

Hydrometeorological Consistency and Structural Differences in High-Resolution Atmospheric Forcing Products over the Gulf Coast

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Abstract

Kilometer-scale meteorological forcing products are increasingly used in hydrologic applications, yet comparable resolution does not ensure consistent atmospheric structure or derived diagnostics. This study compares AORC and NLDAS-3 across the U.S. Gulf Coast and Southeast (Texas to the Carolinas) from 2001–2020 using a common spatial footprint and paired days. Relative to AORC, NLDAS-3 exhibits lower precipitation (PBIAS –8.9%), warmer temperatures (+0.49 °C), reduced shortwave radiation (–10.2 W.m^{–2}), and higher specific humidity (+6.0%). Its precipitation occurs more frequently but at lower intensity, with 31–33% lower return levels. Comparisons against 3,329 GHCN-Daily gauges show AORC better reproduces observed rain-day frequency at 97% of stations. Although temperature-based reference evapotranspiration (ET_o) agrees closely with observations (KGE 0.96–0.98), it masks radiation and humidity differences that shift summer Penman–Monteith ET_o by up to 0.7 mm day^{–1}. Statistical adjustment reduces precipitation bias but leaves event sequencing and cross-variable coupling unchanged. The full evaluation was carried out as an open, reproducible HydroSuite workflow, and its findings show that distributional equivalence does not imply process-structural equivalence.

Keywords

meteorological forcing; AORC; NLDAS-3; Gulf Coast; hydroclimatic diagnostics; reference evapotranspiration; precipitation-tail behavior; hydroclimatology; HydroSuite; HydroLang; web-based hydroinformatics

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1. Introduction

Continuous hydrological modelling at the basin and regional scale depends fundamentally on how well atmospheric forcing data represents the physical conditions that generate runoff, regulate atmospheric water demand, and shape antecedent soil moisture (Archfield, et al., 2015; Todini, 2007). As operational hydrology moves toward kilometer-scale prediction frameworks, model performance increasingly depends on whether gridded forcing products preserve the timing, magnitude, and spatial structure of meteorological events that control surface water response (Kratzert et al., 2019; Nearing et al., 2020).

Regions shaped by localized and rapidly evolving atmospheric processes expose these sensitivities. Small differences in precipitation intensity, humidity, radiation, or wind fields can propagate through land-surface calculations and produce materially different estimates of flood frequency, atmospheric water demand, and water balance (Frame et al., 2022; Klotz et al., 2022; Ewing et al., 2022). This study evaluates how differences in forcing construction affect the hydrometeorological signals used by modern water prediction systems, focusing on the United States Gulf Coast, where closely linked atmospheric processes can introduce errors into gridded meteorological data and, ultimately, water-balance estimates (Misra & Bhardwaj, 2020).

Warm-season thunderstorms produce intense rainfall over small areas, and moisture transport from the Gulf of Mexico maintains high humidity and unstable boundary-layer conditions (Catto et al., 2012; Catto & Pfahl, 2013). Broad vegetation cover links atmospheric demand to land-surface response, while tropical cyclones can concentrate extreme precipitation within narrow corridors (Barlow, 2011; Knapp et al., 2010). The August 2016 Louisiana flood, which exceeded a 1,000-year return period over portions of the Amite River basin, illustrates how localized rainfall extremes can strongly influence hydroclimatic and flood-response interpretation (Gori et al., 2022; van der Wiel et al., 2017).

Recent kilometer-scale archives have reduced the apparent resolution differences among commonly used meteorological datasets. However, comparable grid spacing does not ensure comparable physical information; a field produced from radar estimates and gauge adjustments can preserve different event characteristics than one derived from reanalysis backgrounds, interpolation, and separate observational corrections (Seo et al., 2019). These methodological choices influence the mean state, seasonal cycle, covariance among variables, and upper tail of the precipitation distribution.

This study uses the Analysis of Record for Calibration (AORC) and the North American Land Data Assimilation System Phase 3 (NLDAS-3) to examine those differences. Developed to support the calibration of the National Water Model, AORC provides forcing data at high spatial resolution (~800 m) by integrating Stage IV radar and PRISM climatology (Daly et al., 2008; Fall et al., 2023). Recent literature increasingly contrasts AORC's detailed spatial representation with NLDAS-based datasets across various hydrologic contexts, such as snow modeling (Gan et al., 2024), large-sample basin evaluations (Frame et al., 2024), evapotranspiration estimation (Zhang et al., 2020), and broader meteorological forcing evaluation studies (Dyer et al., 2022; Mizukami & Wood, 2020). Their divergences indicate how forcing construction can alter derived

hydroclimatic diagnostics and modify atmospheric-demand representation (Rasmussen et al., 2023; Slivinski et al., 2019; Sparrow et al., 2024). Divergences in upper-tail precipitation structure, radiation inputs, humidity fields, or diagnostic Penman–Monteith ETo responses identify sensitivities that change how each forcing record characterizes the atmospheric environment.

Benchmarking hydrometeorological forcing products requires observational datasets that provide independent reference records across consistent spatial and temporal domains (Ebert-Uphoff et al., 2017; Li et al., 2025). HydroSuite (Hydroinformatics Lab, n.d.) approaches this need within a broader vision of open, web-native hydroinformatics, bringing together benchmark datasets, computational resources, data standards, visualization capabilities, and research applications in a shared ecosystem (Erazo Ramirez et al., 2024a).

Its development is guided by the idea that hydrological research workflows should be accessible, interoperable, and extensible through open-source technologies, integrating data, computation (Erazo Ramirez et al., 2024b), communication, and community resources (Shahid et al., 2023; Erazo Ramirez et al., 2022; 2026). This ecosystem includes established hydrological benchmarks, such as WaterBench-Iowa for streamflow forecasting (Demir et al., 2022) and IowaRain for radar-based precipitation analysis (Sit et al., 2021), alongside tools for data processing and scientific computing (Agliamzanov et al., 2020).

Within this ecosystem, the present study evaluates AORC, NLDAS-3, and GHCN-Daily observations over the U.S. Gulf Coast and adjoining southeastern states from 2001 to 2020. HydroSuite provides a broader computational environment for conducting this evaluation through an integrated, web-based workflow that connects publicly accessible data sources with analysis and visualization. Its open architecture supports the integration of complementary tools and services across the research process, allowing the evaluation to proceed from data retrieval to statistical assessment and the generation of tables and figures. The study thus demonstrates how HydroSuite’s ecosystem vision can support a reproducible, large-scale evaluation of hydrometeorological forcing products without requiring the analysis to be built around a single library or software package.

2. Background

The AORC is a 30 arc-second (~800 m), hourly gridded meteorological dataset (aggregated here to daily values) produced by the NOAA Office of Water Prediction (OWP) as the primary historical forcing archive for the National Water Model (NOAA Office of Water Prediction, 2020, 2021). It provides eight atmospheric variables (precipitation, 2-meter air temperature, downward shortwave radiation, downward longwave radiation, surface pressure, specific humidity, and two horizontal wind components) over the conterminous United States (CONUS) from 1979 to the near-present. Since 2002, AORC daily precipitation is taken from the NCEP Stage IV analysis, which merges WSR-88D radar estimates with rain-gauge reports through the Multisensor Precipitation Estimator; earlier years rely on NLDAS-2, and the daily totals are constrained by long-term gauge-based and PRISM climatologies before being disaggregated to hourly values (NOAA Office of Water Prediction, 2021). This radar–gauge fusion captures the spatial

heterogeneity of precipitation cells, including the mesoscale convective systems (MCSs) that dominate Gulf Coast warm-season hydrology. Temperature, specific humidity, surface pressure, and downward longwave radiation are derived from NLDAS-2 through 2015 and from the NWS Unrestricted Mesoscale Analysis (URMA) afterwards; shortwave radiation is interpolated from NLDAS-2 without downscaling, and the wind components are taken from NLDAS-2 and later from URMA, a switch that the methods document dates to 2018 for the CONUS record (NOAA Office of Water Prediction, 2021).

NLDAS-3 is the next phase of the North American Land Data Assimilation System, developed by NASA and currently distributed as a beta forcing dataset on Amazon S3 (NASA Water Insight, n.d.). Its forcing covers North and Central America ($7\text{--}72^\circ\text{N}$) on a 0.01° ($\sim 1\text{ km}$) grid from 2001 onward, a substantial resolution upgrade from NLDAS-2, which operated at 0.125° ($\sim 12.5\text{ km}$). The NLDAS-3 forcing is built on MERRA-2 reanalysis backgrounds (Bosilovich et al., 2015; Gelaro et al., 2017) interpolated to the 1-km grid with topographic adjustment based on a Shuttle Radar Topography Mission (SRTM) elevation model (Farr et al., 2007), and its precipitation combines the MERRA-2 background with satellite precipitation from IMERG, downscaled to 1 km using MODIS-derived cloud-frequency patterns (Huffman et al., 2020; NASA Land Data Assimilation Systems, n.d.). Its predecessor NLDAS-2 derived precipitation from the CPC Unified gauge-based analysis (Chen et al., 2008; Xie et al., 2007; Xie, et al., 2010). Unlike AORC, NLDAS-3 does not ingest the NEXRAD Stage IV radar–gauge analysis, so its precipitation relies on coarser reanalysis and satellite estimates, which can limit the representation of convective-scale precipitation structure.

The sensitivity of gridded meteorological products to forcing dataset construction choices has been documented across multiple climatic regimes (Chen, et al., 2014; Livneh et al., 2015), with particular attention to how forcing uncertainty propagates into derived hydroclimatic diagnostics and atmospheric-demand representation. Naz et al. (2018) demonstrated that forcing construction strongly influences diagnostic hydroclimatic signals in the Southeast United States, particularly during convective seasons. Tang et al. (2019) showed that AORC-based precipitation structure better preserves upper-tail precipitation behavior during extreme atmospheric events, attributing the improvement primarily to AORC’s radar-guided spatial precipitation structure.

Studies in the Gulf Coast region specifically have highlighted the vulnerability of both precipitation representation and atmospheric-demand diagnostics to forcing construction choices (Fang et al., 2021). The 2016 Louisiana flood has been analyzed as a case study in convection-permitting precipitation dynamics (Gori et al., 2022; van der Wiel et al., 2017), with implications for the resolution requirements of operational forcing datasets which is critical for flood mitigation, response and recovery decisions (Alabbad et al., 2024; Grant et al., 2024; Kaynak et al., 2025). Reference evapotranspiration estimation from gridded products has received comparatively less attention, particularly in humid subtropical climates where the Hargreaves-Samani (HS) approximation—commonly used when only temperature data are available—tends to overestimate atmospheric water demand relative to the more physically complete FAO-56 Penman-Monteith (PM) formulation, because it cannot represent humidity and cloud effects (Pereira et al., 2015; Xu

& Singh, 2002). This method gap has practical implications for validation studies that compare gridded ET_0 against gauge-observed temperature-based estimates.

The scientific literature leaves several practical questions unresolved for Gulf Coast hydrologic applications. Many comparisons emphasize precipitation because of its direct connection to runoff, but a broader assessment is needed to determine whether differences also appear in other forcing variables that influence water-budget partitioning. Earlier work often contrasted AORC with coarser NLDAS products. With NLDAS-3 now available on a kilometer-scale grid, remaining differences cannot be interpreted only as a function of nominal spatial resolution; the construction of each record must also be considered.

This study is organized around five objectives that connect forcing construction to hydrologically relevant behavior: a) characterize systematic differences in forcing fields by determining where the two records diverge across the core meteorological variables and whether those differences are consistent across seasons and spatial domains; b) characterize differences in upper-tail precipitation structure and determine whether forcing construction alters the scaling and seasonal behavior of extreme precipitation diagnostics; c) use reference ET_0 as a diagnostic of atmospheric demand by evaluating how radiation, humidity, temperature, and wind differences translate into land-surface drying potential in a humid, vegetated environment, and determine whether those sensitivities vary by season or location; d) assess the recoverability of hydrologically relevant signals by examining whether information contained in one forcing record can reproduce the behavior of the other, while using independent in-situ GHCN-Daily observations as point-scale context for interpreting temperature-based ET_0 differences; and e) demonstrate how web-native HydroSuite workflows can retrieve, harmonize, and evaluate multi-decade gridded and station records reproducibly, so that the evaluation can be repeated as the products are revised and extended to other regions.

3. Methodology

The methodology compares the two forcing records at matching temporal and spatial supports, quantifies differences in their distributions and seasonal structure, and evaluates how those differences propagate into hydrologically relevant diagnostics. All analyses were performed for the common 2001–2020 period over the study domain and the Louisiana sub-domain. The diagnostic framework is organized into three primary analyses that address the study’s central questions and is supported by complementary characterization methods. Primary analyses include (i) distributional and temporal forcing-field divergence, (ii) precipitation upper-tail structure and extreme-event characterization, and (iii) ET_0 diagnostic attribution and statistical recoverability. Supporting diagnostics such as STL decomposition, power spectral density, circular seasonal statistics, Taylor diagrams, and spatial coherence maps provide complementary perspectives on the structure identified by the primary analyses.

3.1. Study Area and Data

The primary domain covers the U.S. Gulf Coast and adjoining Southeast states—Texas, Louisiana, Mississippi, Alabama, Florida, Georgia, South Carolina, and North Carolina—between 106.5° W and 79.0° W and 25.8° N and 36.5° N, so the Carolinas are included only west of 79.0° W. All statistics are computed on the common footprint where both AORC and NLDAS-3 provide valid data (1.42 million 0.01° cells); ocean cells and cells outside these states are excluded. This extent retains the west-to-east transition from semi-arid Texas to the humid subtropical environments of Louisiana, Mississippi, Alabama, and Florida. A Louisiana sub-domain provides the finer spatial focus for watershed-level interpretation. It is defined as the rectangle 94.1°–88.75° W and 28.85°–33.05° N, of which only land cells within the common footprint are used (about 175,000 cells, including small parts of eastern Texas and western Mississippi).

Two gridded meteorological records were processed over the common 2001–2020 analysis period. Hourly AORC v1.1 fields were read from the NOAA AORC Zarr archive on Amazon S3, aggregated to daily totals (precipitation) and daily means (all other variables), and clipped to the study region; each daily field is a 30 arc-second (0.0083°, ~800 m) raster. Daily NLDAS-3 forcing files at the native 0.01° grid spacing were retrieved from the NASA NLDAS-3 archive on Amazon S3 through HydroLang and clipped to the study domain. Eight meteorological variables were retained from each record: precipitation, air temperature, shortwave radiation, longwave radiation, surface pressure, specific humidity, zonal wind, and meridional wind (Table 1). NLDAS-3 daily precipitation is stored as a daily total (kg m^{-2} , equivalent to mm) and required no conversion; the units attribute of every variable was checked against the NetCDF metadata, and conversion factors are applied only when the units identify a rate. Both records were compared on a common footprint, and every statistic was computed only on cells and days where both products are valid, giving 7,296 strictly paired days.

Table 1. Forcing variables and post-conversion units.

Variable	AORC Name	NLDAS-3 Name	Units	Notes
Precipitation	<i>precip</i>	<i>Rainf</i>	mm day-1	Daily total ($\text{kg m}^{-2} \equiv \text{mm}$); no conversion
Air Temperature	<i>temp</i>	<i>Tair</i>	°C	-
Shortwave Radiation	<i>shortwave</i>	<i>SWdown</i>	W m-2	-
Longwave Radiation	<i>longwave</i>	<i>LWdown</i>	W m-2	-
Surface Pressure	<i>pressure</i>	<i>PSurf</i>	kPa	Pa ÷ 1000
Specific Humidity	<i>specific_humidity</i>	<i>Qair</i>	kg kg-1	-
Zonal Wind	<i>u_wind</i>	<i>Wind_E</i>	m s-1	10 m to 2m
Meridional Wind	<i>v_wind</i>	<i>Wind_N</i>	m s-1	10m to 2m

Station observations from the Global Historical Climatology Network Daily (GHCN-Daily) dataset provide point-scale context for the gridded records (Menne et al., 2012). Records were accessed through the NOAA NCEI archive for stations in the study states. A station was retained when (i) it reported at least one year of valid daily maximum and minimum temperature during 2001–2020, (ii) its nearest grid cell was valid in both AORC and NLDAS-3, and (iii) it provided at least 24 months with 20 or more days on which the station and both products were valid. Of 2,132 stations with at least one year of temperature data, 1,392 met all criteria and were used for both products, including 96 in the Louisiana sub-domain; stations excluded by criteria (ii) lie outside the common footprint or on water cells. Using one station set for both products ensures that differences in skill reflect the forcing records, not the sample of stations. These records are not treated as a complete replacement for gridded forcing fields; they provide an independent point-scale reference for interpreting temperature-derived atmospheric demand and for contextualizing differences between the gridded products.

Daily precipitation from GHCN-Daily rain gauges was used to test which gridded record better reproduces the observed rain-day structure. All gauges in the study states reporting precipitation were considered, from the Cooperative Observer (COOP), Community Collaborative Rain, Hail and Snow (CoCoRaHS), first-order (ASOS/WBAN), and other networks. A gauge was retained when its nearest grid cell was valid in both products and it provided at least 1,000 days on which the gauge and both products were valid; 3,329 of 4,828 candidate gauges met these criteria (the others lie outside the common footprint). On these identical days, wet-day fraction (≥ 1 mm), the fraction of days with zero precipitation, the fraction of light-rain days (0–1 mm), mean and 90th-percentile wet-day intensity, mean wet- and dry-spell lengths, mean annual totals, and daily and monthly correlations were computed for the gauge and for the AORC and NLDAS-3 cells, and the product closer to the gauge was recorded for each station.

The common analysis period spans 1 January 2001 through 31 December 2020. AORC files are missing for 9 of the 7,305 days, leaving 7,296 paired days that are used in every analysis. Analyses were conducted over the full 20-year record, and annual summaries were retained to identify years that depart from the long-term behavior of either forcing record. Several data-quality nuances inform the interpretation of the time-series results. For example, occasional extreme weather events (such as hurricanes) can skew summary statistics in specific years, demanding a robust analytical approach less sensitive to localized, short-duration extreme values.

3.2. HydroSuite Workflow

The analysis was implemented as a HydroSuite workflow organized in three layers. The data-access layer retrieves every input directly from public archives: daily NLDAS-3 forcing files for 2001–2020 (about 7,300 files and 5 TB) were obtained from the NASA NLDAS-3 archive through HydroLang’s unified retrieval interface, AORC v1.1 from the cloud-optimized Zarr stores on AWS Open Data, and GHCN-Daily records for 5,222 stations from NCEI, the latter two through HydroSuite Python modules developed alongside this study. The processing layer clips each record to the study region and writes daily NetCDF files. The analysis layer maps both products onto the

common footprint, computes all gridded statistics in a single pass over the 7,296 paired days, extracts the station and gauge comparisons, and produces every table and figure. Stages are chained by shell scripts and communicate only through open formats (NetCDF, Zarr, Parquet, CSV), so each stage can be replaced, extended, or rerun independently.

The workflow is designed to be re-executed: each run checks units against the file metadata, verifies that every daily file is readable, records which days were used, and saves checkpoints so that interrupted runs resume. The complete gridded analysis takes about 13 h, the station-based ETo evaluation about 7 h, and the rain-gauge evaluation about 1.5 h. The entire study can be repeated when either product is revised (for example, new NLDAS-3 releases or AORC version changes) or applied to another region by changing the domain definition. The code is openly available (see Data Availability).

3.3. Distributional Comparison and Climatological Bias

Daily forcing values were compared as domain means over the common footprint and at the pixel level, using only days on which both records are valid. AORC was treated as the reference series O_t and NLDAS-3 as the evaluated series S_t over N daily time steps. While AORC serves as the operational baseline for modern hydrologic modeling (e.g., the National Water Model), this comparative structure does not imply absolute physical correctness; AORC may itself contain structural version changes or input artifacts over the multi-decadal record. Metrics were computed for each variable over the full record and after stratification by meteorological season (DJF, MAM, JJA, SON), including bias and percentage bias (PBIAS), root mean square error (RMSE), and Kling-Gupta Efficiency (KGE).

$$\text{Bias} = \frac{1}{N} \sum_{t=1}^N (S_t - O_t), \text{PBIAS} = \frac{\sum_{t=1}^N (S_t - O_t)}{\sum_{t=1}^N O_t} \times 100 \quad (1)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{t=1}^N (S_t - O_t)^2} \quad (2)$$

$$\text{KGE} = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \quad (3)$$

where r is the Pearson correlation coefficient, $\alpha = \sigma_S/\sigma_O$ is the ratio of standard deviations (variability component), and $\beta = \mu_S/\mu_O$ is the bias ratio. A KGE of 1 indicates a perfect match; values below -0.41 indicate performance worse than the observed mean (Knoben, Freer, & Woods, 2019). Daily error distributions were summarized from the series $\varepsilon_t = S_t - O_t$ using Gaussian kernel density estimates with Scott's bandwidth rule. Taylor diagrams were used to summarize correlation and relative variance across the forcing variables (Taylor, 2001). Because the shared annual cycle inflates correlations of raw daily series, the Taylor statistics were computed

from deseasonalized daily anomalies (departures from a 31-day smoothed day-of-year climatology), and each variable was normalized by the standard deviation of its own AORC series. For precipitation, wet days were defined using a threshold of $\geq 1.0 \text{ mm day}^{-1}$; wet-day frequency, mean wet-day intensity, and mean and maximum wet- and dry-spell lengths were computed for every pixel and summarized as the median across the domain.

3.4. Upper-Tail Precipitation Structure Diagnostics

The representation of upper-tail precipitation extremes was evaluated with annual maxima and peaks-over-threshold summaries. For the domain-mean series and for each of 3,000 randomly sampled footprint pixels, the set of annual block maxima $\mathcal{M} = \{P_{\max,y}\}_{y=2001}^{2020}$ was compiled for both AORC and NLDAS-3. By the Fisher-Tippett-Gnedenko theorem, the distribution of block maxima converges to the Generalized Extreme Value (GEV) distribution (Alexander, 2006; Gupta, Carroll, & McKenna, 2023):

$$F(x; \mu, \sigma, \xi) = \exp \left\{ - \left[1 + \xi \left(\frac{x - \mu}{\sigma} \right) \right]^{-1/\xi} \right\}, \quad 1 + \xi \left(\frac{x - \mu}{\sigma} \right) > 0 \quad (4)$$

where μ is the location parameter, $\sigma > 0$ is the scale parameter, and ξ is the shape parameter. The shape parameter governs tail behavior: $\xi > 0$ (Fréchet, heavy tail), $\xi = 0$ (Gumbel, light exponential tail), and $\xi < 0$ (Weibull, bounded upper tail). GEV parameters (μ, σ, ξ) were estimated by the method of L-moments (Hosking, 1990), which is more stable than maximum likelihood for short records. Fitted upper-tail quantiles at exceedance probabilities corresponding to $T \in \{2, 5, 10, 25\}$ ~years were computed as the $(1 - 1/T)$ quantile of the fitted distribution:

$$X_T = \mu - \frac{\sigma}{\xi} \left[1 - \left(-\ln \left(1 - \frac{1}{T} \right) \right)^{-\xi} \right] \quad (5)$$

Empirical plotting positions followed the Weibull formula $T_m = (N + 1)/m$, where m is the descending rank. Uncertainty in fitted quantiles was quantified by 500-iteration non-parametric bootstrapping of the annual maxima, with 5th–95th percentile confidence intervals reported. Because the 20-year record is too short for robust extreme value analysis, the fitted GEV distributions are presented primarily as descriptive summaries of the empirical tail behavior, not tools for far-tail extrapolation, and return periods beyond 25 years are not reported. Because a domain average smooths out the convective extremes of interest, the GEV analysis was carried out both for the domain-mean series and for each of 3,000 randomly sampled footprint pixels, summarized by the median across pixels. A peaks-over-threshold analysis was performed as a sensitivity check with daily values exceeding the 98th percentile of each series declustered (runs of one day) and fitted with a Generalized Pareto Distribution, for the domain mean and for 500 sampled pixels.

3.5. Time Series Structure and Trend Analysis

Monthly mean series were decomposed into trend (T_t), seasonal (S_t), and residual (R_t) components via robust Seasonal-Trend decomposition using LOESS (STL) (Cleveland, et al., 1990; Dagum & Bianconcini, 2016; Theodosiou, 2011):

$$Y_t = T_t + S_t + R_t \quad (6)$$

Monthly anomalies were computed relative to the climatological monthly mean, and a 12-month centered rolling mean was used to emphasize lower-frequency variability after removal of the annual cycle. The non-parametric Mann-Kendall (MK) test was applied to monthly anomaly time series for the forcing variables and derived ET_0 , independently for each dataset. The MK S-statistic summarizes directional consistency across all time pairs:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n \text{sgn}(x_j - x_k) \quad (7)$$

A standardized Z-score transforms S to a p-value under the null hypothesis of no monotonic trend. Trend magnitude was estimated with the Theil–Sen slope estimator (Sen, 1968) and reported in the native units of each variable per month. Trends with $p < 0.05$ were treated as statistically significant. The non-parametric Pettitt test (Pettitt, 1979) was used to identify abrupt changes in the monthly series. This complements the Mann–Kendall test by targeting step-like shifts in the distribution, while the Mann–Kendall test evaluates gradual monotonic change. To characterize intra-annual seasonality, each daily observation was mapped to a unit-circle angle $\theta_t = 2\pi dt/365.25$ (where dt is day of year). The mean resultant length R provides a scalar index of seasonal concentration:

$$R = \frac{1}{N} \left| \sum_{t=1}^N e^{i\theta_t} w_t \right| \quad (8)$$

where w_t is the normalized forcing value. $R = 0$ indicates a perfectly uniform annual distribution; $R = 1$ indicates complete concentration at a single time of year. Mean monthly forcing and the resultant length R were used to compare seasonal phasing between AORC and NLDAS-3 across variables.

3.6. Spatial Coherence and Spectral Analysis

Power spectral density (PSD) was estimated for the monthly domain-mean series of precipitation, temperature, and shortwave radiation (240 months) as the periodogram of the linearly detrended series, with a Hann window applied to reduce spectral leakage. The NLDAS-3-to-AORC power ratio at each frequency f was computed as:

$$\mathcal{R}_{\text{spectral}}(f) = \frac{P_{\text{NLDAS}}(f)}{P_{\text{AORC}}(f)} \quad (9)$$

Values of $\mathcal{R}_{\text{spectral}} > 1$ indicate frequency bands where NLDAS-3 retains more temporal variance than AORC; values < 1 indicate bands suppressed in NLDAS-3 relative to AORC. The ratio was also summarized over period bands (2–6, 6–11, 11–13.5, and >13.5 months) as the ratio of the summed power of the two products within each band. Pixel-level means, bias, and daily Pearson correlation were accumulated over all 7,296 paired days on every second cell of the common grid (0.02°), with AORC sampled to the NLDAS-3 0.01° grid by nearest neighbor.

3.7. Reference ET₀ Diagnostics

ET₀ is used here as an integrated atmospheric diagnostic: differences in PM-ET₀ between the two forcing products reflect differences in the multi-variable atmospheric structure encoded by each record. Daily reference evapotranspiration was computed from the full eight-variable forcing stack using the FAO-56 standardized Penman–Monteith formulation (Allen et al., 1998):

$$ET_{0,\text{PM}} = \frac{0.408 \Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34 u_2)} \quad (10)$$

where Δ is the slope of the saturation vapor pressure curve ($\text{kPa } ^\circ\text{C}^{-1}$), R_n is net radiation ($\text{MJ m}^{-2}\text{d}^{-1}$), $G \sim 0$ is the soil heat flux at daily timestep, γ is the psychrometric constant ($\text{kPa } ^\circ\text{C}^{-1}$), T is mean air temperature ($^\circ\text{C}$), u_2 is wind speed at 2 m height (m.s^{-1}), e_s is saturation vapor pressure (kPa), and e_a is actual vapor pressure (kPa). Actual vapor pressure and 2 m wind speed were derived as:

$$e_a = \frac{Q_{\text{air}} \cdot P_{\text{surf}}}{0.622 + 0.378 \cdot Q_{\text{air}}} \quad (11)$$

$$u_2 = u_{10} \cdot \frac{4.87}{\ln(67.8 \times 10 - 5.42)} \quad (12)$$

Net radiation was computed as $R_n = (1 - \alpha_r)R_s + \varepsilon L\downarrow - \varepsilon \sigma T^4$ with a grass-reference albedo $\alpha_r = 0.23$ and surface emissivity $\varepsilon = 0.98$, using each product's own downward shortwave (R_s) and longwave ($L\downarrow$) radiation, so that differences in both radiation fields enter the calculation. Extraterrestrial radiation was computed at each pixel's latitude. PM-ET₀ was computed for every pixel (every second 0.01° cell) and day and then averaged over the domain. To characterize the sensitivity of inter-dataset ET₀ differences to individual atmospheric drivers, a one-at-a-time (OAT) substitution analysis was performed. Starting from a baseline AORC-only PM-ET₀ computation, each input variable x was replaced with the NLDAS-3 equivalent while holding all other variables fixed at AORC values:

$$\Delta ET_{0,x} = ET_{0,\text{PM}}(\text{AORC}_{-x}, \text{NLDAS}_x) - ET_{0,\text{PM}}(\text{AORC}) \quad (13)$$

for $x \in \{SW_{\text{down}}, LW_{\text{down}}, T, Q_{\text{air}}, P_{\text{surf}}, u_2\}$. The sum $\Sigma_x \Delta ET_{0,x}$ approximates the total inter-dataset ET_0 difference under the assumption of additive separability. Because the Penman–Monteith equation combines these drivers nonlinearly, the individual terms represent scenario-based sensitivities and not uniquely attributable contributions. In this study, the sum of the substitutions ($-0.169 \text{ mm day}^{-1}$) closes to within $0.008 \text{ mm day}^{-1}$ of the actual difference ($-0.160 \text{ mm day}^{-1}$). The degree of closure between $\Sigma_x \Delta ET_{0,x}$ and the actual total difference provides an empirical measure of the interaction residual. GHCN-Daily archives only daily T_{max} and T_{min} ; radiation, humidity, and pressure are unavailable at station scale. The Hargreaves–Samani (HS) formulation (Hargreaves & Samani, 1985) was used to place station observations and gridded temperature fields on a common temperature-based reference ET_0 basis:

$$ET_{0,\text{HS}} = 0.0023 \cdot 0.408 R_a \cdot (T_{\text{mean}} + 17.8) \cdot \sqrt{T_{\text{max}} - T_{\text{min}}} \quad (14)$$

where R_a is extraterrestrial radiation ($\text{MJ m}^{-2} \text{ d}^{-1}$) computed from latitude and day of year, and the factor 0.408 converts it to equivalent evaporation (mm d^{-1}). Since the processed AORC and NLDAS-3 files provide only daily mean temperature, synthetic temperature bounds were reconstructed from each station’s calendar-month median observed diurnal range $\Delta T_{\text{clim},m}$ ($T_{\text{max}} - T_{\text{min}}$):

$$T_{\text{max,grid}} \approx T_{\text{mean}} + \frac{\Delta T_{\text{clim}}}{2}, \quad T_{\text{min,grid}} \approx T_{\text{mean}} - \frac{\Delta T_{\text{clim}}}{2} \quad (15)$$

This approach preserves the locally observed diurnal amplitude while isolating the gridded mean-temperature signal; as a consequence, the station comparison primarily evaluates the gridded mean temperature. The synthetic $T_{\text{max}}/T_{\text{min}}$ are used only for HS; the Penman–Monteith calculations do not use them. The HS–PM comparison herein is intended to illustrate the sensitivity of each formulation to the forcing differences, not to provide a strict quantitative evaluation of forcing accuracy.

3.8. Statistical Adjustment and Recoverability

Two precipitation adjustment approaches were evaluated with a leave-one-year-out cross-validation design. Each year was withheld in turn, while the remaining 19 years were used to estimate the adjustment relationship:

Empirical Quantile Mapping (QM): For each withheld year, empirical quantiles from the 19 training years were used to map NLDAS-3 precipitation to the corresponding AORC quantiles at 101 probability levels (Cannon, Sobie, & Murdock, 2015). Values in the withheld year were adjusted by linear interpolation between quantile nodes.

Ordinary Least-Squares Linear Regression (LR): A linear model, $\text{AORC} = \alpha \cdot \text{NLDAS} + \beta$, was estimated from the 19 training years and applied to the withheld year. Out-of-sample RMSE, Pearson correlation, and PBIAS were computed annually for raw NLDAS-3, quantile-mapped NLDAS-3, and regression-adjusted NLDAS-3 against AORC. Residual errors after adjustment

were interpreted as differences that were not recovered by the statistical mapping (Cannon, 2016; Maraun, 2013).

4. Results

4.1. Climatological Means and Error Distributions

Domain-mean statistics over the full 2001–2020 record are summarized in Table 2. AORC mean precipitation is 3.00 mm day^{-1} versus 2.74 mm day^{-1} for NLDAS-3, a difference of $-0.27 \text{ mm day}^{-1}$ (PBIAS = -8.9%). Temperature means are $18.2 \text{ }^{\circ}\text{C}$ (AORC) and $18.7 \text{ }^{\circ}\text{C}$ (NLDAS-3), a warm bias of $+0.49 \text{ }^{\circ}\text{C}$. Shortwave radiation averages 211.0 W m^{-2} (AORC) versus 200.8 W m^{-2} (NLDAS-3), a deficit of -10.2 W m^{-2} (-4.8%). Longwave radiation is 344.3 W m^{-2} (AORC) and 352.8 W m^{-2} (NLDAS-3), an excess of $+8.5 \text{ W m}^{-2}$ ($+2.5\%$). Specific humidity is higher in NLDAS-3 ($+0.0006 \text{ kg kg}^{-1}$; PBIAS = $+6.0\%$), and 2-m wind speed is lower by -0.22 m s^{-1} (PBIAS = -9.2%).

Table 2. Domain-mean climatological statistics (AORC vs. NLDAS-3, 2001–2020, common footprint of the study domain). RMSE and bias are computed with AORC as reference.

Variable	AORC mean	NLDAS mean	Bias	PBIAS (%)	RMSE
Precip (mm day ⁻¹)	3.00	2.74	-0.27	-8.9	1.15
Temperature (°C)	18.2	18.7	0.49	–	0.75
Shortwave (W m ⁻²)	211.0	200.8	-10.2	-4.8	21.9
Longwave (W m ⁻²)	344.3	352.8	8.5	2.5	12.1
Sp. humidity (kg kg ⁻¹)	0.0096	0.0102	0.0006	6.0	0.0009
Wind 2 m (m s ⁻¹)	2.43	2.20	-0.22	-9.2	0.48

Error probability density functions (Figure 1) show that the daily domain-mean errors are close to symmetric for precipitation (skewness -0.19), temperature (-0.22), and pressure (0.02), so the precipitation difference behaves as a consistent offset. The warm temperature bias is seasonal, increasing from $+0.27 \text{ }^{\circ}\text{C}$ in DJF and $+0.47 \text{ }^{\circ}\text{C}$ in MAM to $+0.66 \text{ }^{\circ}\text{C}$ in JJA. Shortwave errors are left-skewed (-0.30) and largest in summer (JJA bias = -24.3 W m^{-2} ; PBIAS = -8.6%), tapering to -1.8 W m^{-2} in DJF. Longwave errors peak in the cool season (DJF: $+13.5 \text{ W m}^{-2}$; JJA: $+1.3 \text{ W m}^{-2}$). Specific-humidity and wind errors are right-skewed (1.25 and 1.22); for wind, this reflects the 2018 step change in the AORC record.

A multi-variable Taylor diagram (Figure 2) compares each forcing variable with its own AORC series using deseasonalized daily anomalies, so that the shared annual cycle does not inflate the agreement. Raw daily correlations are high for the thermodynamic variables ($r \geq 0.986$ for temperature, pressure, longwave, and specific humidity), for shortwave radiation (0.959), and for precipitation (0.947), but anomaly correlations separate the variables more clearly with pressure (0.998), temperature (0.981), longwave (0.956), and precipitation (0.947) agreeing most closely, followed by specific humidity (0.928), shortwave radiation (0.853), and 2-m wind (0.783). Normalized standard deviations of the anomalies are near 1.0 for temperature, pressure, longwave,

and humidity, below 1 for precipitation (0.90) and wind (0.72), and above 1 for shortwave radiation (1.36), indicating larger day-to-day shortwave variability in NLDAS-3. Wind speed is the least consistent variable between the two records.

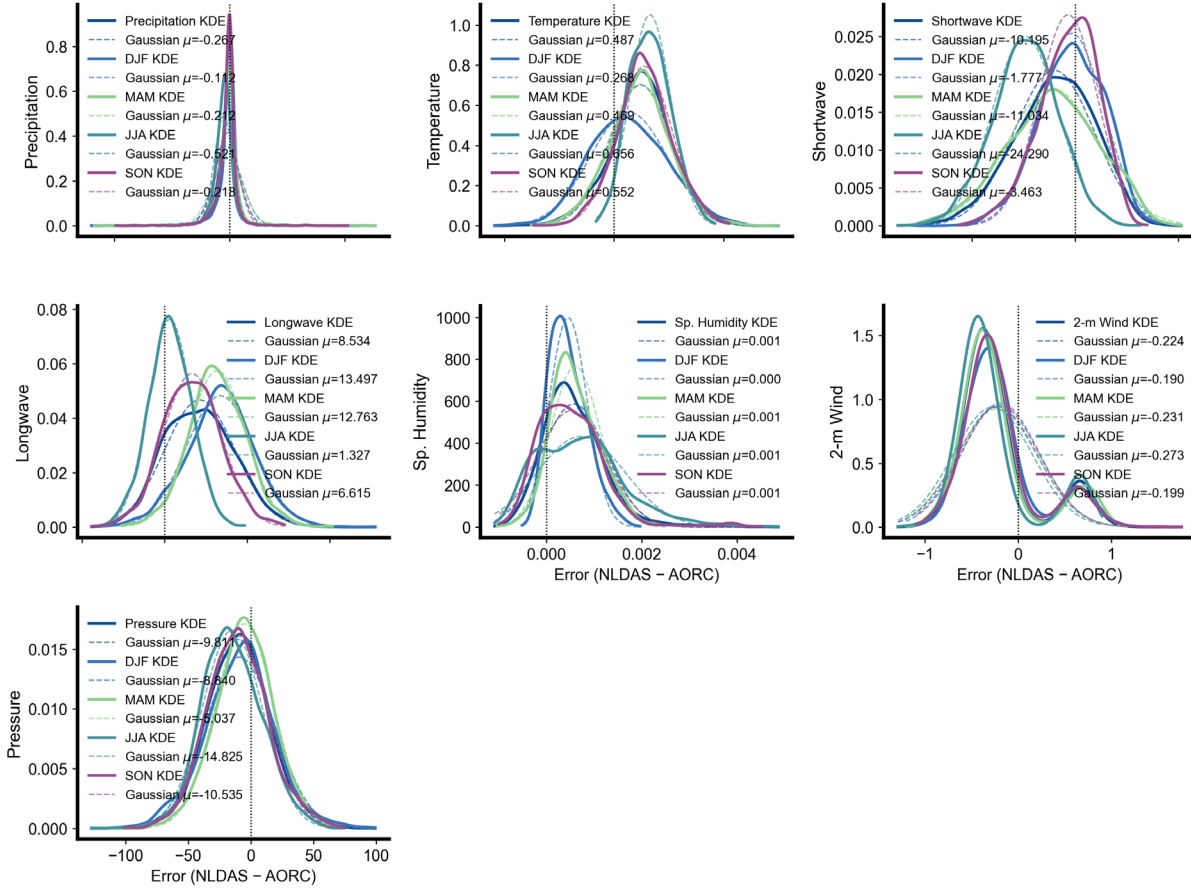


Figure 1. Kernel density estimates of daily error distributions (NLDAS-3 minus AORC) for all seven forcing variables, full period 2001–2020, common footprint. Seasonal sub-populations (DJF, MAM, JJA, SON) are overlaid.

4.2. Precipitation Extremes

Upper-tail contrasts between the two records depend on the spatial scale at which they are evaluated (Table 3; Figure 3). For the domain-mean series, GEV fits to the 20 annual maxima give 2-year levels of 20.3 mm day^{-1} (AORC) and 18.5 mm day^{-1} (NLDAS-3) and 25-year levels of 26.3 and 23.7 mm day^{-1} ; the bootstrap confidence intervals overlap at every recurrence interval, so domain averaging largely removes the difference. At the pixel scale, which is the scale relevant to watershed response, the contrast is large and consistent. Across 3,000 sampled footprint pixels, the median NLDAS-3 return level is 31–33% below AORC at every recurrence interval (2 yr: 54 vs. 79 mm day^{-1} ; 10 yr: 85 vs. 126 mm day^{-1} ; 25 yr: 102 vs. 152 mm day^{-1}), and the peaks-over-threshold analysis gives the same result (10-yr level 88 vs. 127 mm day^{-1}). Because the record is 20 years long, return periods beyond 25 years are not reported, and the fitted quantiles should be

read as descriptors of tail shape. The key structural finding is that AORC preserves a substantially heavier upper tail at the scale of individual cells, which domain averaging conceals.

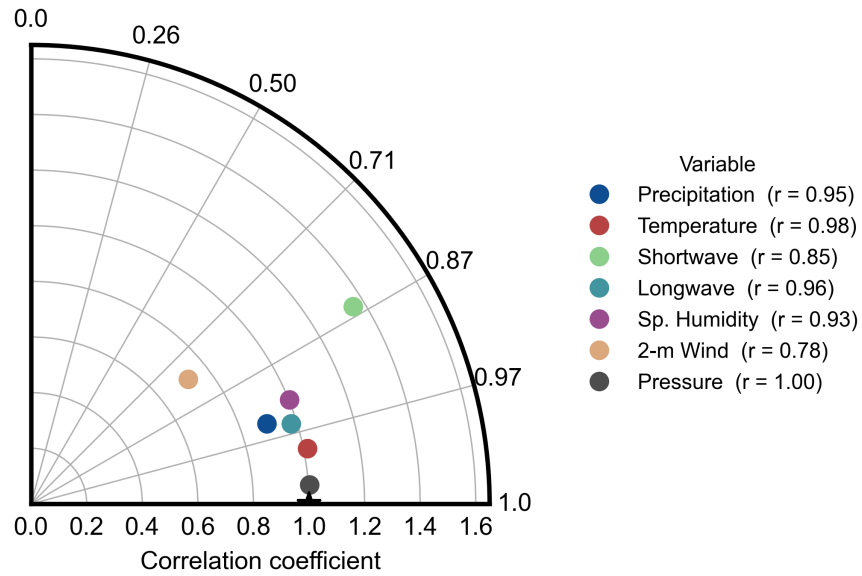


Figure 2. Multi-variable Taylor diagram for all seven forcing variables. Statistics use deseasonalized daily anomalies, and each variable is normalized by the standard deviation of its own AORC series. The black star marks the AORC reference at ($\theta = 0^\circ$, $\sigma_n = 1$). Angular position encodes the variable correlation; radial distance encodes normalized standard deviation. Pressure, temperature, longwave, and precipitation plot closest to the reference; shortwave radiation ($r = 0.85$) and 2-m wind ($r = 0.78$) show the lowest anomaly correlations.

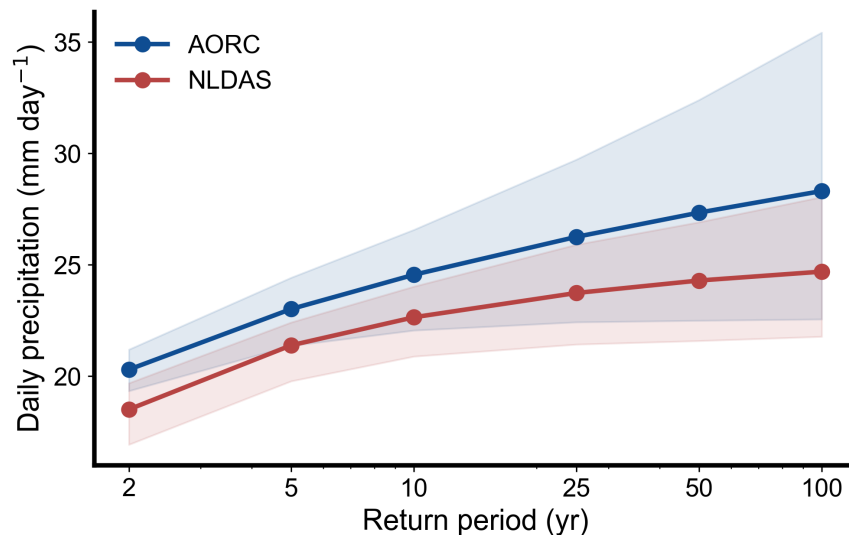


Figure 3. Precipitation tail structure analysis: seasonal cycle, probability density function for wet days, and L-moment GEV upper-tail quantile curves with 90% bootstrap confidence envelopes for the domain-mean AORC and NLDAS-3 series, full 2001–2020 period.

4.3. Temporal Trends

Mann-Kendall tests on monthly anomaly series are summarized in Table 4. The most prominent finding is a statistically significant decreasing trend in AORC 2-m wind speed ($p < 0.001$; Theil-Sen slope $-0.0022 \text{ m s}^{-1} \text{ month}^{-1}$, or $\sim -0.26 \text{ m s}^{-1}$ per decade), for which NLDAS-3 shows no corresponding trend ($p = 0.53$). The Pettitt test locates a change point in the AORC wind series in mid-2017 ($p < 0.001$), consistent with the replacement of NLDAS-2 inputs by URMA analyses in AORC v1.1 from January 2018 (NOAA Office of Water Prediction, 2021). AORC 2-m wind averages 2.58 m s^{-1} in 2001–2017 and 1.55 m s^{-1} in 2018–2020, whereas NLDAS-3 remains at 2.20 m s^{-1} in both periods (Figure 4). Before 2018 the AORC series shows only a weak increasing trend ($p = 0.011$; $+0.0005 \text{ m s}^{-1} \text{ month}^{-1}$) and NLDAS-3 none ($p = 0.95$). The full-record AORC wind trend is treated as a data-construction artifact. Because the step also affects full-period wind statistics, wind comparisons are interpreted with this discontinuity in mind.

Table 3. GEV fitted upper-tail quantiles (mm day^{-1}) of daily precipitation, 2001–2020, estimated by L-moments. Domain-mean rows: values in parentheses are 90% bootstrap confidence intervals ($n = 500$ resamples). Pixel rows: median across 3,000 sampled footprint pixels. Return periods beyond 25 years are omitted because of the 20-year record.

Dataset	T = 2 yr	T = 5 yr	T = 10 yr	T = 25 yr
AORC (domain mean)	20.29 (19.33–21.19)	23.01 (21.36–24.42)	24.55 (22.05–26.57)	26.25 (22.42–29.72)
NLDAS-3 (domain mean)	18.50 (16.92–19.68)	21.38 (19.77–22.41)	22.64 (20.88–24.02)	23.73 (21.42–25.90)
AORC (pixel median)	79.1	106.6	126.0	152.1
NLDAS-3 (pixel median)	53.9	72.0	85.3	101.9

AORC precipitation shows a significant increasing trend ($p = 0.017$; slope $+0.0024 \text{ mm day}^{-1} \text{ month}^{-1}$); NLDAS-3 shows a weaker, non-significant increase ($p = 0.065$; $+0.0016 \text{ mm day}^{-1} \text{ month}^{-1}$). No significant monotonic trends were detected for temperature, shortwave, longwave, specific humidity, pressure, or ET_0 in either product. The Pettitt test identified significant change points in precipitation for both products at the end of 2012 (AORC $p = 0.005$; NLDAS-3 $p = 0.025$), in AORC specific humidity in early 2015 ($p = 0.040$), and in AORC 2-m wind in mid-2017 ($p < 0.001$); no other variable showed a significant change point. Robust STL decomposition of the monthly series is consistent with these results: the seasonal component accounts for 97% of the monthly temperature variance in both products, the peak-to-trough seasonal amplitude of shortwave radiation is 12% smaller in NLDAS-3 than in AORC (171.5 vs. 194.2 W m^{-2}), and the trend component of AORC wind spans 1.23 m s^{-1} , compared with 0.20 m s^{-1} for NLDAS-3, reflecting the 2018 step.

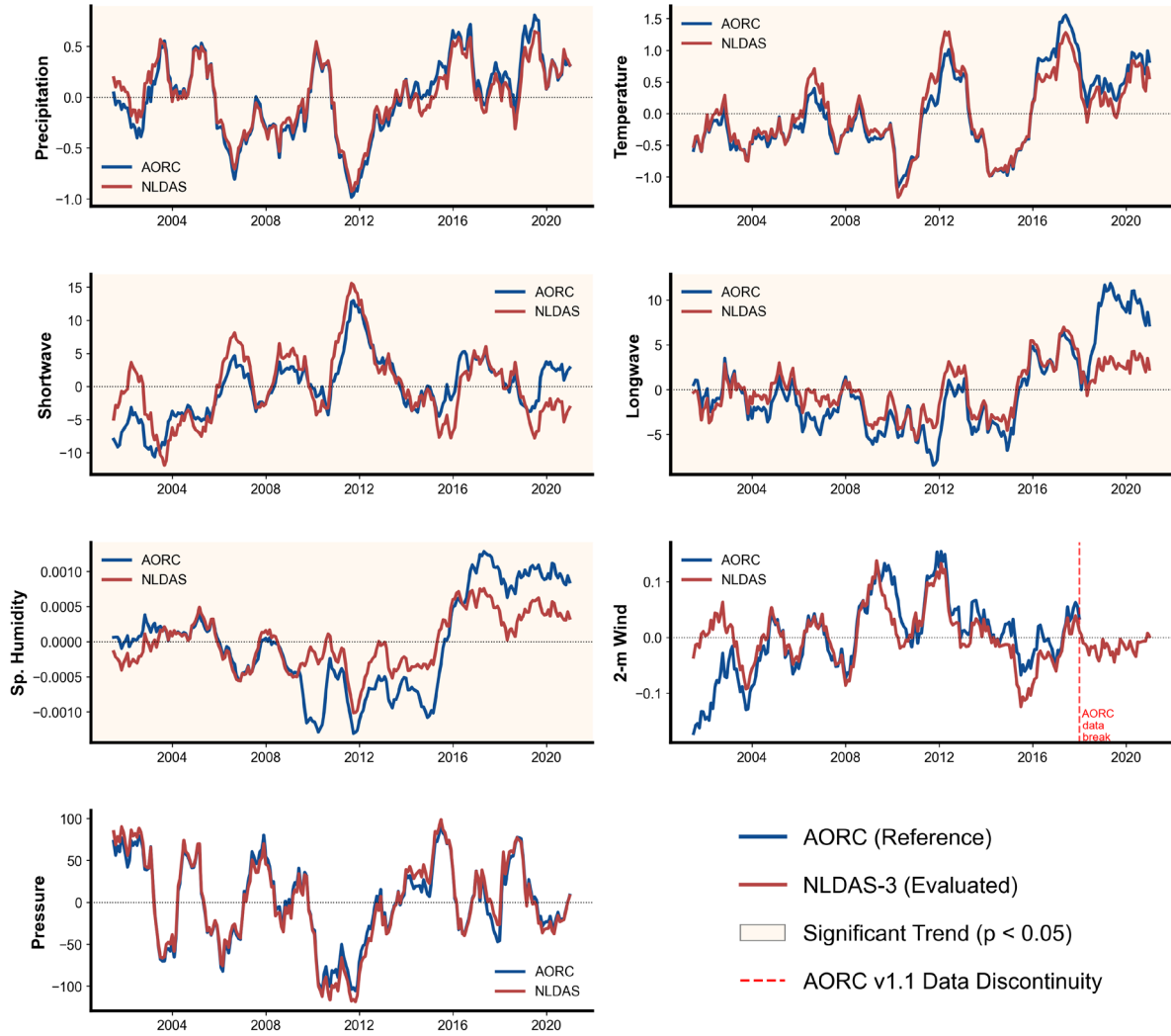


Figure 4. Twelve-month rolling anomalies for all forcing variables, 2001–2020. AORC in blue; NLDAS-3 in red. Orange panel backgrounds indicate variables with a statistically significant Mann–Kendall trend ($p < 0.05$). The red dashed vertical line in the wind panel marks the documented AORC v1.1 source-data discontinuity at January 2018, after which AORC near-surface wind drops from 2.58 to 1.55 m s^{-1} on average; AORC wind is plotted only for 2001–2017.

Table 4. Mann-Kendall trend test results for monthly anomaly series, 2001–2020. Significant trends ($p < 0.05$) are in bold.

Variable	Dataset	MK p-value	Slope (units mo ⁻¹)	Trend
Precipitation	AORC	0.017	+0.00235 mm	increasing
Precipitation	NLDAS-3	0.065	+0.00155 mm	none
Temperature	AORC	0.328	+0.0054 °C	none
Temperature	NLDAS-3	0.410	+0.0045 °C	none
Shortwave	AORC	0.551	+0.029 W m ⁻²	none
Shortwave	NLDAS-3	0.861	+0.009 W m ⁻²	none

Pressure	AORC	0.845	−0.000037 kPa	none
Pressure	NLDAS-3	0.759	−0.000063 kPa	none
Wind 2 m	AORC	<0.001	−0.00220 m s ^{−1}	decreasing
Wind 2 m	NLDAS-3	0.530	−0.00014 m s ^{−1}	none

4.4. Louisiana Sub-Domain Analysis

The analyses previously mentioned are based on the full study domain. This section zooms to the Louisiana sub-domain, which spans the humid subtropical Gulf Coast environment for which the analysis is most operationally relevant. Comparisons are made across three complementary diagnostics: domain-scale sensitivity, precipitation intermittency, and spatial coherence of gridded fields.

4.4.1. Scale Sensitivity

Table 5 and Figure 5 compare bias metrics between the full study domain and the Louisiana sub-domain for three key variables. RMSE increases in the smaller Louisiana domain for all three variables, as expected for a smaller spatial average, while correlations are lower for precipitation ($r = 0.938$ vs. 0.947) and shortwave radiation (0.897 vs. 0.959) but higher for wind (0.868 vs. 0.796). The NLDAS-3 precipitation deficit is similar in both domains (PBIAS -7.7% in Louisiana vs. -8.9% overall). The most notable domain-scale contrast is in 2-m wind speed. The Louisiana wind PBIAS (-24.4%) is about 2.6 times the full-domain value (-9.2%), indicating that NLDAS-3 near-surface wind departs more strongly from AORC in the Gulf Coast sub-region than at the domain scale. This scale dependency highlights the difficulty of resolving localized atmospheric dynamics and sharp gradients at the land–sea boundary, even when both records are mapped to the same 1-km grid. Wind contributes relatively little to the full-domain PM-ET₀ difference (-0.032 mm day^{−1}; Table 8), but the larger Louisiana wind deficit is consistent with the larger Louisiana ET₀ difference (-0.42 mm day^{−1}, -13.4% , vs. -0.16 mm day^{−1} for the full domain). Shortwave radiation RMSE also increases markedly in Louisiana (37.7 vs. 21.9 W m^{−2}), consistent with larger cloud-related differences over the humid coastal sub-domain; both records take their shortwave radiation from coarse-resolution sources (NLDAS-2 for AORC and reanalysis-based fields for NLDAS-3), so neither resolves cloud cover at the 1-km grid scale.

Table 5. Domain-scale bias metrics for selected variables: full study domain vs. Louisiana sub-domain, 2001–2020.

Domain	Variable	RMSE	r	MAE	PBIAS (%)
Study domain	Precipitation	1.15	0.947	0.61	−8.9
Louisiana	Precipitation	2.84	0.938	1.17	−7.7
Study domain	Shortwave (W m ^{−2})	21.9	0.959	17.3	−4.8
Louisiana	Shortwave (W m ^{−2})	37.7	0.897	29.0	−7.8
Study domain	Wind 2 m (m s ^{−1})	0.48	0.796	0.42	−9.2
Louisiana	Wind 2 m (m s ^{−1})	0.82	0.868	0.69	−24.4

4.4.2. Precipitation Intermittency

Intermittency statistics (Table 6; Figure 6) show that the two products deliver rainfall in substantially different ways. Evaluated pixel by pixel with a wet-day threshold of 1 mm day⁻¹ and summarized as the median across the domain, NLDAS-3 records a wet-day fraction of 36.1% versus 26.6% for AORC (+36%), but with a mean wet-day intensity 36% lower (8.2 vs. 12.7 mm day⁻¹). Wet spells are longer in NLDAS-3 (mean 2.46 vs. 1.75 days; maximum 19 vs. 10 days), while dry spells are slightly shorter (mean 4.67 vs. 4.95 days; maximum 46 vs. 51 days). The 90th-percentile wet-day intensity is 38% lower in NLDAS-3 (19.4 vs. 31.1 mm day⁻¹), whereas the 20-year total differs by only -8.6%.

NLDAS-3 distributes a similar rainfall total over more, lighter rain days, with only 19% of days having zero precipitation at a typical NLDAS-3 pixel, compared with 66% for AORC, consistent with a reanalysis- and satellite-based field downscaled to 1 km, which spreads rainfall in space and time, whereas the radar-gauge-based AORC field preserves intermittent, intense convective cells. The contrast is largest in summer, when a typical NLDAS-3 pixel is wet on 47% of days, compared with 33% for AORC, with a mean wet-day intensity of 6.5 versus 11.1 mm day⁻¹. These differences are invisible in domain-mean series, where both products are wet on about 64% of days. For continuous hydrological simulation, this structural difference matters independently of the mean bias, because infiltration, runoff generation, and soil-moisture recharge depend on the intensity and sequencing of rainfall as well as its total.

Table 6. Precipitation intermittency statistics, 2001–2020 (wet day ≥ 1 mm day⁻¹; medians across footprint pixels; P90 intensity and 20-year total from 3,000 sampled pixels).

Metric	AORC	NLDAS	Difference
Wet-day fraction	0.266	0.361	+35.7%
Mean wet-day intensity (mm day ⁻¹)	12.66	8.17	-35.5%
Mean wet-spell length (days)	1.75	2.46	+40.8%
Maximum wet spell (days)	10	19	+90.0%
Mean dry-spell length (days)	4.95	4.67	-5.6%
Maximum dry spell (days)	51	46	-9.8%
P90 wet-day intensity (mm day ⁻¹)	31.14	19.43	-37.6%
20-year total (mm)	24 426	22 322	-8.6%

Rain gauges provide an independent check on the two rain-day structures (Table 7; Figure 7). At 3,329 GHCN-Daily gauges, the median observed wet-day fraction is 0.24; AORC gives 0.27 and NLDAS-3 0.37, and AORC is closer to the gauge at 97% of stations. The contrast is sharper for completely dry days, when gauges record zero precipitation on 71% of days, AORC on 64%, and NLDAS-3 on only 20%, while light rain below 1 mm occurs on 5% of days at the gauges, 8% in AORC, and 45% in NLDAS-3. AORC is also closer in wet-day intensity (13.2 vs. 14.7 mm day⁻¹ observed; NLDAS-3 8.5 mm day⁻¹) and 90th-percentile intensity (32.3 vs. 36.1 mm day⁻¹; NLDAS-3 20.1 mm day⁻¹) at more than 99% of gauges, and in annual totals at 83% of gauges

(observed 1,320 mm; AORC 1,305 mm; NLDAS-3 1,179 mm). The result holds in every network (AORC is closer in wet-day fraction at 99.9% of COOP, 94.6% of CoCoRaHS, and 99.7% of first-order stations) and AORC also correlates better with the gauges at the daily ($r = 0.64$ vs. 0.59 ; 0.77 vs. 0.69 at first-order stations with midnight-to-midnight days) and monthly (0.93 vs. 0.86) scales. The gauges do not show the frequent light rain seen in NLDAS-3, which likely reflects how its beta precipitation field is constructed from coarser reanalysis and satellite estimates — a feature that future releases could address

Table 7. Precipitation structure at GHCN-Daily rain gauges and co-located grid cells (medians across 3,329 gauges, 2001–2020, identical days for all three sources), and the share of gauges at which AORC is closer than NLDAS-3.

Metric	Gauges	AORC	NLDAS-3	AORC closer (% of gauges)
Wet-day fraction (≥ 1 mm)	0.243	0.275	0.370	97.4
Days with zero precipitation	0.709	0.643	0.197	99.2
Light-rain days (0–1 mm)	0.051	0.082	0.448	–
Wet-day intensity (mm day ⁻¹)	14.7	13.2	8.5	99.8
P90 wet-day intensity (mm day ⁻¹)	36.1	32.3	20.1	99.8
Mean wet-spell length (days)	1.63	1.72	2.38	–
Mean dry-spell length (days)	4.97	4.57	4.29	–
Annual total (mm)	1 320	1 305	1 179	83.0
Daily correlation with gauge	–	0.64	0.59	–
Monthly correlation with gauge	–	0.93	0.86	–

4.4.3. Spatial Coherence over Louisiana

Figure 8 shows the spatial coherence of gridded precipitation between AORC and NLDAS-3 over the study domain, including the Louisiana sub-region. Daily pixel-level correlations, which are not mapped, are moderate (median $r = 0.79$ over the domain and 0.82 in Louisiana), lower than the domain-mean correlation ($r = 0.95$), because individual convective cells are placed differently by the two records even where regional rainfall agrees. The NLDAS-3 precipitation deficit is spatially heterogeneous, with AORC exceeds NLDAS-3 most along the Gulf and Atlantic coastal plains from Louisiana to Florida (by 0.43 – 0.49 mm day⁻¹ east of 91° W and south of 31° N) and least in interior Texas (by 0.11 – 0.16 mm day⁻¹), matching the AORC – NLDAS-3 convention of the bias map. Domain-mean statistics mask spatial variability that is relevant for watershed-scale applications in the coastal zone.

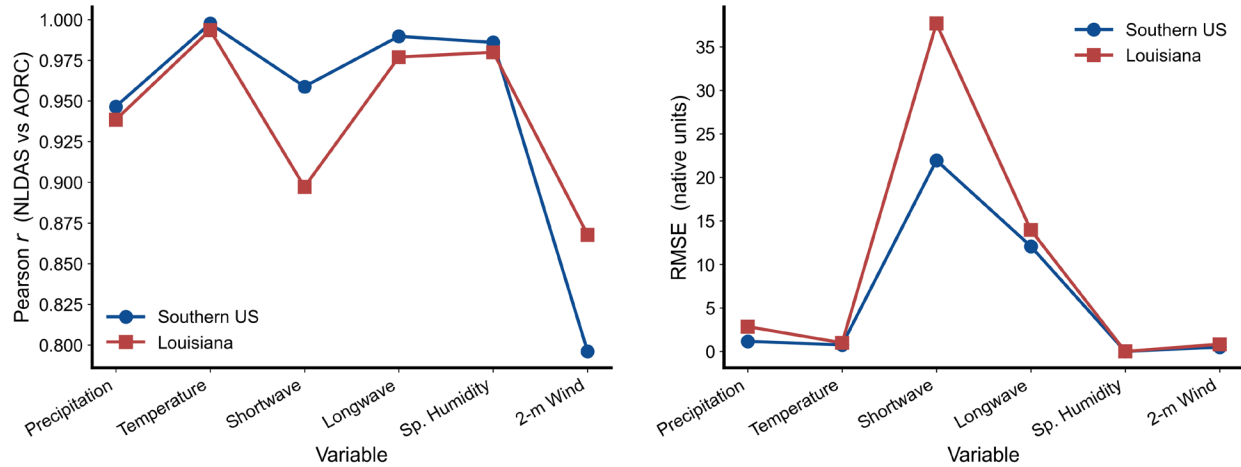


Figure 5. Scale-sensitivity comparison of RMSE and Pearson r for the forcing variables between the full study domain and the Louisiana sub-domain, 2001–2020. AORC serves as the reference in all cases.

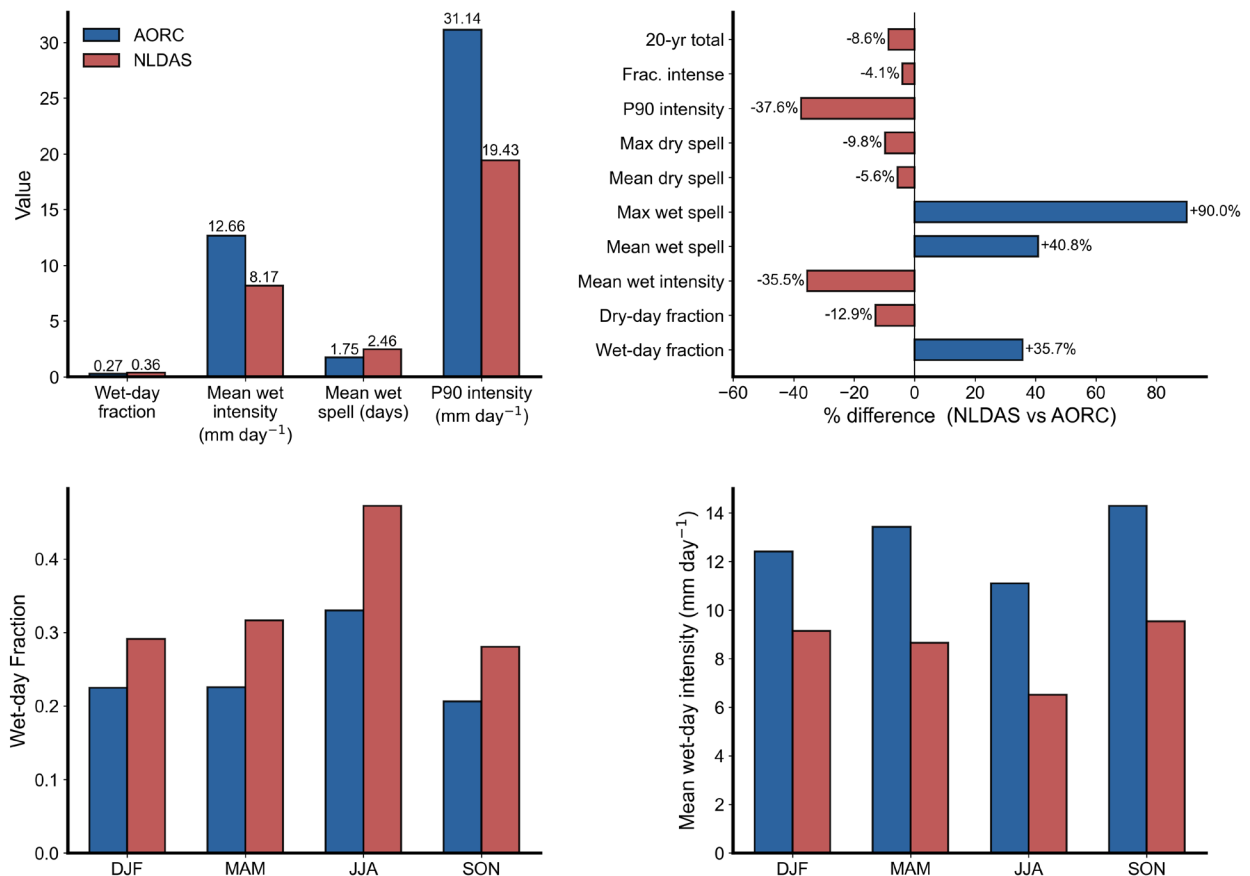


Figure 6. Precipitation intermittency diagnostics for AORC (blue) and NLDAS-3 (red), 2001–2020 (wet day $\geq 1 \text{ mm day}^{-1}$; medians across footprint pixels). Top left: wet-day fraction, mean wet-day intensity, mean wet-spell length, and 90th-percentile wet-day intensity. Top right: percentage difference of each metric (NLDAS-3 relative to AORC), including the dry-day fraction

and the share of total precipitation falling on days above the wet-day 90th percentile (“Frac. intense”). Bottom: seasonal wet-day fraction (left) and mean wet-day intensity (right). NLDAS-3 has more wet days and longer wet spells but weaker wet-day intensity in every season, most strongly in summer.

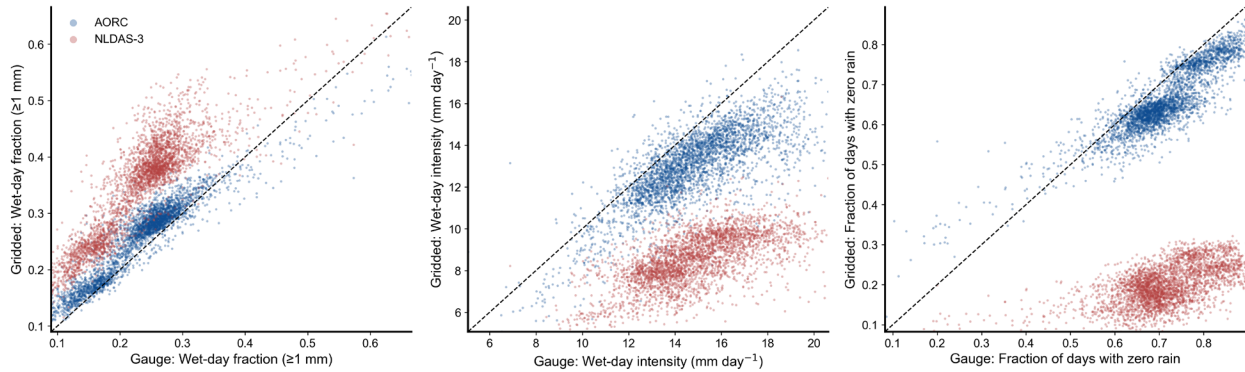


Figure 7. Precipitation structure at 3,329 GHCN-Daily rain gauges versus the co-located AORC (blue) and NLDAS-3 (red) grid cells, 2001–2020, on days valid in all three: wet-day fraction (≥ 1 mm), mean wet-day intensity, and fraction of days with zero precipitation. The dashed line is 1:1.

4.5. Reference ET_0 Attribution

PM- ET_0 computed pixel by pixel from AORC fields averages 3.37 mm day^{-1} over the domain and record; NLDAS-3 yields 3.20 mm day^{-1} . The net difference is $-0.160 \text{ mm day}^{-1}$ (NLDAS-3 lower; PBIAS = -4.8% ; RMSE = 0.43 mm day^{-1} ; $r = 0.979$; anomaly $r = 0.84$). The scenario-based sensitivity analysis (Table 8; Figure 9) indicates that the net response emerges from compensating atmospheric controls. Shortwave radiation contributes $-0.168 \text{ mm day}^{-1}$ through its effect on net radiation, and specific humidity $-0.156 \text{ mm day}^{-1}$ by reducing the vapor pressure deficit; together they exceed the total difference. They are partly offset by downward longwave radiation ($+0.134 \text{ mm day}^{-1}$), which raises net radiation in NLDAS-3, and by temperature ($+0.053 \text{ mm day}^{-1}$), through higher saturation vapor pressure. Wind speed contributes $-0.032 \text{ mm day}^{-1}$ and pressure is negligible ($0.000 \text{ mm day}^{-1}$). The sum of the individual substitutions ($-0.169 \text{ mm day}^{-1}$) closes to within $0.008 \text{ mm day}^{-1}$ of the actual difference, so interactions among the drivers are small. Shortwave radiation is the largest single driver of the net ET_0 deficit, while the radiative compensation between shortwave and longwave radiation illustrates how forcing products with similar mean atmospheric demand may still encode different internal forcing-variable structure.

Table 8. OAT variable-substitution attribution of mean annual PM- ET_0 difference (NLDAS-3 minus AORC).

Driver	$\Delta ET_{0,x} \text{ (mm day}^{-1}\text{)}$	Direction
Temperature	+0.053	NLDAS raises demand
Specific humidity	-0.156	NLDAS reduces VPD
Shortwave	-0.168	NLDAS reduces R_n

Wind speed	-0.032	NLDAS reduces transfer
Pressure	0.000	negligible
Longwave	+0.134	NLDAS raises R_n
Net	-0.160	NLDAS lower

4.6. GHCN Temperature-Based Contextual Evaluation and HS-PM Method Gap

Skill scores against GHCN-Daily station observations are reported in Table 9. Over the full study domain, AORC HS-ET₀ has a mean station bias of +0.98 mm month⁻¹ (± 1.58 SD) with a mean KGE of 0.974. NLDAS-3 shows a larger bias of +2.48 mm month⁻¹ (± 2.08 SD) and a KGE of 0.963. Within the Louisiana sub-domain, AORC bias is +0.75 mm month⁻¹ (KGE = 0.979) and NLDAS-3 bias is +1.92 mm month⁻¹ (KGE = 0.971). Station-scale correlations are high for both products ($r = 0.987$ – 0.988). Because the gridded HS estimates use each station's observed diurnal temperature range, these scores mainly evaluate the gridded mean temperature; the larger NLDAS-3 bias is consistent with its warmer temperature field.

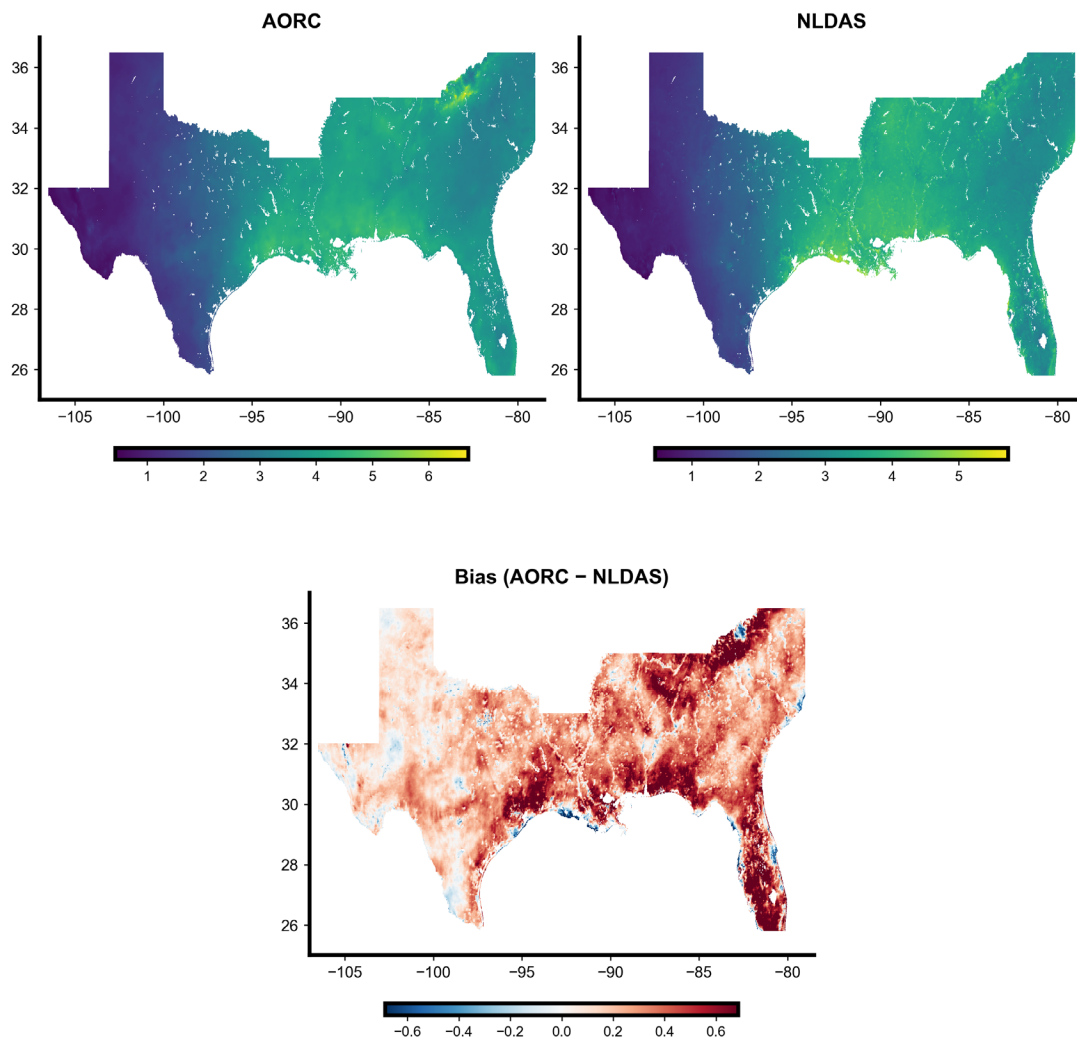


Figure 8. Spatial coherence of daily precipitation between AORC and NLDAS-3 (AORC sampled to the NLDAS-3 0.01° grid; maps at 0.02°), 2001–2020. Top: AORC and NLDAS-3 mean daily precipitation (mm day⁻¹). Bottom: pixel-level bias expressed as AORC – NLDAS-3 (mm day⁻¹), so red indicates that NLDAS-3 is drier than AORC. The deficit is largest along the Gulf and Atlantic coastal plains and smallest in interior Texas.

Table 9. GHCN-Daily station-level evaluation metrics for HS-ET₀ (mm month⁻¹), 2001–2020. The same 1,392 stations (96 in Louisiana) are used for both products.

Region	Product	N sta.	Bias	RMSE	r	KGE
Study domain	AORC	1392	+0.98	7.66	0.987	0.974
Study domain	NLDAS-3	1392	+2.48	7.77	0.988	0.963
Louisiana	AORC	96	+0.75	7.11	0.987	0.979
Louisiana	NLDAS-3	96	+1.92	7.17	0.988	0.971

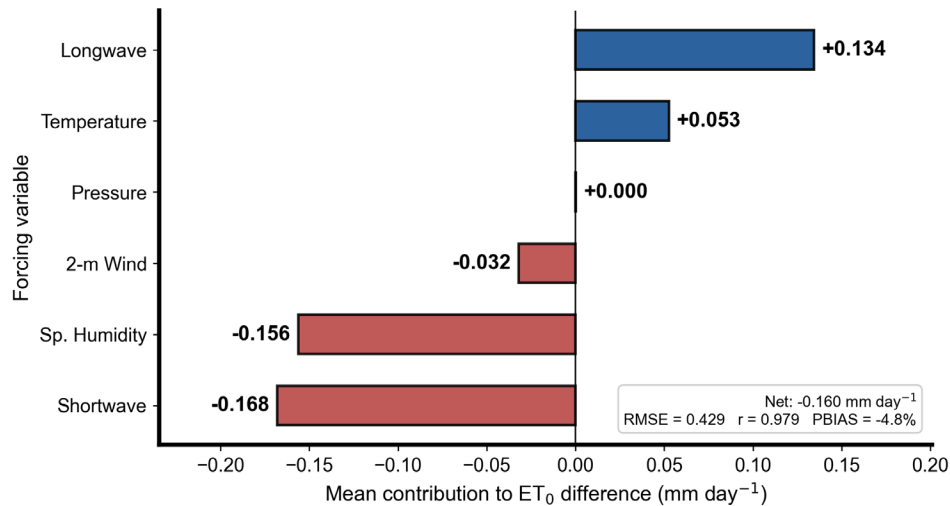


Figure 9. Attribution of the domain-mean PM-ET₀ difference (NLDAS-3 – AORC, 2001–2020) by one-at-a-time substitution. Each bar is the change in mean ET₀ when a single AORC forcing variable is replaced by its NLDAS-3 counterpart, with all other inputs held at AORC values; blue bars increase and red bars decrease NLDAS-3 ET₀ relative to AORC. Inset: net difference and agreement statistics of daily domain-mean ET₀.

Monthly mean ET₀ estimates from the method comparison are shown in Table 10 and Figure 10; all five estimates are averaged over the same 1,392 stations. Annually, GHCN-derived HS-ET₀ averages 3.81 mm day⁻¹, AORC HS-ET₀ 3.85 mm day⁻¹, and NLDAS-3 HS-ET₀ 3.90 mm day⁻¹, while PM-ET₀ averages 3.26 mm day⁻¹ (AORC) and 3.08 mm day⁻¹ (NLDAS-3). HS exceeds PM in every month, but the method gap (PM – HS, AORC) is largest in spring (–0.97 mm day⁻¹ in April) and smallest in midsummer (–0.17 mm day⁻¹ in July), when the PM/HS ratio reaches 0.97 (0.65 in winter). The forcing gap behaves differently under the two methods: with HS it never exceeds 0.08 mm day⁻¹, because HS responds only to temperature, whereas with PM

it reaches 0.72 mm day^{-1} in July as the shortwave and humidity differences enter the calculation. In summer, the PM forcing gap is therefore larger than the method gap.

Table 10. Monthly mean ET_0 (mm day^{-1}) from five estimates averaged over the same 1,392 stations, and derived gaps, full period 2001–2020 (selected months).

Month	GHCN HS	AORC HS	NLDAS HS	AORC PM	NLDAS PM	Method Gap (PM–HS, AORC)	Forcing Gap (AORC – NLDAS, PM)
Jan	1.76	1.77	1.78	1.15	1.20	–0.61	–0.04
Apr	4.49	4.54	4.59	3.58	3.59	–0.97	–0.02
Jul	5.77	5.81	5.89	5.64	4.92	–0.17	+0.72
Oct	3.24	3.31	3.37	2.72	2.65	–0.59	+0.07

4.7. Statistical Adjustment Recoverability

LOYO-CV results for daily precipitation are shown in Figure 11. Across the 20 withheld years, raw NLDAS-3 RMSE ranges from 0.58 to 2.74 mm day^{-1} and PBIAS from -13.5% to -3.6% (mean -8.8%). Quantile mapping removes most of the bias, bringing PBIAS within -4.9% to $+6.4\%$ in every year (mean $+0.3\%$) and reducing the mean RMSE from 0.98 to 0.93 mm day^{-1} ; linear regression performs similarly (PBIAS -5.7% to $+6.0\%$). Neither adjustment changes the correlation (mean $r = 0.942$ before and after), and both perform worst in 2019 and 2020 ($r \sim 0.64$ – 0.67), the years following the 2018 AORC source-data change.

The unresolved residual structure indicates that portions of the inter-dataset differences are embedded in event sequencing and co-variability, not in marginal precipitation distributions alone. The structure diagnostics quantify this, after quantile mapping, the lag-1 autocorrelation of daily precipitation remains 0.50 (AORC: 0.45), the share of AORC’s top-5% event days that are also top-5% days in the adjusted series stays at 0.81 , unchanged from the raw series, and the coupling between precipitation and shortwave anomalies remains -0.55 (AORC: -0.58). Statistical adjustment is not equivalent to reconstructing the forcing structure underlying those differences. This is significant for hydrologic applications because runoff, soil-moisture recharge, and antecedent wetness respond to the ordering and clustering of events as well as to the marginal precipitation amount. Bias correction can reduce mean error and improve distributional agreement, but it cannot fully restore event timing or cross-variable consistency (Ehret et al., 2012; Maraun et al., 2017). The LOYO-CV results support the use of quantile mapping as a practical first-order adjustment for hydrologic forcing applications (Teutschbein & Seibert, 2012).

4.8. Spatial Distribution of ET_0 Bias

The station-level bias map (Figure 12) shows small, mostly positive HS- ET_0 biases for both products. AORC biases are smallest in Texas, Louisiana, and Florida ($+0.6$ to $+0.8 \text{ mm month}^{-1}$ on average) and largest in Georgia and South Carolina ($+1.6$ to $+1.7 \text{ mm month}^{-1}$). NLDAS-3-based HS- ET_0 shows a larger mean bias ($+2.48 \text{ mm month}^{-1}$) nearly everywhere, with the largest values in western Texas ($+3.3 \text{ mm month}^{-1}$ west of 98° W) and South Carolina ($+3.1 \text{ mm month}^{-1}$).

Station-to-station variability is also higher for NLDAS-3 (SD: 2.08 vs. 1.58 mm month⁻¹), consistent with its warmer and more spatially variable temperature field. The Taylor diagram (Figure 13) summarizes multi-metric skill across all 1,392 stations. Both products achieve high correlations ($r = 0.987$ – 0.988), and the AORC mean plots slightly closer to the reference point than the NLDAS-3 mean. Skill in the Louisiana sub-domain is similar (Table 9; RMSE 7.1–7.2 mm month⁻¹, vs. 7.7–7.8 mm month⁻¹ for the full domain).

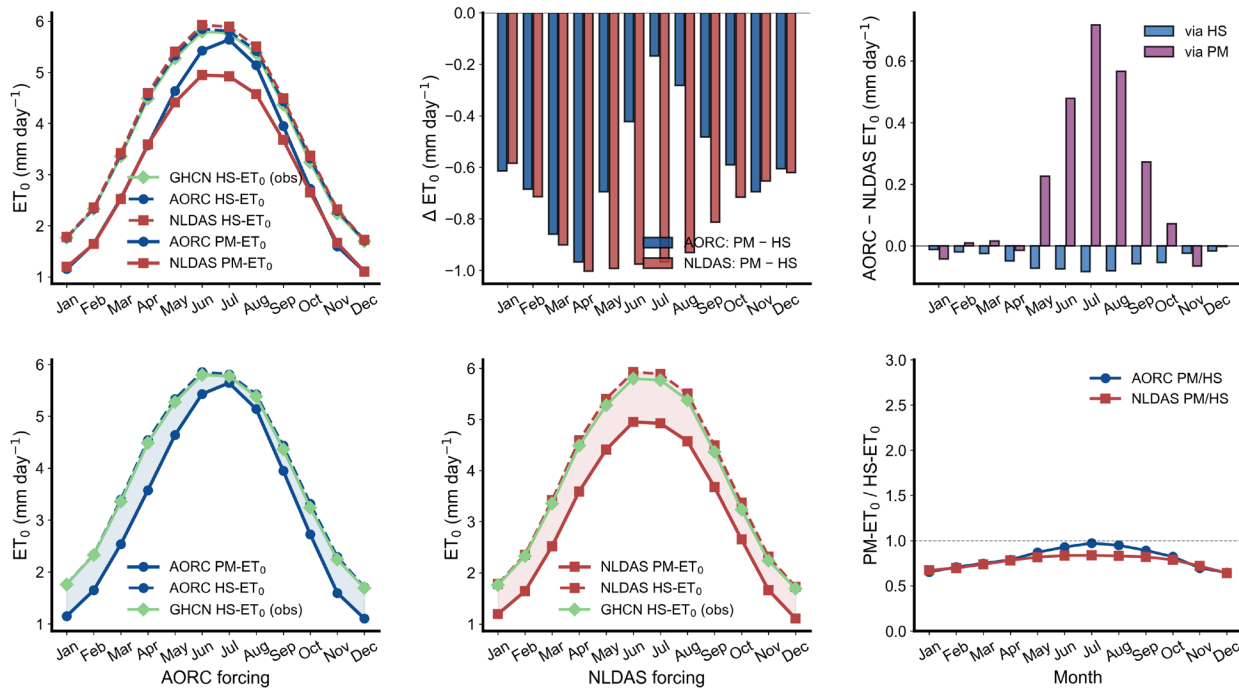


Figure 10. Monthly climatology of five ET_0 estimates at the same 1,392 stations: GHCN HS, AORC HS, NLDAS-3 HS, AORC PM, and NLDAS-3 PM. Under HS the forcing gap (AORC minus NLDAS-3) is nearly zero; under PM it reaches 0.7 mm day⁻¹ in summer, exceeding the method gap (PM minus HS).

4.9. Directional Annual Cycle Analysis

Directional (circular) statistics quantify the timing and sharpness of the seasonal signal in each forcing variable (Table 11; Figures 14 and 15). Temperature, specific humidity, and both radiation fields peak in early to late summer (days 168–208), with strong seasonal concentration ($R \geq 0.68$), and the two products agree in timing to within 5 days. Precipitation has the weakest seasonal concentration ($R = 0.06$ – 0.09), with AORC more concentrated than NLDAS-3; its mean peak timing differs by only 5 days (AORC day 190, NLDAS-3 day 185), so the products agree on the seasonal phase of rainfall even though they differ strongly in its intermittency. Wind speed peaks in late winter in both products (days 65–71), pressure in early January (days 5–6), and PM- ET_0 in early July, 4 days earlier in NLDAS-3 than in AORC (day 184 vs. 188).

4.10. Spectral Structure

Power spectra of the monthly domain-mean series show that the two products share the annual cycle of temperature but not that of shortwave radiation or precipitation. For temperature, NLDAS-3 power is within 2% of AORC in the annual band and within 6% at sub-annual periods (2–11 months), and 24% higher at interannual periods (>13.5 months). Shortwave radiation has 30% less power in the annual band in NLDAS-3, consistent with its weaker summer maximum (JJA bias -24.3 W m^{-2}), but 1.6–3.0 times more power at sub-annual and interannual periods, in line with its larger anomaly variability in the Taylor analysis (normalized standard deviation 1.36). The largest contrast is in precipitation: the annual band, which holds the strongest spectral peak of AORC (8.9% of its total variance at the 12-month period), carries about 60% less power in NLDAS-3 (4.1% of variance), so that the strongest NLDAS-3 peak falls at about 34 months instead; power at other periods is 12–16% lower. The weaker annual precipitation signal in NLDAS-3 agrees with its lower seasonal concentration ($R = 0.059$ vs. 0.090 ; Table 11) and with a deficit concentrated in the warm season (JJA PBIAS -14.5% vs. -4.2% in DJF).

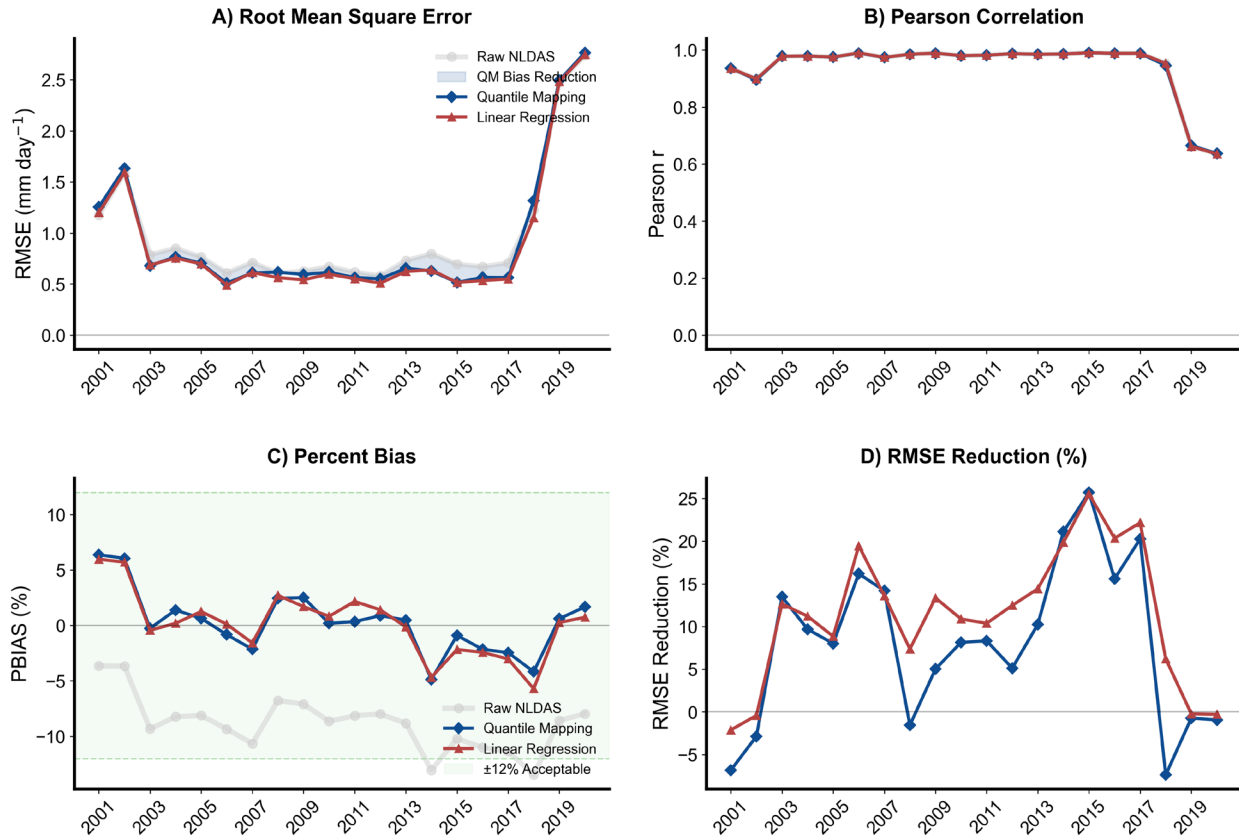


Figure 11. Leave-one-year-out cross-validation (LOYO-CV) bias-correction performance for daily precipitation, 2001–2020: (A) RMSE (mm day^{-1}), (B) Pearson r , (C) PBIAS (%) with $\pm 12\%$ acceptable shaded green band, and (D) RMSE reduction relative to raw NLDAS-3 (%), for raw NLDAS-3 (grey), quantile mapping (blue), and linear regression (red) as a function of the left-out

year. Both corrections remove most of the bias but leave the correlation unchanged; skill is lowest in 2019–2020.

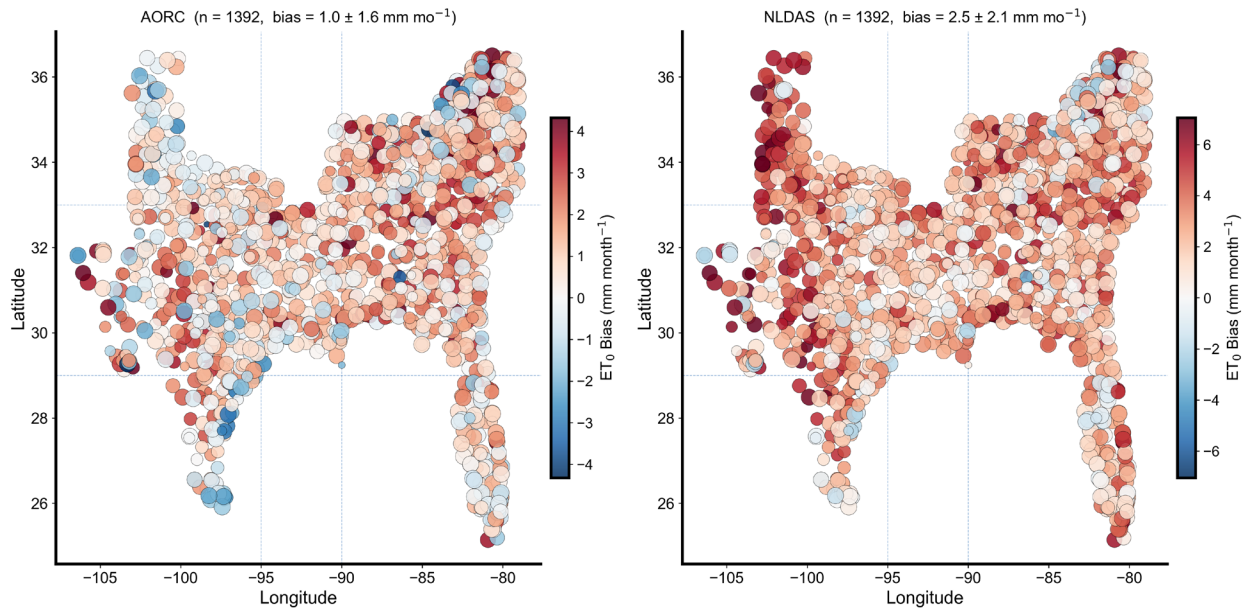


Figure 12. Spatial distribution of HS-ET₀ bias (mm month⁻¹, gridded product minus GHCN-Daily station observation) for AORC (top) and NLDAS-3 (bottom), 2001–2020, at the same 1,392 stations. Dot size scales with the number of qualifying station months; color indicates signed bias.

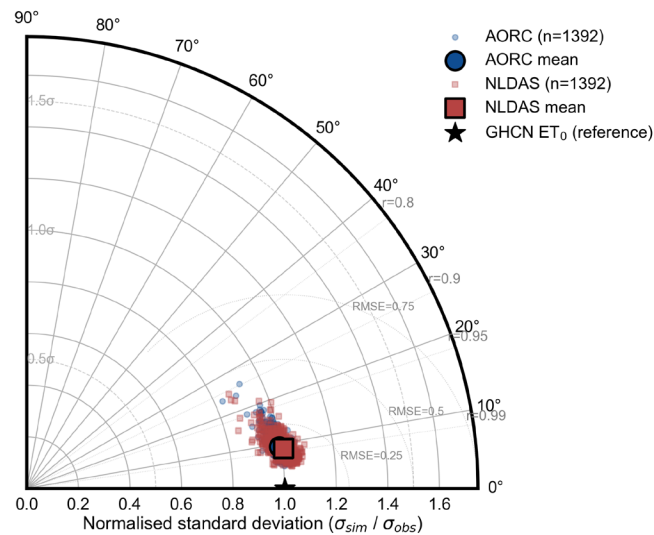


Figure 13. Normalized Taylor diagram of monthly HS-ET₀ from AORC and NLDAS-3 against GHCN-Daily station estimates at the same 1,392 stations, 2001–2020. Radial distance is the standard deviation of each gridded series normalized by that of its station series, so the GHCN-Daily reference (star) lies at 1 on the horizontal axis; angular position gives the correlation, and dotted arcs mark constant normalized RMSE. Small symbols are individual stations and large

symbols the means across stations; the AORC mean (blue circle) plots slightly closer to the reference than the NLDAS-3 mean (red square).

Table 11. Directional annual cycle statistics for all forcing variables and PM-ET₀, full study period. Mean DOY is the resultant-mean direction (day of annual peak); R is the resultant length (0 = uniform distribution, 1 = concentration at a single day); σ_c is the circular standard deviation (days).

Variable	Dataset	Dataset	Mean DOY	R	σ_c (days)
Precipitation		AORC	190	0.090	127
		NLDAS-3	185	0.059	138
Temperature		AORC	202	0.740	45
		NLDAS-3	203	0.741	45
Shortwave		AORC	173	0.741	45
		NLDAS-3	168	0.678	51
Longwave		AORC	208	0.763	43
		NLDAS-3	205	0.740	45
Specific humidity		AORC	206	0.752	44
		NLDAS-3	206	0.752	44
Wind 2 m		AORC	71	0.241	98
		NLDAS-3	65	0.320	88
Pressure		AORC	5	0.567	62
		NLDAS-3	6	0.567	62
PM-ET ₀		AORC	188	0.784	40
		NLDAS-3	184	0.752	44

5. Discussion

5.1. Interpreting the Bias Structure

The systematic biases identified are consistent with differences in how AORC and NLDAS-3 ingest and process their respective source data streams. Once both records are evaluated on the same footprint, the NLDAS-3 warm bias is modest (+0.49 °C) and seasonal, increasing from +0.27 °C in winter to +0.66 °C in summer. It is consistent with the interpolation of reanalysis backgrounds (MERRA-2 in NLDAS-3) to the 0.01° grid; one possible explanation is an underrepresentation of nocturnal cooling associated with regional land-cover heterogeneity, a process more faithfully captured in the station-informed AORC temperature field.

The shortwave radiation deficit in NLDAS-3 (−8.6% in JJA) may arise from differences in cloud fraction representation between the two forcing lineages. AORC shortwave is interpolated from NLDAS-2 without downscaling (NOAA Office of Water Prediction, 2021), whereas NLDAS-3 shortwave derives from its MERRA-2 background. One possible explanation is more frequent cloud in the reanalysis-based NLDAS-3 fields during scattered convection, which would lower mean shortwave even when precipitation totals are similar. The coincident longwave excess in NLDAS-3 (+8.5 W m^{−2}, largest in winter) is consistent with greater cloud or humidity in the

NLDAS-3 atmosphere, since both effects reduce incoming solar radiation while increasing downward longwave emission.

These biases propagate into derived hydroclimatic quantities through nonlinear combinations of variables. In the reference ET_0 calculation, the shortwave deficit and the longwave excess partly offset each other through net radiation, while the higher NLDAS-3 humidity lowers the vapor pressure deficit more than its warmer temperature raises it. The resulting ET_0 difference is not a simple reflection of any single bias; it is consistent with the combined structure of the forcing fields. Interpreting the HS results requires acknowledging the limitations of the input data. Because daily maximum and minimum temperatures are not available in the processed gridded files, they were reconstructed from each station's calendar-month climatological diurnal range. The gridded HS estimates share the station's diurnal range and differ from the station HS estimates only through mean temperature, which contributes to the high station-scale agreement (KGE 0.96–0.98). The Penman–Monteith calculations do not use this reconstruction. Future studies can remove this limitation by aggregating $T_{\max}$ and $T_{\min}$ directly from the hourly AORC and NLDAS-3 fields, or by integrating satellite-derived diurnal land surface temperature (e.g., from GOES or MODIS).

5.2. Why ET_0 Correction Requires Radiation Adjustment

The attribution results indicate that temperature correction alone would not necessarily move NLDAS-3 toward AORC-like PM- ET_0 behavior. Removing the warm temperature contribution without addressing shortwave and longwave radiation and humidity would change the balance among the Penman–Monteith terms, potentially increasing the net separation between the two records. This is important because many applied hydrologic studies correct temperature and precipitation while leaving radiation fields unchanged.

In the Gulf Coast, this issue is most relevant during the humid warm season, when soil moisture depletion, low-flow development, and antecedent conditions before late-summer storms are strongly affected by atmospheric water demand. If a forcing record underrepresents radiation-driven drying during this period, differences in radiation-driven atmospheric demand would be expected to alter antecedent drying behavior in continuous hydrologic simulations (Kratzert et al., 2019; Lees et al., 2021). The practical concern is not the ET_0 value alone, but how the diagnostic response signals differences that could propagate through land-surface memory.

5.3. Method Gap vs. Forcing Gap in ET_0 Estimation

The HS-to-PM method gap is moderate in this humid setting. Annually, station-averaged HS- ET_0 exceeds PM- ET_0 by about 18% (3.85 vs. 3.26 mm day⁻¹ for AORC), with the PM/HS ratio ranging from 0.65 in winter to 0.97 in midsummer. More important than its size is that the two formulations respond differently to forcing differences. Because HS depends only on temperature, its AORC–NLDAS-3 forcing gap never exceeds 0.08 mm day⁻¹, whereas the PM forcing gap reaches 0.72 mm day⁻¹ in July, when the NLDAS-3 shortwave and humidity differences are largest; in summer, the forcing gap under PM exceeds the method gap. GHCN-based temperature observations are widely available and are often used to contextualize gridded ET_0 estimates through HS or

Thornthwaite approaches. In humid subtropical climates such as the Gulf Coast, such temperature-only formulations cannot detect the radiation- and humidity-driven differences that separate forcing products.

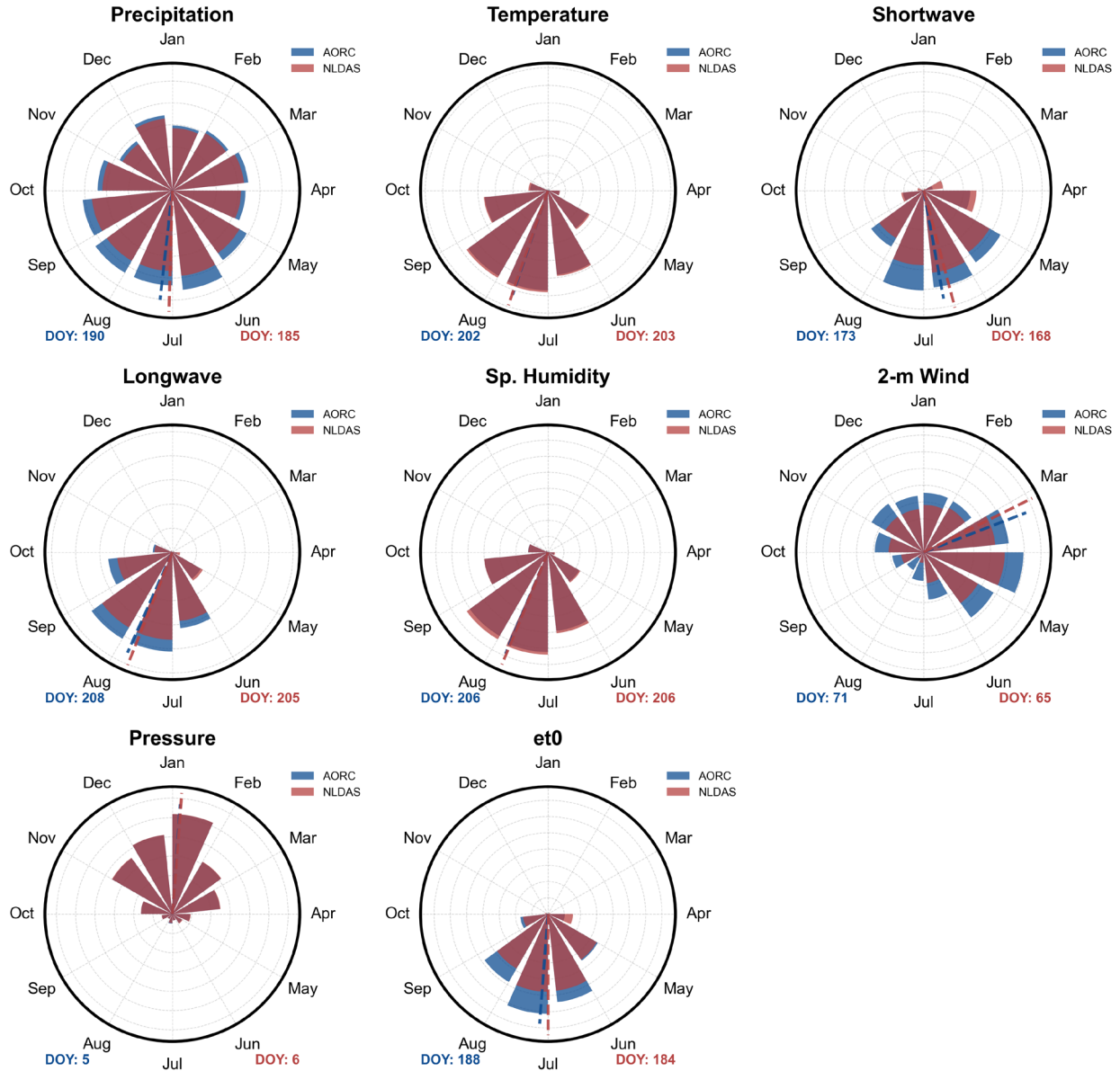


Figure 14. Directional annual cycle of the seven forcing variables and PM-ET₀. Rose bars show the monthly sum of the circular weights (daily precipitation, or positive anomalies from the annual mean for the other variables) for AORC (blue) and NLDAS-3 (red); dashed lines mark the circular mean direction, and the DOY labels give the mean peak day of AORC (left) and NLDAS-3 (right), as listed in Table 11.

This does not preclude the use of temperature-based ET₀ estimates, but it does limit how they should be interpreted. Close agreement between gridded and station HS-ET₀ in the Gulf Coast

(KGE 0.96–0.98 here) primarily confirms the mean temperature field and says little about the radiation and humidity fields that drive most of the PM-ET₀ difference between products. The PM/HS ratios reported here are best interpreted as study-specific diagnostics for this humid subtropical setting. For applied hydrologists, the practical recommendation is that GHCN temperature records can validate the temperature component of a forcing product but not its atmospheric demand; evaluating radiation and humidity requires independent observations such as pyranometer or flux-tower networks.

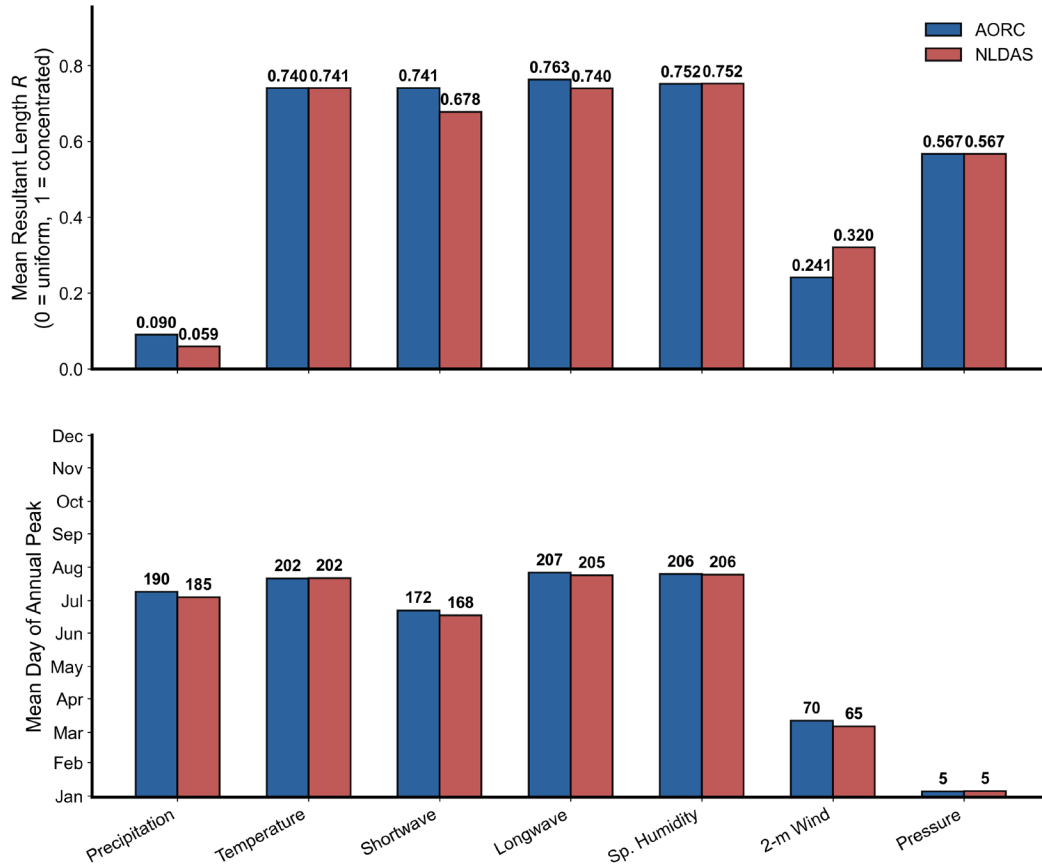


Figure 15. Seasonal concentration index (R) for all forcing variables. Bar heights are annotated with the exact R value. Shortwave and longwave radiation, temperature, and specific humidity are all strongly concentrated in summer ($R \geq 0.68$), confirming consistent seasonal structure. The largest relative difference in seasonal concentration is in precipitation ($R = 0.090$ vs. 0.059), whose mean peak timing differs by only 5 days (AORC day 190 vs. NLDAS-3 day 185). Wind speed peaks in late winter in both products (days 65–71).

5.4. Hydrologic Recoverability and Bias Correction Limits

A central finding of this study is the distinction between distributional equivalence and process-structural equivalence. Quantile mapping successfully aligns the marginal precipitation distributions, reducing systematic bias to within $\pm 6.4\%$ in every year. The unchanged event hit rate (0.81), persistence (lag-1 autocorrelation 0.50 vs. 0.45 in AORC), and precipitation–shortwave

coupling after adjustment demonstrate that distributional correction does not reconstruct the underlying forcing structure. For hydrologic applications where antecedent wetness, storm clustering, and multi-variable coherence matter, this distinction has direct operational consequences. Bias-corrected forcing may appear statistically equivalent while producing systematically different hydrologic responses.

The LOYO-CV framework demonstrates that quantile mapping reliably reduces systematic bias in NLDAS-3 precipitation relative to AORC when trained on the remainder of the record. The consistency of post-correction skill across the 20-year period supports the use of leave-one-out cross-validation as a robust evaluation protocol for multi-year forcing datasets (Feng, et al., 2020; Ma et al., 2020) and confirms that the trained correction is not strongly sensitive to which single year is withheld for testing.

5.5. Web-Enabled Hydroclimatic Discovery with HydroSuite

Several central findings of this study emerged only because independently hosted web archives could be combined in a single workflow. The light-rain structure of NLDAS-3 is visible in the gridded comparison, but its interpretation rests on 3,329 GHCN-Daily gauges drawn from a third archive; the AORC 2018 wind discontinuity becomes evident only when the two forcing records are compared over identical days; and the radiative compensation that keeps the PM-ET₀ difference small appears only when each record's shortwave and longwave fields enter the same calculation. No single data center distributes these sources together, and assembling them by hand for a 20-year, kilometer-scale domain would be time-consuming. Web-native access to cloud-optimized archives, combined with a common workflow that harmonizes grids, units, and time steps, turns such multi-source comparisons into routine analyses.

The approach also changes how forcing evaluations can be maintained. Both products evolve, as NLDAS-3 is distributed as a beta release, and AORC v1.1 already contains a documented source-data change. Because every step from retrieval to figures is scripted and reads from the public archives, the evaluation can be repeated as the products are revised, extended to other regions or periods, and audited by others. In this sense, HydroSuite serves as infrastructure for transparent, cumulative knowledge about the forcing data on which hydrologic prediction depends.

5.6. Limitations

Several limitations shape the interpretation of these results. First, AORC is used as the reference record because of its role in National Water Model forcing, not because it is free of uncertainty. Its precipitation field inherits errors from Stage IV radar quantitative precipitation estimates and gauge networks. In areas with sparse WSR-88D radar coverage, limited gauge density, or localized terrain effects, AORC may contain artifacts that can be difficult to separate from physical precipitation structure.

The AORC 2-m wind field contains a documented source-data step change at January 2018 when its mean drops from 2.58 to 1.55 m s⁻¹, while NLDAS-3 is unchanged, producing a statistically significant but artifactual downward trend. Although the discontinuity is confined to a

single variable, it affects full-period wind statistics and the wind component of the ET_0 comparison, and it coincides with the weakest bias-correction skill (2019–2020). It illustrates a broader limitation of reanalysis-derived forcing products: changes in input sources or processing can introduce non-climatic signals that masquerade as trends. Users of AORC v1.1 should apply caution when interpreting temporal changes in the wind field after 2017.

The extreme-value results are also constrained by record length. The 2001–2020 analysis period provides only 20 annual block maxima for GEV fitting, so return levels carry substantial uncertainty; levels beyond 25 years were not estimated, and even the 25-year levels are sensitive to individual extreme years such as 2016 and 2017. Longer records or regional frequency analysis would provide more stable tail estimates.

Occasional data-quality shifts and localized extremes can affect parts of the intercomparison. In the years following the 2018 AORC source-data change (2019–2020), the co-temporal relationship between the two precipitation records weakens ($r \sim 0.64$ – 0.67), which degrades the statistical-adjustment results. For the bulk of the 20-year record, quantile mapping provides robust and consistent bias correction across varying inter-annual states.

The observational comparison is limited by station distribution. GHCN-Daily station density is uneven across the study domain with Texas contributing 518 of the 1,392 temperature stations and Louisiana 96. Skill measures and temperature-derived ET_0 comparisons in sparsely sampled areas may be less representative than those in the Gulf Coast and Mississippi alluvial plain, where station coverage is stronger. The rain-gauge evaluation has three further limits. A gauge samples a point, whereas a grid cell represents an area of about 1 km², so cells are expected to be wet slightly more often than a single gauge. Many gauges report 24-h totals ending in the morning, whereas the gridded days run from 00 to 24 UTC, which reduces daily correlations but not the frequency and spell statistics. Finally, the gauges are not fully independent of the products since AORC precipitation is gauge-adjusted through Stage IV, and NLDAS-3 precipitation draws on gauge-calibrated satellite and reanalysis estimates. That AORC matches the gauges closely despite these factors, and NLDAS-3 does not, supports the robustness of the result.

Finally, the primary analyses rely on domain-mean summaries complemented by pixel-level statistics. Domain means are useful for identifying broad forcing differences, but they can mask sub-regional biases that matter for individual watersheds or localized flood response—as the contrast between domain-mean and pixel-scale extremes and intermittency shows. Watershed-scale (e.g., HUC8) evaluation remains an important extension for future work.

This study evaluates hydroclimatic consistency and forcing-derived diagnostics, not downstream hydrologic simulation skill. Inferred implications for runoff generation, soil-moisture memory, or flood response should be interpreted as physically motivated sensitivities, not demonstrated hydrologic outcomes.

6. Conclusions

The comparison shows that the two kilometer-scale forcing records differ in precipitation, temperature, radiation, humidity, and wind. Over the 2001–2020 study domain, NLDAS-3 has

lower mean precipitation than AORC (PBIAS = -8.9%), slightly warmer air temperature ($+0.49^\circ\text{C}$), lower shortwave radiation (-10.2 W m^{-2}), higher longwave radiation ($+8.5\text{ W m}^{-2}$), higher specific humidity ($+6.0\%$), and lower 2-m wind speed (-9.2% , affected by a 2018 discontinuity in AORC wind). These are not only mean offsets: the temperature and shortwave differences are strongly seasonal, and the two precipitation records differ in how rain is delivered.

The precipitation results indicate that the two records should not be treated as interchangeable for analyses that depend on upper-tail precipitation structure or event-scale delivery. At the pixel scale, NLDAS-3 return levels are 31–33% lower than AORC, and NLDAS-3 spreads a similar rainfall total over more, lighter rain days (wet-day fraction $+36\%$, wet-day intensity -36%); both contrasts largely disappear in domain means. At 3,329 GHCN-Daily stations, AORC is closer to the observed wet-day fraction, intensity, and zero-rain frequency at 97–99.8% of gauges, while the frequent light rain of NLDAS-3 is not seen in the observations. Bias adjustment removes most annual precipitation bias in the leave-one-year-out tests (PBIAS within $\pm 6.4\%$), but it leaves event timing, persistence, and cross-variable coupling unchanged, and its skill degrades in 2019–2020. This constrains the use of statistical correction for reconstructing event timing, spatial structure, or changed co-variability.

The reference ET_0 analysis shows a different pattern. PM- ET_0 differs only modestly between the two forcing products (NLDAS-3 lower by 0.160 mm day^{-1} ; PBIAS = -4.8%), because the shortwave and humidity deficits are partly offset by higher longwave radiation and temperature. The station-based HS comparison confirms the mean temperature field of both products (KGE 0.96–0.98) but is nearly blind to the radiation and humidity differences that dominate the PM difference; in summer, the PM forcing gap exceeds the HS–PM method gap. This result supports using ET_0 here as a diagnostic of forcing-variable interactions, not as a validation of atmospheric demand from temperature observations alone.

The results demonstrate that kilometer-scale forcing products with comparable nominal spatial resolution may still preserve substantially different hydroclimatic structures because of differences in forcing construction, observational ingestion, and atmospheric representation. These differences appear not only in precipitation magnitude, but also in rainfall intermittency, radiative balance, atmospheric-demand diagnostics, and upper-tail precipitation behavior. The findings support evaluating forcing datasets as integrated hydroclimatic systems, not interchangeable meteorological inputs. One of the most operationally significant findings is the distinction between distributional and process-structural equivalence. Statistical adjustment can align marginal distributions without recovering event-scale temporal structure or cross-variable covariance. This implies that bias-corrected forcing products should not be assumed interchangeable for applications sensitive to storm sequencing, antecedent moisture, or multi-variable forcing coherence. As a beta release, NLDAS-3 already matches AORC closely in its thermodynamic variables and provides a more temporally consistent wind record; the precipitation-intermittency differences identified here offer a concrete, reproducible benchmark for future releases.

Finally, the study demonstrates that a web-native, open workflow can carry a kilometer-scale, multi-decade forcing evaluation from data retrieval to publication. Built on HydroSuite, the

analysis draws AORC, NLDAS-3, and GHCN-Daily directly from public archives, harmonizes them on a common footprint, and can be rerun end to end as the products evolve. Such workflows make forcing evaluation repeatable and extensible, and turn the web into a working environment for hydroclimatic discovery.

Data Availability

AORC v1.1 forcing data are freely available from the NOAA AORC archive on Amazon S3 (<https://registry.opendata.aws/noaa-nws-aorc/>). NLDAS-3 daily forcing data were retrieved from the NASA NLDAS-3 archive on Amazon S3 using HydroLang, part of the HydroSuite framework. GHCN-Daily station records are publicly available from the NOAA National Centers for Environmental Information (NCEI) at <https://www.ncei.noaa.gov/products/land-based-station/global-historical-climatology-network-daily>. The analysis code, with instructions to reproduce every table and figure from these public archives, is available at HydroSuite GitHub repository and <https://github.com/uihilab/hydrosuite> and case study analysis repository: <https://github.com/uihilab/HydroSuite-Analysis>.

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Author Contributions

C.E.: Conceptualization, methodology, software development, formal analysis, writing—original draft. I.D.: Methodology, funding acquisition, writing—review and editing.

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