least 120 valid months spanning 15 or more years were required per station; 76 stations qualified. A stricter vertical-coverage sensitivity is described in Section 2.6 and Supplementary Section S1.

For the final analysis, complete IGRA2 station records covering 2005–2025 were used. Station observations for June 2021–May 2022 were obtained directly from NOAA/NCEI and processed using the same profile quality-control criteria and PWV calculation procedure as all other periods. The final dataset contained 19,053 matched station-month samples.

2.2. AIRS Level-3 Monthly PWV

We used the Aqua/AIRS Level-3 Monthly Standard Physical Retrieval (AIRS-only), $1^\circ \times 1^\circ$, Version 7.0 product (AIRS3STM) for 2005–2025 [39]. The product provides separate total-column water-vapor retrievals for ascending and descending branches together with valid-observation counts. AIRS has provided a near-global atmospheric sounding record since the Aqua mission began in 2002 [16–21].

After extracting ascending and descending PWV together with the corresponding valid-observation counts, a count-weighted monthly combined PWV was calculated as follows:

$$PWV_{\text{AIRS}} = \frac{N_A PWV_A + N_D PWV_D}{N_A + N_D} \quad (1)$$

where PWV_A and PWV_D are the monthly ascending and descending retrievals, respectively, and N_A and N_D are the corresponding valid-observation counts. Using a simple arithmetic mean of the two branches instead produced nearly identical overall validation statistics. AIRS PWV at each radiosonde station was obtained by bilinear interpolation from the surrounding grid cells.

For the cloud-robustness analysis, ascending and descending AIRS cloud fraction (CloudFrc) and their valid-observation counts were extracted from the same Level-3 product. Monthly cloud fraction was combined using count weighting where possible; if count fields were unavailable, the mean of the valid branch values was used. CloudFrc was treated only as an auxiliary environmental-state variable for association and robustness analyses, not as an independently established causal driver of PWV error. The datasets and principal processing steps used in the evaluation are summarized in Table 1.

2.3. Radiosonde PWV Calculation

Saturation vapor pressure was calculated using the Bolton formulation [40]:

$$e_s = 6.112 \exp\left(\frac{17.67 T_c}{T_c + 243.5}\right) \quad (2)$$

where T_c is temperature in degrees Celsius. Actual vapor pressure was calculated as $e = (\text{RH}/100)e_s$, and specific humidity q was calculated as follows:

$$q = \frac{0.622 e}{p - 0.378 e} \quad (3)$$

where p is atmospheric pressure. Total-column PWV was then obtained by vertically integrating specific humidity in pressure coordinates:

$$PWV = \frac{1}{g} \int q dp \quad (4)$$

where $g = 9.80665 \text{ m s}^{-2}$. Pressure p and vapor pressure e were expressed in the same units (hPa) when calculating specific humidity. Before vertical integration, pressure was converted to Pa, and the integral was evaluated with the trapezoidal rule. The resulting kg m^{-2} is numerically equivalent to millimeters of liquid-water depth. Pressure therefore serves as the vertical coordinate for radiosonde PWV integration rather than as an independent validation variable.

Table 1. Datasets and principal processing steps used in the AIRS–IGRA evaluation.

Dataset	Variables	Resolution/Sampling	Period	Role
IGRA2	Pressure, temperature, and relative-humidity profiles	Station profiles, aggregated to monthly means	2005–2025	Reference PWV
AIRS V7 L3	Total-column PWV, CloudFrc; ascending/descending branches and valid-observation counts	$1^\circ \times 1^\circ$ monthly	2005–2025	Satellite PWV; auxiliary orbit/cloud analyses
Station metadata	Latitude, longitude, elevation	Station attributes	Static	Spatial/elevation analyses
SuomiNet GNSS	Ground-based PWV and reported uncertainty	Daily aggregates; common monthly observations	BJFS 2010–2020	Independent site-specific constraint

2.4. Spatial and Temporal Matching

PWV from individual radiosonde profiles was first aggregated to station-month means and then matched to AIRS at the same station-month scale. The analysis therefore evaluates agreement between AIRS Level-3 monthly PWV and monthly mean radiosonde PWV, not instantaneous retrieval errors at individual satellite overpasses.

The final dataset comprised 76 stations and 19,053 matched station-month observations. Orbit-branch analyses used only station-months for which both ascending and descending AIRS retrievals were available.

2.5. Statistical Evaluation and Trend Analysis

AIRS–IGRA agreement was quantified using Pearson correlation (R), mean bias, mean absolute error (MAE), and root-mean-square error (RMSE). Bias was defined as AIRS minus IGRA, so negative values indicate AIRS values lower than the radiosonde reference. Because several error metrics were non-normally distributed and some relationships were nonlinear, environmental associations were evaluated with Spearman rank correlation.

To separate moisture variability from fixed geography and station-specific seasonality, we first centered PWV and AIRS–IGRA differences within stations. Station-by-calendar-month leave-one-year-out (LOO) anomalies then referenced each target year to all other available years for that station and calendar month, requiring at least eight available years in each group. The original correlation analysis used 2000 station-cluster bootstrap replicates, resampling complete station time series. Within each season, IGRA PWV quartiles Q1–Q4 described relative moisture states. Pair-mean PWV versus AIRS–IGRA difference was retained only as a descriptive proportional-bias diagnostic because the variables share

terms algebraically. Full progressive tests and subsequent model specifications are reported in Supplementary Section S2.

Normalized RMSE, MAE, and absolute bias were calculated by dividing each station metric by its long-term mean IGRA PWV. Ascending and descending retrievals for the same station-month were paired; $\Delta AD = PWV_A - PWV_D$ denotes their monthly difference, with 3000 station-cluster bootstrap replicates used for confidence intervals. Absolute-value difference slopes (mm mm^{-1}), anomaly-response slopes (mm mm^{-1}), and temporal trends (mm yr^{-1}) are explicitly distinguished throughout.

A station annual mean required at least 10 matched months. Station trends were estimated by the Theil–Sen method [41] after at least eight qualifying annual means, with 95% slope intervals used to assess sign uncertainty. Cross-station consistency was summarized by Pearson r , Spearman ρ , sign agreement, mean absolute trend difference, and equal-variance Deming (orthogonal) regression. These symmetric slopes relate two uncertain trend estimates and are not fractions of a true trend. Station bootstrap resampling used 3000 replicates. Shortened periods 2005–2021 and 2005–2020 were retained as sensitivity tests. Network annual bias, MAE, RMSE, and R were assessed using Theil–Sen slopes and Mann–Kendall tests [42,43], with full-period fixed-network and mid-record checks described in Supplementary Section S5.

2.6. Robustness and Independent GNSS Analyses

Radiosonde sensitivity tests varied the minimum profile count per month and imposed stricter vertical coverage: at least 10 valid humidity levels, top pressure ≤ 300 hPa, a valid pressure span ≥ 300 hPa, and bottom pressure at least 90% of the elevation-adjusted standard surface pressure. Baseline and strict calculations were compared on identical station-months. These criteria constrain coverage but do not establish full-column closure. Details, endpoint summaries, and retained sample sizes are given in Supplementary Section S1.

Moisture-state robustness was tested using multivariable models with CloudFrc, elevation, latitude, calendar-month effects, and year effects; a station-fixed-effect model absorbed all time-invariant site characteristics. An additional model used station-by-calendar-month LOO anomalies with cloud-anomaly and year controls. Model coefficients used station-clustered standard errors. Partial rank correlations and variance inflation factors provided complementary diagnostics. Equal-variance Deming regression was applied to AIRS versus IGRA LOO anomalies, with 3000 station-bootstrap replicates; error-variance ratios $\lambda = 0.25\text{--}4$ were examined, where λ is the AIRS-to-IGRA measurement-error variance ratio. Unlike a regression of AIRS–IGRA on IGRA, this response formulation avoids placing IGRA algebraically on both axes. The ratio is assumed rather than independently calibrated (Supplementary Section S2).

A normalized AIRS valid-observation proxy was defined as the sum of ascending and descending monthly valid counts divided by twice the number of days in the month. It measures Level-3 sampling availability, not the fraction of all attempted retrievals that succeeded. Cloud and availability models were evaluated as statistical diagnostics rather than causal mediation tests (Supplementary Section S3).

Monthly segmented models included a linear pre-break time term, a January-2022 level term, a post-break slope-change term, and calendar-month fixed effects. Heteroskedasticity- and autocorrelation-consistent (HAC) standard errors used 12 lags. January 2022 was a mission-motivated reference date; January break dates from 2020 through 2024 were sensitivity tests rather than a procedure to identify a unique causal breakpoint. The primary model was repeated for the strict fixed network (Supplementary Section S4).

The full-record fixed network required at least 10 matched months in every year from 2005 through 2025. Bilinear and nearest-cell AIRS sampling were compared on their

common sample. Stations were also grouped by tertiles of long-term mean IGRA PWV to assess climatic-regime trend consistency. Signed and absolute station trend differences were tested against station-mean IGRA PWV and elevation, both separately and using partial Spearman correlations controlling the other environmental variable. These tests are descriptive and do not identify physical causes (Supplementary Section S5).

An independent ground-based SuomiNet GNSS check used daily-to-monthly PWV aggregates with at least 10 valid UTC days per month. AIRS was sampled at the actual GNSS receiver coordinates as well as at the nearby IGRA location. The primary BJFS comparison retained 89 common months during 2010–2020. Because several years had incomplete seasonal coverage, difference trends were fitted to the common monthly records with a linear time term, calendar-month fixed effects, and HAC standard errors with 12 lags. BJFS and the nearby Beijing radiosonde are separated by 49.2 km. Other available GNSS records and their quality limitations are documented in Supplementary Section S6; the analysis is a site-specific constraint, not a second national validation network.

3. Results

3.1. Monthly and Seasonal AIRS–IGRA PWV Agreement

AIRS closely reproduced monthly radiosonde PWV variability across the 76-station Chinese network (Figures 1 and 2). Across 19,053 matched station-months, R was 0.984, mean AIRS–IGRA bias was -1.34 mm, and RMSE was 3.36 mm (Table 2). Agreement in the large seasonal and spatial PWV range coexisted with systematic negative differences at higher moisture values.

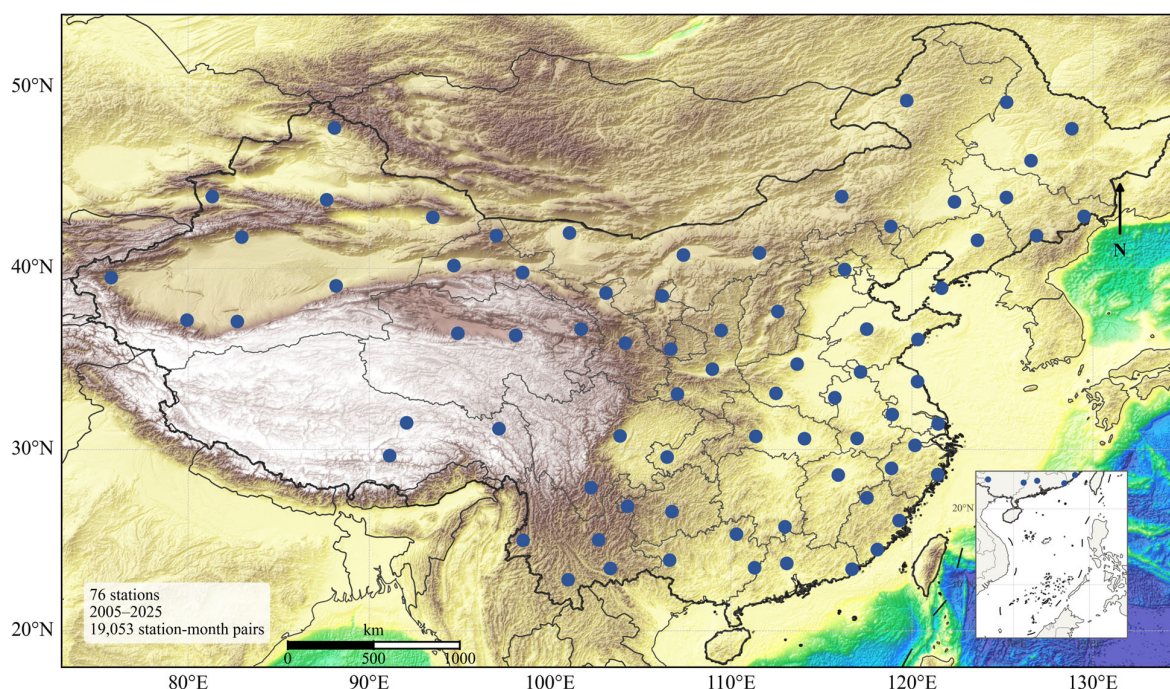


Figure 1. Spatial distribution of the 76 IGRA2 stations used during 2005–2025. Terrain shading provides geographic context. The final comparison contains 19,053 matched station-months. Blue dots denote the IGRA2 stations. Terrain colors represent shaded relief and are used only for geographic context; they do not encode an analyzed variable.

Seasonal contrasts were pronounced. DJF bias was -0.05 mm with RMSE 1.40 mm; JJA bias was -3.03 mm with RMSE 5.18 mm, although JJA correlation remained high ($R = 0.964$). For the combined wettest within-season quartile, R was 0.970 while bias and RMSE were -3.02 and 4.87 mm. Thus, high monthly correlation did not imply

small systematic differences. Spatial and season–moisture distributions are provided in Supplementary Figures S4 and S5.

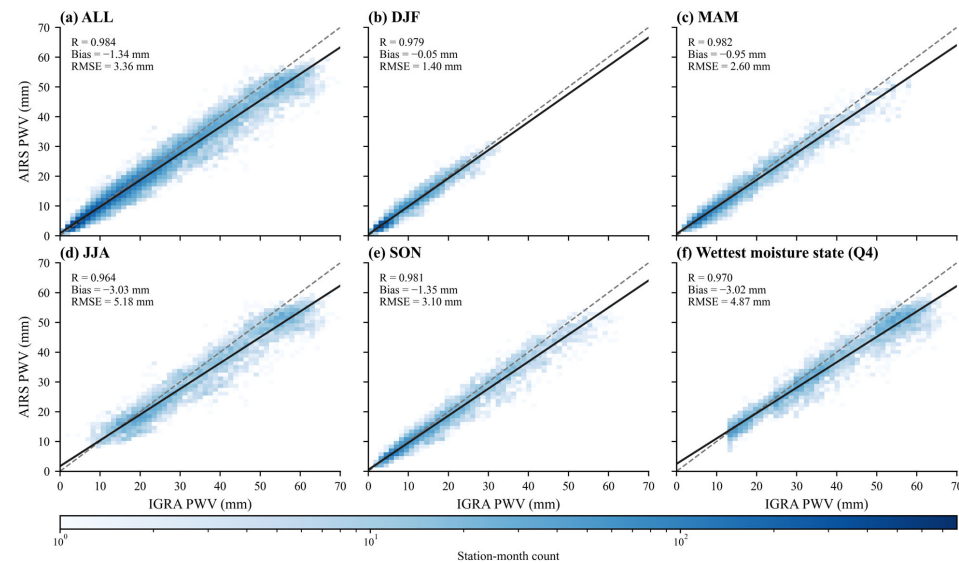


Figure 2. Monthly AIRS–IGRA PWV agreement for all samples, DJF, MAM, JJA, SON, and the combined wettest within-season quartile (Q4). Color shows sample density on a logarithmic scale; the dashed line is 1:1 and the solid line is the descriptive OLS fit. Each panel reports R, mean bias, and RMSE.

Table 2. Monthly AIRS–IGRA agreement by season and moisture subset.

Subset	R	Bias (mm)	RMSE (mm)
All samples	0.984	−1.34	3.36
DJF	0.979	−0.05	1.40
MAM	0.982	−0.95	2.60
JJA	0.964	−3.03	5.18
SON	0.981	−1.35	3.10
Wettest within-season Q4	0.970	−3.02	4.87

3.2. Robust Moisture-State Dependence

Moisture-state dependence persisted after removing fixed station differences and the station-specific mean seasonal cycle (Figure 3). The station-by-calendar-month LOO correlation between IGRA anomalies and AIRS–IGRA difference anomalies was $\rho = -0.722$ (95% station-cluster bootstrap CI -0.741 to -0.704). The AIRS-on-IGRA OLS anomaly-response slope was 0.473. Equal-variance Deming regression increased the response slope to 0.560 (95% station-bootstrap CI 0.519–0.596), but it remained below unity across the tested variance ratios (Supplementary Tables S6–S12 and Figure S2).

The moisture coefficient remained negative after explicit cloud and geographic adjustment ($-0.2284 \text{ mm mm}^{-1}$), station fixed effects ($-0.2385 \text{ mm mm}^{-1}$), and the LOO anomaly model ($-0.5307 \text{ mm mm}^{-1}$). The LOO partial Spearman correlation controlling cloud anomaly and year was approximately -0.675 . Stricter radiosonde coverage also retained a strong LOO association ($\rho = -0.778$). These results establish persistence across statistical controls, not a unique physical cause (Supplementary Sections S1 and S2).

Cloud coefficients changed markedly across specifications, whereas the moisture association remained comparatively stable. Cloudier conditions were associated with lower AIRS valid-observation availability, but adding the availability proxy did not attenuate the moisture coefficient. Wetter stations also had larger absolute errors without a corresponding

monotonic increase in normalized errors. Detailed cloud, availability, and normalization diagnostics are therefore treated as supporting evidence rather than separate main-text findings (Supplementary Tables S13–S19).

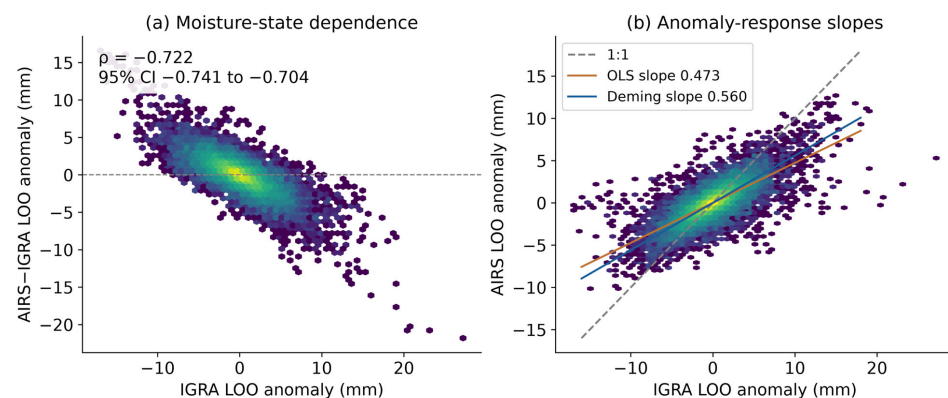


Figure 3. Station-by-calendar-month LOO moisture diagnostics ($N = 19,053$). **(a)** IGRA anomaly versus AIRS–IGRA difference anomaly; the correlation interval resamples station clusters. **(b)** AIRS-on-IGRA anomaly response, with OLS and equal-variance Deming slopes. The Deming 95% station-bootstrap interval is 0.519–0.596. Density shading is logarithmic. The response slope is distinct from a temporal trend. In panel **(b)**, line colors distinguish the 1:1 line, OLS fit, and Deming fit as indicated in the legend.

3.3. Ascending–Descending Differences and Early-2020s Evolution

Across 19,051 station-months with both branches available, the mean ascending-minus-descending PWV was +0.561 mm (95% station-cluster bootstrap CI +0.461 to +0.663 mm). The separation was largest in JJA (+1.236 mm), increasing to +1.687 mm in JJA 2022–2025 (Figure 4; Supplementary Table S20). Both branches were evaluated against the same monthly IGRA reference, so these statistics describe monthly branch differences and do not establish which branch has better instantaneous retrieval accuracy.

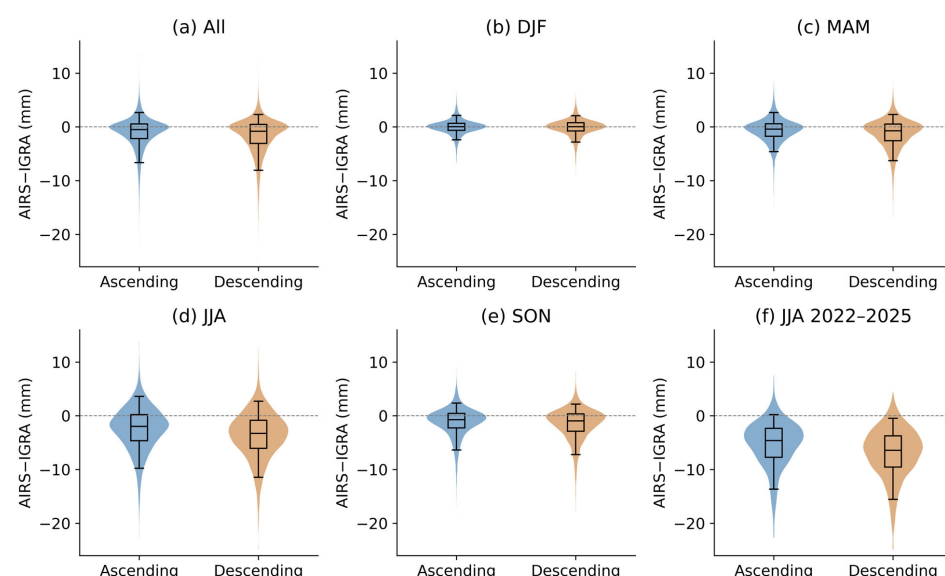


Figure 4. Monthly branch-minus-IGRA distributions for paired samples: **(a)** all months; **(b)** DJF; **(c)** MAM; **(d)** JJA; **(e)** SON; and **(f)** JJA during 2022–2025. Violin shapes show distributions; boxes span the interquartile range, center lines show medians, and whiskers span the 5th–95th percentiles. The dashed line denotes zero. Ascending and descending monthly aggregates share the same IGRA reference; the figure does not compare instantaneous overpass accuracy.

The January-2022 segmented AIRS–IGRA model identified a slope change of $-0.466 \text{ mm yr}^{-1}$ (95% CI -0.706 to -0.227 ; $p < 0.001$); the immediate level change was not significant. The strict fixed-network slope change was similar ($-0.475 \text{ mm yr}^{-1}$). In contrast, the ascending–descending series did not show a significant January-2022 joint level-and-slope break ($p = 0.141$). Nearby candidate dates also supported changes in bias evolution, so the evidence is interpreted as an early-2020s transition rather than a uniquely identified January-2022 event or causal proof of Aqua free drift (Supplementary Tables S21–S23 and Figure S6).

3.4. Long-Term Network-Scale Temporal Consistency

The network annual AIRS–IGRA bias became more negative during 2005–2025, with a Theil–Sen trend of $-0.141 \text{ mm yr}^{-1}$ ($p < 0.001$), while the annual R showed no significant trend (Figure 5). The strict full-record fixed network retained 73 stations and produced a nearly identical bias trend of $-0.138 \text{ mm yr}^{-1}$. Changes in station-network composition therefore do not explain the observed divergence (Supplementary Table S29).

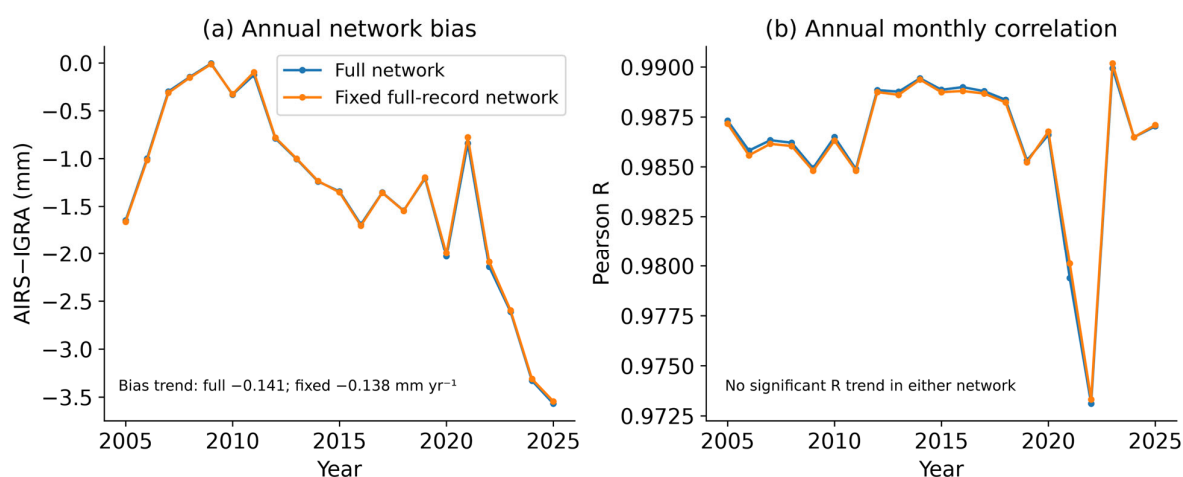


Figure 5. Annual network bias and correlation for the full and strict fixed networks. The fixed network contains 73 stations with at least 10 matched months in every year of 2005–2025. Bias trends are -0.141 and $-0.138 \text{ mm yr}^{-1}$, respectively. Annual correlation has no significant temporal trend in either network.

The principal temporal result also persisted under different reference and spatial treatments. Stricter vertical screening changed the common-sample bias from -1.195 to -0.662 mm , but the strict annual bias trend remained negative (approximately $-0.193 \text{ mm yr}^{-1}$). Bilinear and nearest-cell sampling yielded annual bias trends of -0.1411 and $-0.1408 \text{ mm yr}^{-1}$, respectively. Spatial sampling affects local comparisons, especially in heterogeneous terrain, but these checks did not remove the network-level trend (Supplementary Tables S2, S5, S24, and S28).

3.5. Station-Scale Trend Consistency and an Independent GNSS Constraint

The station-scale trend correspondence was substantially weaker than the monthly agreement (Figure 6a). Across 76 stations, Pearson r was 0.545, Spearman ρ was approximately 0.541, trend signs agreed at 65.8% of stations, and the mean absolute trend difference was approximately 0.131 mm yr^{-1} . The equal-variance orthogonal slope was approximately 0.271. This is a symmetric association between two uncertain sets of station trends, not an estimate that AIRS captures 27.1% of a true climate trend. Shortened-record results also showed limited correspondence (Supplementary Table S31).

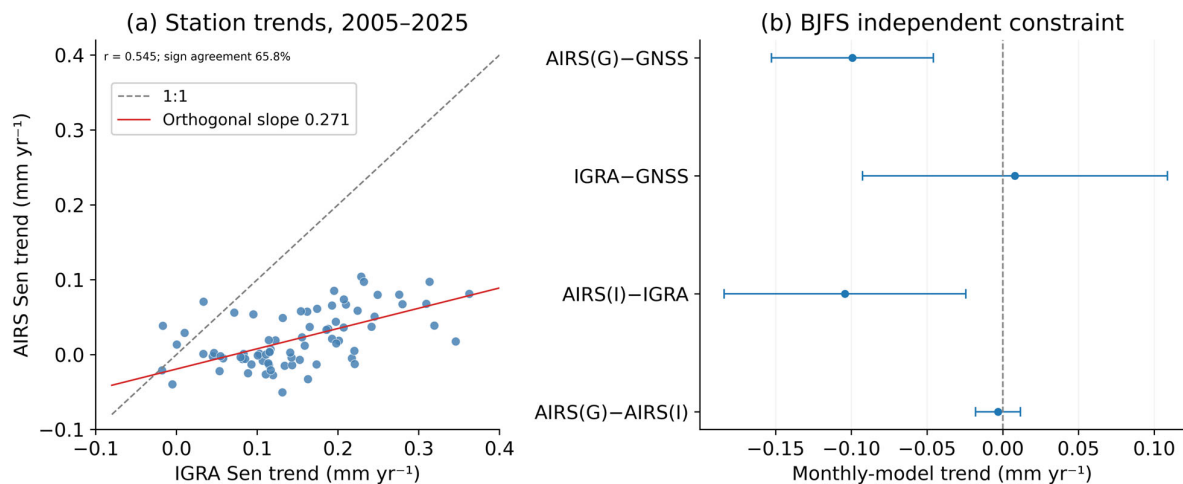


Figure 6. (a) Station-scale AIRS and IGRA Theil–Sen trends during 2005–2025 (76 stations). The dashed line is 1:1; the solid line is the equal-variance orthogonal fit. Individual trend uncertainty is summarized in Table S31. (b) BJFS difference trends and 95% HAC intervals from the common 89-month record during 2010–2020. G and I denote AIRS sampled at the GNSS and IGRA coordinates, respectively. Monthly calendar-season-adjusted GNSS trends are not the same estimator as panel (a).

The climatic-regime stratification showed that the limited trend consistency was not confined to humid stations. The station trend differences exhibited modest raw associations with the station-mean IGRA PWV and elevation, but neither retained a significant partial association after controlling the other. The environmental variables themselves were strongly inversely associated. The regime uncertainty, and all raw and partial environmental tests are reported in Supplementary Tables S32 and S33. A complementary year–month visualization of the network-mean IGRA PWV, AIRS PWV, and AIRS–IGRA difference across climatological moisture tertiles is shown in Supplementary Figure S9.

At BJFS, the independent exact-coordinate GNSS comparison used 89 common months during 2010–2020 (Figure 6b). AIRS–GNSS decreased by $-0.099 \text{ mm yr}^{-1}$ (95% CI -0.153 to -0.046 ; $p < 0.001$), whereas IGRA–GNSS had a near-zero, nonsignificant trend of $+0.008 \text{ mm yr}^{-1}$ (95% CI -0.093 to $+0.109$; $p = 0.876$). AIRS–IGRA decreased by $-0.104 \text{ mm yr}^{-1}$ ($p = 0.010$). The trend in AIRS sampled at the GNSS coordinate minus AIRS at the IGRA coordinate was small and nonsignificant (approximately $-0.003 \text{ mm yr}^{-1}$; $p = 0.678$). These contrasts support an AIRS contribution to the local divergence; the single-site record and remaining spatial separation preclude nationwide attribution (Supplementary Tables S34–S37 and Figure S8).

4. Discussion

4.1. High Monthly Agreement Does Not Guarantee Equivalent Long-Term Consistency

The central finding is that excellent monthly AIRS–IGRA agreement does not necessarily imply equivalent long-term climate-record consistency. Large seasonal and spatial PWV contrasts can sustain a high correlation even when the difference between two records evolves over time. The much smaller long-term signal is consequently more sensitive to modest nonstationarity in bias. Monthly agreement, a trend in network annual bias, and cross-station agreement of individual trends answer different questions and should not be used interchangeably.

This distinction extends established AIRS validation work rather than replacing it. Previous studies documented environmental and sampling dependencies [20,24–31]; the present record shows that strong monthly correlation can persist alongside a negative bias trend and only moderate station-scale trend correspondence. Comparisons of AIRS

radiance-based and operational-retrieval trends have likewise highlighted differences in water-vapor trends [33], while CLIMCAPS work emphasizes retrieval and sampling uncertainty in climate applications [34,35]. The trend comparisons here assess the consistency between observations rather than identifying an error-free climate reference.

4.2. Moisture-State Dependence Is Robust, but Its Physical Origin Is Not Unique

The moisture association survives within-station and seasonal controls, covariate adjustment, station fixed effects, stricter radiosonde coverage, and errors-in-variables regression. Its persistence cannot be explained solely by static geography or the mean seasonal cycle. Nevertheless, a statistically persistent coefficient does not by itself identify a physical mechanism. The direct AIRS-on-IGRA anomaly response reduces the shared-variable concern affecting difference-on-IGRA regressions, but it still depends on uncertain observations and an assumed measurement-error variance ratio.

Cloud-dependent sampling [24,25], reduced infrared sensitivity to lower-tropospheric water vapor [33], and state-dependent retrieval behavior [26,29–31] are plausible contributors. Our availability diagnostic confirms an association between cloudiness and fewer valid observations, but the moisture coefficient does not weaken when that proxy is included. The CloudFrc coefficient also changes in magnitude and sign across controls. These findings do not support a single cloud or monthly retrieval-count explanation; CloudFrc is retained as an auxiliary environmental-state indicator.

Larger absolute differences at wetter stations should also be separated from the relative performance. Normalized errors do not systematically worsen with station-mean PWV, and climate-regime trend consistency is a different question from within-station monthly moisture dependence. Neither result justifies a general claim that long-term AIRS trends are least reliable at humid stations.

4.3. Ascending–Descending Differences and the Early-2020s Change

Ascending and descending observations sample different parts of the diurnal cycle. Under nominal Aqua operations their approximate local crossing times were 13:30 and 01:30, respectively [16]. Real day–night PWV variability, cloud conditions, surface–atmosphere thermal contrast, retrieval availability, and temporal sampling may all contribute to the observed monthly branch separation [24,25]. Comparisons against a common monthly radiosonde mean cannot isolate branch-specific instantaneous retrieval errors.

Aqua’s transition to free drift in January 2022 [44] motivates the timing check but does not establish the cause of the subsequent AIRS–IGRA change. The segmented model detects a slope change rather than a significant immediate step, and the result persists in the fixed network. However, the paired branch-difference series lacks a comparable January-2022 joint break, the simple availability proxy also lacks a clear break, and nearby candidate years support changes in bias evolution. The evidence therefore supports an early-2020s transition with unresolved contributions from sampling, retrieval behavior, reference-record changes, and contemporaneous atmospheric variability.

4.4. Reference-Record and Spatial-Representativeness Uncertainty

IGRA2 quality control is not equivalent to homogenization. Changes in radiosonde instrumentation and observing practice can alter humidity records and inferred trends [6,9,36–38]. Consequently, the national AIRS–IGRA bias trend cannot be attributed uniquely to AIRS. The BJFS GNSS contrast supplies an independent local constraint: a negative AIRS–GNSS trend occurs while the IGRA–GNSS interval spans zero. Nonsignificance is not proof that IGRA is perfectly stable, and this one-site comparison cannot resolve the relative contributions throughout China.

Vertical coverage also affects the reference. On the same 16,716 station-months, the strict screen makes mean bias less negative but increases RMSE from 3.17 to 3.69 mm (Supplementary Table S2). The screen changes the retained profiles and their moisture structure, rather than simply adding an unobserved column. It is therefore a sensitivity test, not a correction to a known true PWV. Strong LOO moisture dependence and a negative annual bias trend remain, while residual uncertainty from unobserved layers and sensor changes persists.

AIRS grid cells represent an area, whereas radiosondes sample a moving trajectory. Similar network trends under nearest-cell and bilinear sampling show that the interpolation choice does not explain the main temporal result. Their local differences increase with terrain heterogeneity, and individual station trend signs remain sensitive to spatial sampling. The two interpolation schemes sample the same gridded field, so their agreement does not quantify the complete grid-to-profile representativeness error (Supplementary Tables S24 and S28).

4.5. Implications, Scope, and Remaining Limitations

The supported application scope is AIRS Version 7 Level-3 monthly PWV over the sampled Chinese station network during 2005–2025. AIRS reproduces broad PWV climatology, the seasonal cycle, and substantial monthly-to-interannual variability, but the sub-unity anomaly response cautions against assuming identical amplitudes. Small long-term regional trends require independent observations, reference homogenization, and explicit checks on temporal and spatial sampling. The findings do not establish global behavior or instantaneous overpass accuracy.

The remaining limitations include sparse independent GNSS coverage, incomplete reference homogeneity, imperfect spatial collocation, and the limited ability of monthly Level-3 fields to diagnose retrieval physics. The statistical controls constrain alternative interpretations without uniquely attributing mechanisms. Vertically resolved retrievals, collocated overpass observations, and broader homogeneous independent records would be needed to resolve those questions; they are outside the present analysis.

Stable long-term atmospheric observations also provide a broader context for studies of cross-layer atmospheric coupling, large-scale wave variability, and stratospheric disturbances [45–47].

5. Conclusions

The 2005–2025 comparison of AIRS Version 7 Level-3 monthly PWV with IGRA2 at 76 Chinese stations yields excellent monthly agreement (19,053 station-months; $R = 0.984$; bias = -1.34 mm; RMSE = 3.36 mm), but weaker long-term consistency. Moisture-state dependence remains strong after station and seasonal controls (LOO $\rho = -0.722$), and the equal-variance Deming anomaly-response slope remains below unity (0.560).

The ascending-minus-descending PWV averages $+0.561$ mm, with larger summer differences. The early-2020s change in the AIRS–IGRA bias evolution is supported by segmented models, but neither its timing nor the branch diagnostics establishes Aqua free drift as the cause.

The network annual bias trends are similar for the full and strict fixed networks (-0.141 and -0.138 mm yr $^{-1}$), while the annual correlation shows no significant trend. The station trends have only moderate correspondence ($r = 0.545$; sign agreement 65.8%), and limited consistency is not confined to humid stations. Strict vertical coverage and alternative spatial sampling retain the principal conclusions.

BJFS GNSS provides site-specific evidence of an AIRS contribution to local divergence, while IGRA inhomogeneity and limited independent coverage prevent unique nationwide

attribution. Excellent monthly AIRS–IGRA agreement does not necessarily imply equivalent long-term climate-record consistency. The strongest support is for monthly-scale climatology and broad variability over China; small long-term trends require independent constraints, homogeneous references, and careful treatment of sampling stability.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs18213635/s1>, Sections S1–S6 provide radiosonde, moisture-state, cloud and sampling, structural-change, spatial and trend, and independent GNSS diagnostics (Tables S1–S37; Figures S1–S9).

Author Contributions: C.T.: Supervision, Methodology, Visualization, Writing—review and editing. W.L.: Investigation, Writing—original draft. P.W.: Project administration, Resources, Methodology, Writing—review and editing. Y.W.: Data curation, Writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported by the Youth Open Project of National Space Science Data Center (No. NSSDC2502004).

Data Availability Statement: The AIRS3STM Version 7.0 monthly product is publicly available through the NASA Goddard Earth Sciences Data and Information Services Center (GES DISC) [39], DOI: 10.5067/UBENJB9D3T2H. IGRA2 radiosonde data are publicly available from NOAA/NCEI [38], DOI: 10.7289/V5X63K0Q. The processed station-month dataset, statistical summaries, and analysis/plotting code used to reproduce the results and figures in this study are available from the corresponding author upon reasonable request. SuomiNet GNSS records were used for the independent check described in Supplementary Section S6; the processed common-month GNSS diagnostics are available with the analysis materials from the corresponding author.

Acknowledgments: The authors are grateful for the support from the Specialized Research Fund for the State Key Laboratory of Solar Activity and Space Weather.

Conflicts of Interest: The authors declare no conflicts of interest.

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