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Temporal Inhomogeneities in High-Resolution Gridded Precipitation Products for the Southeastern United States

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Abstract. High-resolution gridded precipitation products are widely used in hydroclimatic analyses, although their long-term stability has not been thoroughly evaluated. This study investigates temporal inhomogeneities in five widely used precipitation datasets—Daymet, gridMET, nClimGrid, PRISM, and TerraClimate—across the southeastern United States during 1980–2024. Annual precipitation totals were derived from both monthly and daily data and compared with a reference time series constructed from 120 U.S. Cooperative Observer Program (COOP) gauges. Residual-mass curves and Mann–Whitney *U* tests were applied to identify temporal inhomogeneities, and trend magnitudes were estimated using the Kendall–Theil robust line. Significant inhomogeneities were detected in most datasets, with nearly 80% of discontinuities concentrated between 2002 and 2018. These shifts corresponded closely to changes in gauge-network composition and data-processing procedures. Daymet and PRISM exhibited wetting biases linked to the expansion of the Community Collaborative Rain, Hail, and Snow (CoCoRaHS) network and the concurrent decline of COOP gauges, whereas nClimGrid showed a drying bias resulting from increased reliance on Automated Surface Observing System tipping-bucket gauges, which underestimate rainfall. Step increases in TerraClimate and gridMET totals reflected transitions in input data and reprocessing of precipitation forcing fields. These inhomogeneities produced disparate multi-decadal trends ranging from 19 to 48 mm dec^{-1} compared with a non-significant reference trend of 30 mm dec^{-1}. Among all datasets and combinations tested, the Daymet–nClimGrid pair was the only one without detectable discontinuities and reproduced the reference trend most accurately. This combination provides a homogeneous, temporally consistent dataset for multi-decadal precipitation analyses across the Southeast. Overall, the results demonstrate that unrecognized inhomogeneities in gridded precipitation products can substantially bias regional trend assessments and underscore the need to evaluate and, when necessary, combine datasets to ensure temporal stability in long-term hydroclimatic studies.

1 Introduction

High-quality, multi-decadal precipitation data are essential for research and decision-making. Such records enable rigorous assessment of variability and long-term trends (New et al., 2001) and provide a robust foundation for model calibration and evaluation (Döll et al., 2016; Tango et al., 2025). Reliable long-term observations also underpin integrated and adaptive management of water resources, supporting sustainable planning for agriculture, ecosystems, and regional development (Yang et al., 2021; Ferencz et al., 2024;).

Spatial limitations remain a persistent challenge in precipitation measurement. Although gauge networks provide the foundation for precipitation observation, gauge distribution is often sparse and uneven (Kidd et al., 2017). These deficiencies are most pronounced in complex terrain and other data-sparse regions (Michelon et al., 2021).

To extend coverage beyond existing gauges, gridded precipitation products were developed. These datasets integrate gauge, satellite, and reanalysis information through interpolation or merging algorithms to generate spatially continuous precipitation estimates (Mankin et al., 2025). Gauge-informed products generally provide higher spatial accuracy than those derived solely from remote sensing or reanalysis (Zandler et al., 2019; Muche et al., 2020; de la Fraga et al., 2024; Mankin et al., 2025). However, the limited availability of gauges in complex terrain still constrains accuracy, and many products perform poorly in mountainous regions (Zandler et al., 2019; de la Fraga et al., 2024; Wang and Tian, 2025).

High-resolution gridded precipitation products are particularly well-suited to the needs of the hydrology community, which relies on them more than any other discipline. Gridded precipitation datasets provide the spatially distributed input data required to drive hydrologic models (Livneh et al., 2015; Newman et al., 2015; Shuai et al., 2022). Among many other applications, gridded precipitation products are also employed to quantify basin-scale water balances (Laiti et al., 2018) and to support hydrologic forecasting and management (Mankin et al., 2025).

Despite the widespread use of gridded precipitation products, especially within the hydrology community, the temporal stability of these datasets remains insufficiently evaluated. Apparent long-term trends can be distorted by inhomogeneities—systematic, non-climatic shifts in the statistical properties of a time series (Peterson et al., 1998). Only a handful of studies (e.g., Guentchev et al., 2010; Mizukami and Smith, 2012; McAfee et al., 2014; Ferguson and Mocko, 2017; Henn et al., 2018) have explicitly identified or investigated such inhomogeneities in gridded precipitation products. Accordingly, this study evaluates the temporal stability of multiple high-resolution precipitation datasets across a large, climatically uniform region during 1980–2024. The objectives are to (1) detect and characterize temporal inhomogeneities and the factors contributing to them, (2) quantify biases that influence multi-decadal trends, and (3) determine which individual products or product combinations exhibit the greatest temporal stability for regional trend analyses.

This study focuses on the southeastern United States (Fig. 1), encompassing Alabama, Florida, Georgia, Mississippi, North Carolina, South Carolina, and Tennessee, with a total area of approximately 882,000 km². The Southeast was selected because much of it has a humid subtropical climate—hot summers, mild winters, and high annual precipitation (Kunkel et al., 2013; Labosier and Quiring, 2013)—and includes numerous long-term reference gauges from the U.S. Cooperative Observer Program (COOP), the nation's most consistent climate network (National Research Council, 1998).

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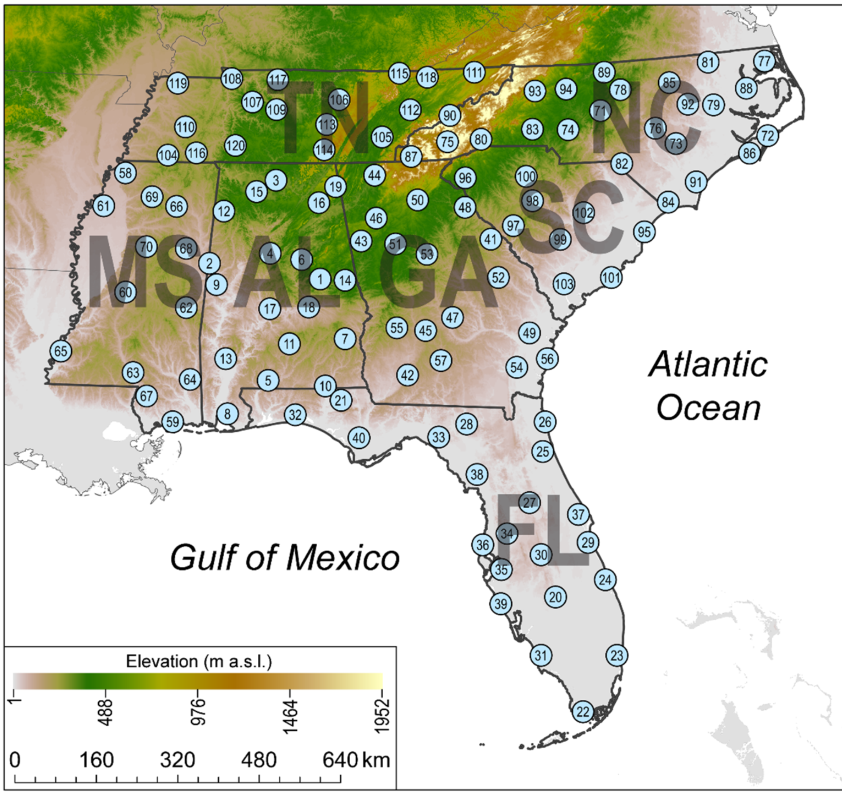

ID	COOP#	ID	COOP#	ID	COOP#
1	010160	41	090311	81	314456
2	010184	42	091500	82	314860
3	010655	43	091640	83	314996
4	010764	44	091863	84	315116
5	011080	45	092266	85	315123
6	011620	46	092485	86	315830
7	011725	47	092966	87	316001
8	012813	48	093060	88	316853
9	013160	49	093538	89	317202
10	013251	50	093621	90	319123
11	013519	51	094700	91	319467
12	013645	52	095863	92	319476
13	014193	53	095988	93	319555
14	014502	54	096219	94	319675
15	015635	55	097087	95	381093
16	017207	56	097808	96	381770
17	017366	57	098703	97	384607
18	018038	58	220237	98	385200
19	018469	59	220792	99	386527
20	080236	60	221389	100	387722
21	081544	61	221707	101	388405
22	083020	62	221860	102	388440
23	083163	63	221865	103	389469
24	083207	64	224966	104	400137
25	083874	65	226177	105	400284
26	084366	66	227106	106	402009
27	085076	67	227128	107	402489
28	085099	68	228374	108	402589
29	085612	69	229079	109	403280
30	085973	70	229743	110	404561
31	086078	71	310286	111	404858
32	086240	72	311606	112	404946
33	087025	73	311881	113	405882
34	087851	74	311975	114	406162
35	088782	75	312200	115	406493
36	088824	76	312500	116	408160
37	088942	77	312719	117	408562
38	089120	78	313555	118	408868
39	089176	79	313638	119	409219
40	089566	80	313976	120	409502

Figure 1. Locations of the 120 reference gauges in the southeastern United States. All gauges are part of the U.S. Cooperative (USC) network. The seven states that comprise the southeastern United States are Alabama (AL), Florida (FL), Georgia (GA), Mississippi (MS), North Carolina (NC), South Carolina (SC), and Tennessee (TN).

2 Data

Monthly precipitation totals from a dispersed network of 120 COOP gauges across the Southeast during 1980-2024 were used to produce a reference time series (Fig. 1). All gauges had at least 90% of months with precipitation totals. Only 1.6% of gauge-months were missing. The missing monthly totals were replaced with the mean total from the three closest gauges. The gauges ranged in elevation from 1 m a.sl. to 668 m a.sl.; therefore, none of the gauges were located in high-elevation areas. Monthly totals for each gauge were summed to produce annual precipitation values, which were then averaged across all gauges to form the regional reference time series.

Precipitation estimates were obtained for five high-resolution gridded products (Daymet, gridMET, nClimGrid, PRISM, and TerraClimate) for 1980–2024. For each product, annual precipitation totals were derived from the available daily and monthly data. Daymet provides daily precipitation estimates for North America at 1-km resolution, with monthly values derived by aggregating daily fields (Thornton et al., 2021). Daymet data were not yet released for 2024 at the time of analysis; therefore, the Daymet series extends through 2023. nClimGrid provides daily and monthly precipitation estimates for the conterminous United States at ~4-km resolution, generated independently using climatologically aided interpolation of station data (Vose et al., 2014). PRISM provides daily and monthly precipitation estimates for the United States at ~4-km resolution, generated using station observations integrated with topographic and other spatial predictors (Daly et al., 2008). Because daily PRISM data were not available for 1980, annual totals for that year in the series were derived from monthly PRISM precipitation estimates to maintain a complete 1980–2024 record. gridMET provides daily precipitation estimates for the conterminous United States at ~4-km resolution, generated by combining high-resolution PRISM climatologies with temporally varying fields from the North American Land Data Assimilation System (NLDAS-2) using the METDATA downscaling method (Abatzoglou, 2013). TerraClimate provides monthly precipitation estimates for the global land surface at ~4-km resolution, generated by combining WorldClim climatologies with time-varying anomalies derived primarily from the Climatic Research Unit Time Series (CRU TS) and Japanese 55-year Reanalysis (JRA-55) datasets (Abatzoglou et al., 2018). When calculating regional means, approximately 2.5 % of grid cells (those exceeding 668 m a.s.l.) were excluded to restrict the analysis to the low- and mid-elevation portions of the Southeast and to minimize the aforementioned precipitation inaccuracies associated with mountainous areas.

Information on precipitation gauges underlying each gridded product was compiled for 1980–2024. Gauges were classified by network, and spatial coverage was assessed by identifying the 40-km grid cell containing each gauge across the Southeast. For each network, the number of grid cells containing at least one gauge was tallied and divided by the total number of grid cells in the region to calculate percent coverage.

In addition to analyzing each gridded product individually, time series were generated for all possible pairwise and multi-product combinations. Combinations were produced separately for the daily and monthly datasets, with each series calculated as the mean of the contributing products (e.g., Daymet and nClimGrid). For the four products available at both temporal scales, this yielded six two-product combinations, four three-product combinations, and one four-product combination, for a total of 11 unique combinations.

3 Methods

3.1 Residual-Mass Curves

Residual-mass curves were constructed as a diagnostic of the homogeneity of precipitation time series and combinations of those series. This approach originates from hydrological consistency testing, in which cumulative residuals are plotted over time to reveal systematic deviations (Searcy and Hardison, 1960). In this study, residuals were obtained from linear regressions in which the reference time series served as the predictor and the product time series as the predictand. For a homogeneous record, the cumulative residuals are expected to remain near zero, fluctuating randomly without systematic

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drift, whereas sustained deviations or changes in slope indicate shifts, biases, or other inconsistencies (Buishand, 1984; Helsel and Hirsch, 2002).

3.2 Testing for Differences

To identify the most significant discontinuity—defined here as an abrupt, non-climatic shift in a time series representing a temporal inhomogeneity—in each product time series, a nonparametric split-sample approach was applied. For each potential breakpoint year, residuals (i.e., observations minus product estimates) before and after that year were compared using the Mann–Whitney U test ($\alpha = 0.01$, two-tailed), with a minimum of eight years required in each group, yielding candidate breakpoints between 1988 and 2017. The Mann–Whitney U test has been shown to be effective for identifying shifts in hydroclimatic time series (Yue and Wang, 2002), and similar split-sample approaches have been applied in climate homogenization studies to test for differences before and after potential discontinuities (Easterling and Peterson, 1995).

3.3 Trend Analyses

Trends in annual precipitation for 1980–2024 were computed for each gridded product and the reference time series. The Kendall–Theil robust line, calculated as the median of the slopes between all pairs of observations (Helsel and Hirsch, 2002), provided a nonparametric estimate of the trend magnitude. The statistical significance of each trend was assessed with Kendall's tau correlation test ($\alpha = 0.01$, one-tailed).

4 Results

4.1 Spatial Variations in Precipitation

Mean annual precipitation patterns and totals are broadly consistent among the five precipitation products, with Daymet producing slightly higher values than the others (Fig. 2). This comparison provides spatial context for the subsequent temporal analyses by illustrating that the datasets yield similar climatological means across the Southeast. Mean annual totals for 1980–2023 range from 1,347 mm for nClimGrid to 1,431 mm for Daymet. Precipitation totals are smallest (~1,100 mm) across central Georgia, South Carolina, and North Carolina and largest (~2,000 mm) in the Blue Ridge and Cumberland Mountains.

4.2 Changes in Gauges

All products showed substantial temporal changes in gauge numbers across 1980–2024, most notably increasing coverage by CoCoRaHS (Community Collaborative Rain, Hail, and Snow Network) gauges and decreasing coverage by COOP gauges (Fig. 3). Daymet was initially dominated by COOP gauges but by the end of the period CoCoRaHS gauges were most prevalent. Both CoCoRaHS and weather-bureau gauges increased in coverage, with CoCoRaHS rising from <1% in 2006 to

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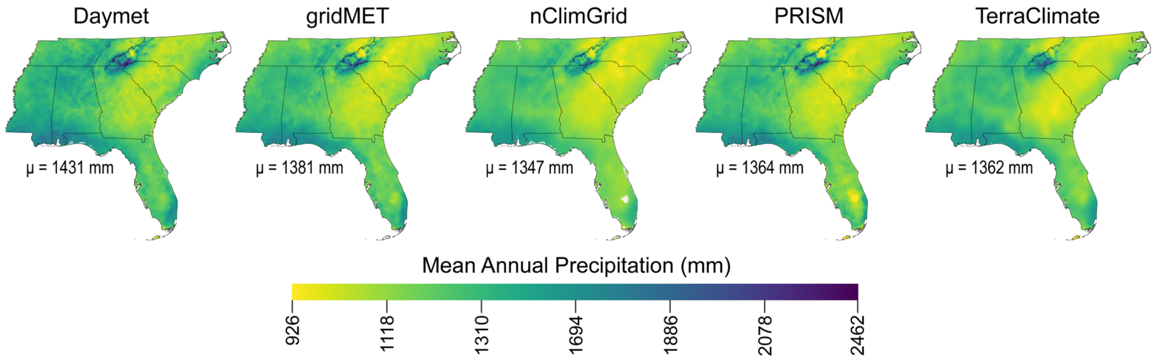

Figure 2. Mean annual precipitation totals (in mm) during 1980-2023 for the five precipitation products. gridMET, nClimGrid, PRISM, and TerraClimate have been resampled to 1-km resolution to match the resolution of Daymet.

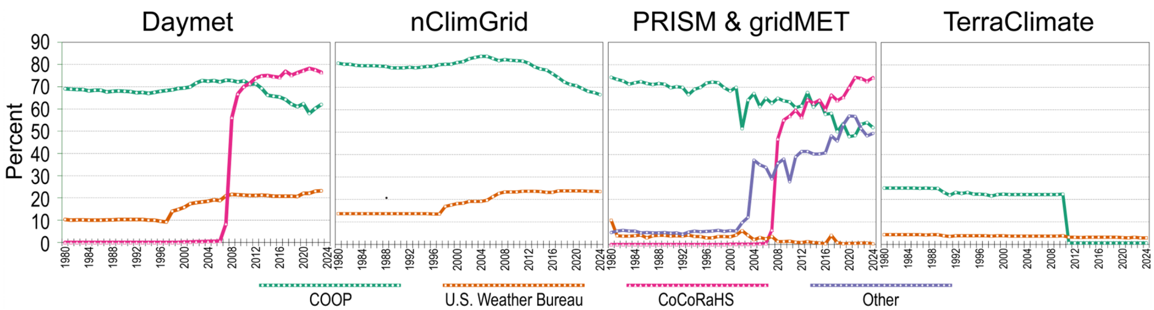

Figure 3. Differences in annual precipitation between monthly products and daily products.

78% in 2021, while COOP gauges began decreasing around 2011. nClimGrid consistently relied more on COOP than weather-bureau gauges, but the difference in 2024 (67% vs. 24%) was much smaller than in 1980 (81% vs. 14%). Coverage by weather-bureau gauges began increasing in 1998, while COOP coverage declined after 2012. PRISM, which used gauges from 15 networks, showed a similar pattern, with increasing CoCoRaHS and decreasing COOP coverage. CoCoRaHS coverage rose from <1% in 2006 to ~75% in 2021. There was also an increase in gauges from other networks and a steady decline in COOP coverage. TerraClimate had much less gauge coverage overall, with a maximum of 25% from cooperative gauges and an abrupt decline from 22% to <1% between 2010 and 2011. Information on gauge coverage for gridMET was unavailable.

4.3 Comparison of Monthly and Daily Versions of Products

Monthly and daily versions of Daymet, nClimGrid, and PRISM had either identical or nearly identical results (Fig. 4). Consequently, monthly results—which include TerraClimate—are shown in the paper, while the daily results—which include gridMET—are presented in the supporting information.

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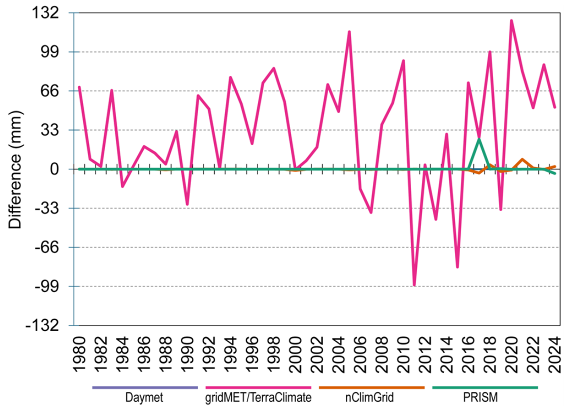

Figure 4. Percent coverage of the southeastern United States over time by gauge networks used in the five precipitation products.

4.4 Residual-Mass Curves

Among the initial products, Daymet had the most optimal residual-mass curve, and combining products resulted in the best residual-mass curves (Fig. 5 and S1). The best residual-mass curves are those with relatively small cumulative sums of the absolute values of residuals. Daymet had much lower cumulative sums than the other four initial products. The overall best products were combinations of products, and those products were nClimGrid-PRISM, Daymet-nClimGrid-TerraClimate, Daymet-nClimGrid-PRISM, Daymet-gridMET-nClimgrid, and Daymet-nClimGrid.

The residual-mass curves also revealed potential discontinuities, most of which occurred during the third and fourth decades of the 45-year record (Fig. 3 and S2). In each panel of the figures, the year associated with the largest absolute residual corresponded to the year preceding the potential discontinuity. For Daymet, gridMET, nClimGrid, PRISM, and TerraClimate, the potential discontinuities were centered on 2008, 2016, 2005, 2002, and 2011, respectively. For all products and combinations of products, over 80% of the potential discontinuities occurred during 2002-2016.

4.5 Discontinuities

Most products exhibited significant discontinuities, and the timing of these shifts generally aligned with the potential discontinuities identified from the residual-mass curves (Fig. 6 and S2). Approximately 80 % of products showed at least one significant discontinuity. The initial products—Daymet, gridMET, nClimGrid, PRISM, and TerraClimate—had discontinuities centered on 2012, 2016, 2005, 2002, and 2011, respectively. Nearly 90 % of all discontinuities, including those from product combinations, occurred between 2002 and 2018. A few products showed discontinuities in the early 1990s, all of which included nClimGrid as a component. Ideally, no discontinuities should be present in homogeneous time series, and the only products without detectable discontinuities were TerraClimate, Daymet–nClimGrid, nClimGrid–PRISM, and nClimGrid–PRISM–TerraClimate.

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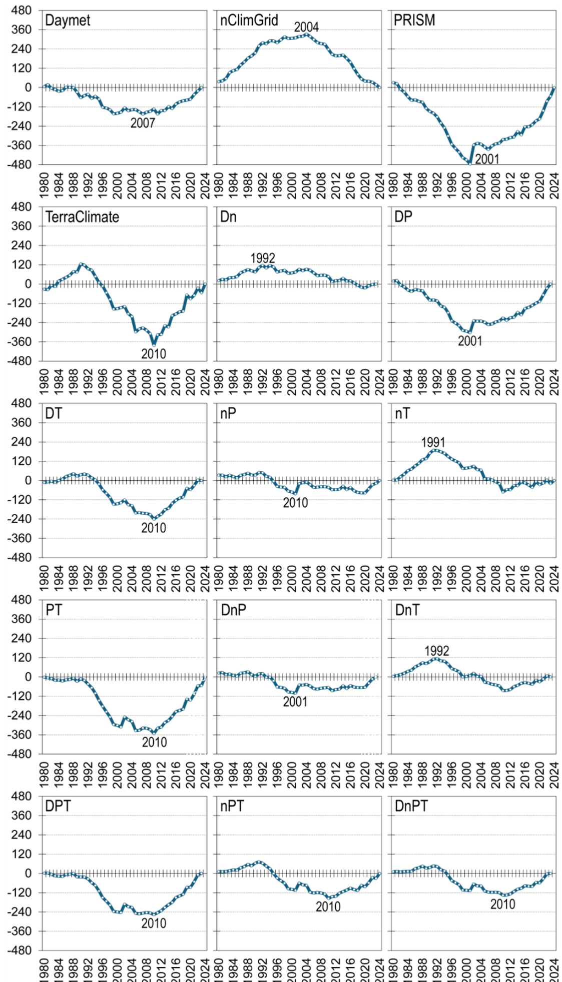

Figure 5. Residual-mass curves for products and combination of products. Abbreviations for Daymet, nClimGrid, PRISM, and TerraClimate, are D, n, P, and T, respectively.

4.6 Time Series of Differences

With respect to differences from the reference time series before and after a discontinuity, most products shifted from either underestimates to overestimates or from overestimates to larger overestimates (Fig. 7 and S3). Both gridMET and PRISM shifted from underestimates to overestimates. Daymet shifted from overestimates to larger overestimates. nClimGrid shifted from underestimates to larger underestimates. TerraClimate did not exhibit a significant discontinuity and therefore showed no shift. Considering all products collectively, about half shifted from underestimates to overestimates, one-third from

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overestimates to larger overestimates, and roughly 17 % from underestimates to larger underestimates; none shifted from overestimates to underestimates.

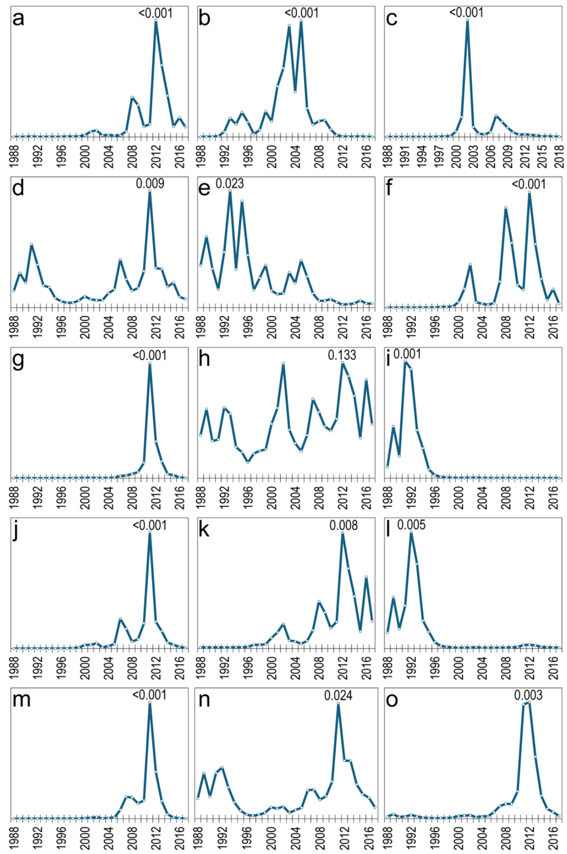

Figure 6. Inverse p-values for (a) Daymet, (b) nClimGrid, (c) PRISM, (d) TerraClimate, (e) Dn, (f) DP, (g) DT, (h) nP, (i) nT, (j) PT, (k) DnP, (l) DnT, (m) DPT, (n) nPT, and (o) DnPT. Abbreviations for Daymet, nClimGrid, PRISM, and TerraClimate, are D, n, P, and T, respectively. The two-tailed p-values are from Mann-Whitney *U* tests that compared differences from the reference time series before and after each of the years shown (i.e., 1988-2018).

4.7 Trends

The products exhibited a wide range of precipitation trends, with only a few approximating the reference trend of 30 mm dec^{-1}, which was not significant (Fig. 8 and S4). Daymet, gridMET, nClimGrid, PRISM, and TerraClimate had trends of 38, 38, 19, 48, and 36 mm dec^{-1}, respectively. Among the individual products, nClimGrid produced the smallest trend and PRISM the largest trend. The trend for PRISM, as well as those for the combinations Daymet–PRISM, Daymet–gridMET–PRISM, Daymet–PRISM–TerraClimate, gridMET–PRISM, and PRISM–TerraClimate, were statistically significant. The

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products within 10 % of the reference trend were Daymet–gridMET–nClimGrid, Daymet–nClimGrid, gridMET–nClimGrid–PRISM, and nClimGrid–TerraClimate.

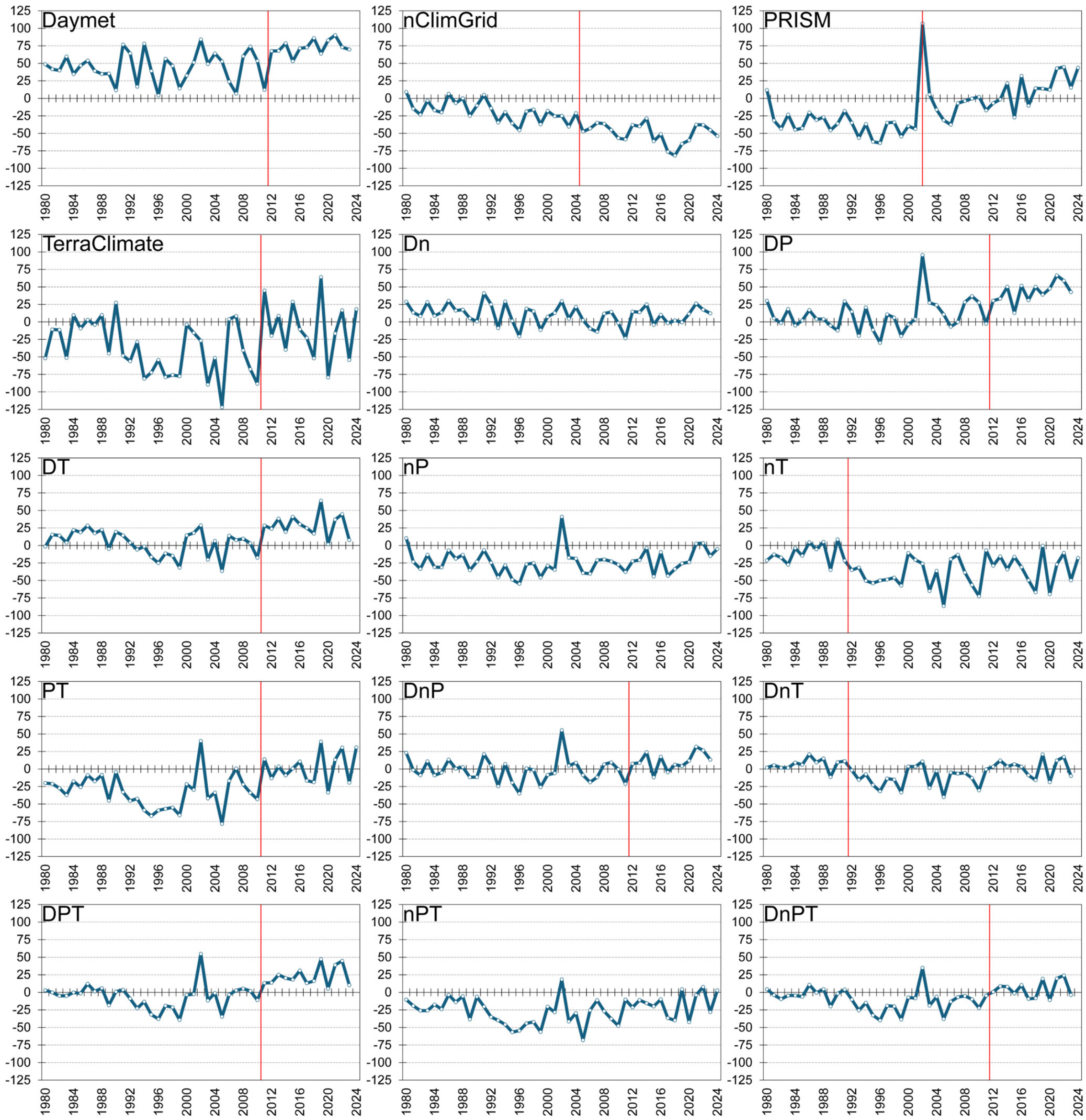

Figure 7. Time series of differences between the mean of the 120 references gauges and the means for the southeastern United States that area specific to products and combination of products. Abbreviations for Daymet, nClimGrid, PRISM, and TerraClimate, are D, n, P, and T, respectively.

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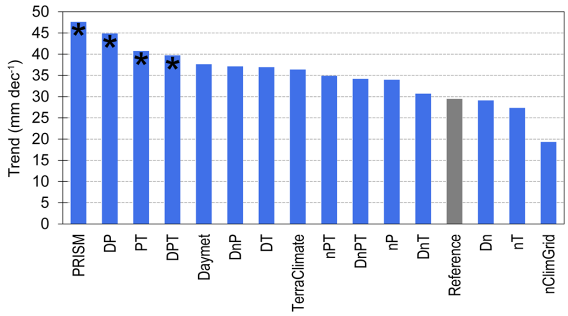

Figure 8. Precipitation increases per decade (in mm) for the reference and 15 other time series. Abbreviations for Daymet, nClimGrid, PRISM, and TerraClimate, are D, n, P, and T, respectively. Asterisks denote significant ($\alpha = 0.01$, one-tailed) trends.

5 Discussion

5.1 Inhomogeneities and Biased Trends of Products

The introduction and proliferation of CoCoRaHS gauges—and to a lesser degree the decline of COOP gauges—caused a wetting bias in the Daymet and PRISM time series. Decadal precipitation increases were 28% and 62% larger, respectively, than those from the reference gauges (Fig. 6). CoCoRaHS gauges generally record slightly higher precipitation totals than COOP gauges, with increases of about 1–5% (CoCoRaHS, 2019; Goble et al., 2019). CoCoRaHS coverage in the Southeast was negligible in 2006 but reached about 75% by 2021, surpassing all other networks by 2012 and 2014 for Daymet and PRISM, respectively (Fig. 2). The largest inhomogeneity in the Daymet series occurred in 2012, coinciding with this expansion. Although PRISM experienced similar network shifts, its main inhomogeneity appeared in 2002 due to anomalously high precipitation; correcting those values shifts the discontinuity to 2007, aligning with the network transition.

Expansion of ASOS (Automated Surface Observing Systems) gauges, along with the decline of COOP gauges, produced a drying bias in nClimGrid. The decadal precipitation increase for nClimGrid was 34% smaller than that of the reference series (Fig. 6). ASOS instruments use heated tipping-bucket gauges in which each tip represents 0.01 inch of liquid-equivalent precipitation (Wade, 2003). These gauges underestimate rainfall (Dunn et al., 2025), with undercatch of 2–10% relative to COOP observations (National Research Council, 2012). ASOS coverage rose from <1% in 1993 to 19% in 2021 (Fig. 9), while COOP coverage declined from 80% to 70% (Fig. 2). The largest inhomogeneity in nClimGrid occurred in 2005, coinciding with growing ASOS influence.

Abrupt increases in TerraClimate precipitation totals in 2011 and gridMET totals in 2016 were attributable to changes in input data. Increases in decadal precipitation for TerraClimate and gridMET were 23% and 28% larger than those of the reference gauges (Fig. 6 and S5). The 2011 TerraClimate shift reflected the substitution of JRA-55 anomalies following a sharp gauge decline (Abatzoglou et al., 2018), while the 2016 gridMET inhomogeneity coincided with a reprocessed precipitation forcing that incorporated late-reporting gauges (Xia et al., 2016).

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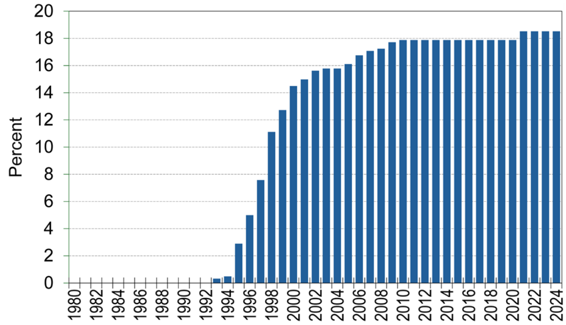

Figure 9. Percent coverage of the southeastern United States over time by Automated Surface Observing Systems (ASOS) gauges.

5.2 Optimal Dataset for Multi-Decadal Precipitation Analyses

Combining Daymet and nClimGrid results in a more homogeneous and reliable dataset for multi-decadal precipitation analyses in the Southeast. Among the 15 monthly and 15 daily datasets evaluated using annual precipitation totals, this combination yields the fourth-smallest cumulative sum of absolute residuals (Fig. 5) and has no significant inhomogeneities (Fig. 6). The precipitation trend (29 mm dec^{-1}) of Daymet–nClimGrid closely matched the reference trend (30 mm dec^{-1}), and no other product reproduced the reference trend as accurately (Fig. 8). Season-specific analyses also revealed no evidence of inhomogeneities and exhibited trends nearly identical to those of the reference series (Fig. 10), further supporting the reliability of the dataset for multi-decadal assessment. Although using this dataset reduces the spatial resolution inherent to Daymet, the resulting gain in temporal homogeneity makes the Daymet–nClimGrid product the most robust dataset for regional, multi-decadal precipitation assessments.

6 Conclusion

Gridded precipitation datasets commonly used for hydroclimatic analyses exhibit widespread temporal inhomogeneities that can distort long-term trend assessments. Evaluation of five high-resolution products and their combinations for the southeastern United States during 1980–2024 revealed significant inhomogeneities in about 80% of the series, primarily between 2002 and 2018, linked to changes in gauge networks and data processing. Wetting biases in Daymet and PRISM reflected the expansion of CoCoRaHS and decline of COOP gauges, whereas a drying bias in nClimGrid arose from increased reliance on ASOS tipping-bucket gauges. Step changes in TerraClimate and gridMET corresponded to shifts in input data and processing. These inhomogeneities produced precipitation trends ranging from 19 to 48 mm dec^{-1}, compared with a non-significant reference trend of 30 mm dec^{-1}. Combining Daymet and nClimGrid removed detectable inhomogeneities and reproduced the reference trend, providing the most temporally stable dataset for multi-decadal analyses. Overall, the results underscore the need to assess and, where possible, improve the temporal stability of gridded precipitation datasets used in long-term hydroclimatic analyses.

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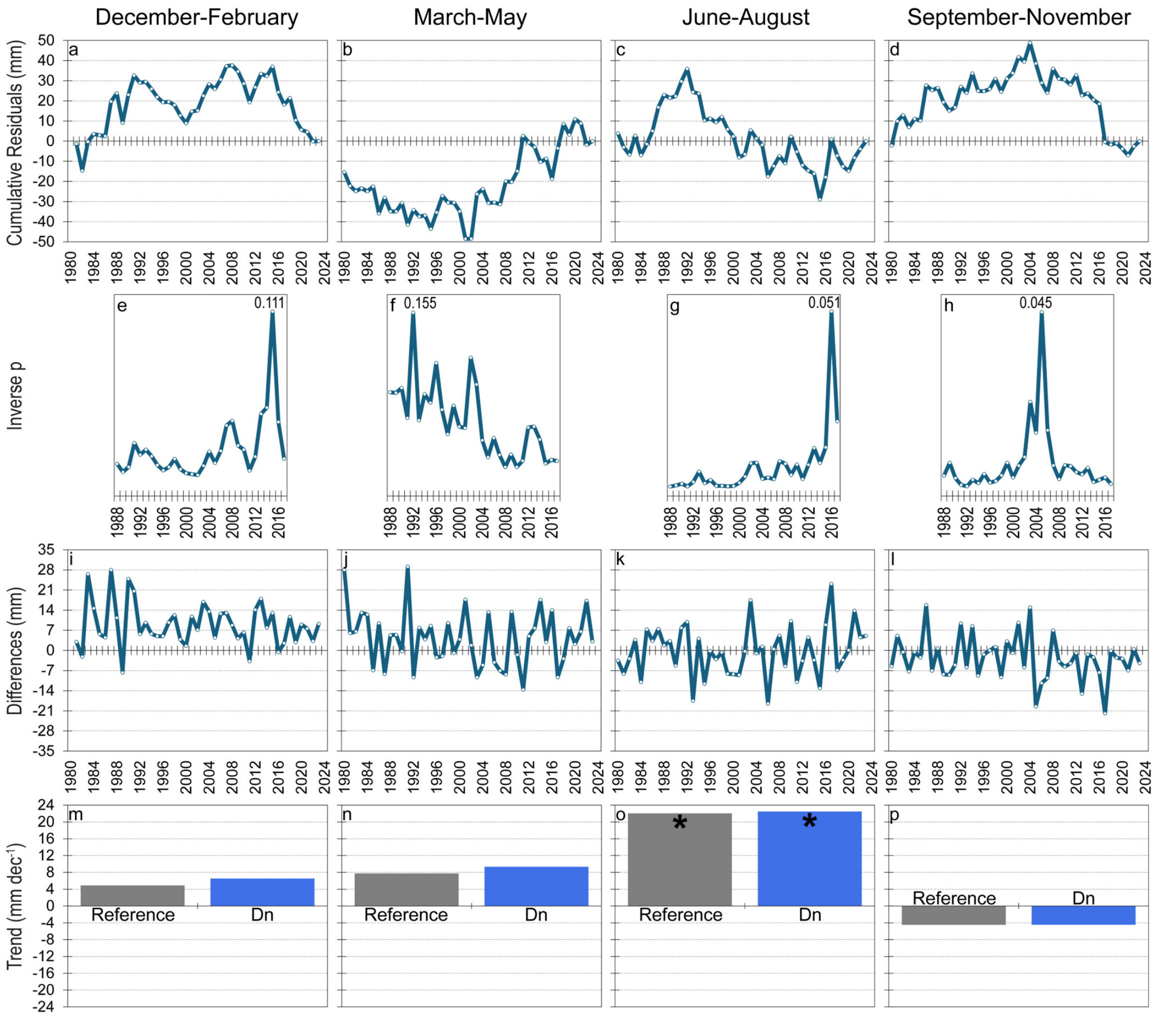

Figure 10. Residual-mass curves (a-d), inverse p-values (e-h), times series of differences (i-l), and trends (m-p) for the Daymet-nClimGrid combination for December-February, March-May, June-August, and September-November. For the inverse-p panels (e-h), the two-tailed p-values are from Mann-Whitney *U* tests that compared differences from the reference time series before and after each of the years shown (i.e., 1988-2018). The values in the difference panels (i-l) are precipitation totals from the products minus totals from the reference gauges. For the trends panels (m-p), the reference trend pertains to the reference time series and asterisks denote significant (α = 0.01, one-tailed) trends over 1980-2023.

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Data availability. Data used in this paper are available at https://data.mendeley.com/datasets/37bm8hvpmk/1.

Competing interests. The author does not have any competing interests.

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