GLOBAL EXTREME WEATHER AND CLIMATE CHANGE DASHBOARD

Methodology, Variables & Sources

How this dashboard detects, corrects for chance, and sources every trend -- every headline variable's data provenance and reliable window, and the full literature behind it.

A project by Roger Pielke Jr., author of The Honest Broker

Generated September 20, 2026 · globalextremeweather.thehonestbroker.org

Contents

01 Detection and Attribution

02 Detection and time of emergence

03 Testing every variable at once: correcting for chance across the full set

04 Reliable trend windows, and excluding the in-progress year

05 Coverage limits

06 Data currency

07 Per-continent coverage

08 Per-variable notes

09 Appendix A: Variable & Data Source Directory

10 Appendix B: Full Bibliography

Methodology

The IPCC detection standard this dashboard applies throughout, the Benjamini-Hochberg multiple-comparisons correction across its 72 headline variables, each variable's reliable trend window and known coverage limits, a data-currency and per-continent coverage table, and a per-variable methodology note for every phenomenon tracked here, in that order. A downloadable PDF version bundles all of this with a full variable/source directory and bibliography.

Publicly available data, funded by taxpayers and governments around the world, makes this site possible. Open science serves everyone.

Detection and Attribution

This dashboard tracks detection only, following the IPCC framework the sibling US dashboard uses (Glossary, AR5/AR6/SR15, "Detection and Attribution"). The homepage defines both terms and the combined IPCC-likelihood-plus-magnitude "detected change" standard this site applies throughout.

Detection and time of emergence

Detection asks whether a change has already appeared in the observational record. Time of emergence asks when a signal rises above the noise around it, and the literature answers that in several different ways: AR6 WG1 Chapter 12 names two definitions in its opening sentence on the subject, states that heterogeneous methodologies hamper any homogeneous reading across studies, and adopts a signal-to-noise convention only where a study does not specify otherwise. A third approach asks how many years a record must run before a projected signal could show up at all, and gives an answer in decades or centuries. TheDetection and Time of Emergence page sets out the three, reproduces AR6's Table 12.12, and places this site's verdicts beside it, including drought, where the two disagree.

One emergence timescale appears on this site, for TXx, on the page above. lib/trend.ts computes the standard Weatherhead et al. (1998) years-to-detection figure for every variable on every build, and nothing renders it, because the slope it receives comes from the record under test. That calculation becomes post-hoc power, which cannot justify that record's null result. Substituting a projected slope assessed independently of the record removes that objection, and AR6 supplies such a projection for one variable here. A published figure would need a projected signal assessed independently of the observations, and AR6 quantifies projections of that kind for only a few phenomena.

Testing 72 variables at once: correcting for chance across the full set

Testing 72 variables independently at IPCC's flat 10% example threshold (p<0.10 in the Mann-Kendall test — see Detection and Attribution above) means chance alone produces some positive results even when no underlying change exists: a 10% per-test false-positive rate yields several "significant" results out of 72 tests by chance alone, regardless of anything real happening in the climate system. This site corrects for that directly rather than only disclosing it. Of the 72 headline variables, 57 hold enough data to test at all (the rest sit under the 30-year minimum record length, excluded before significance even enters the picture). Every chart, stat tile, and summary table on this site ranks those 57 p-values together and applies a Benjamini-Hochberg false-discovery-rate correction at IPCC's 10% standard: each result has to clear a bar that tightens the more other results test more strongly, rather than the same flat 10% cutoff no matter how many tests ran. A flat, uncorrected p<0.10 threshold alone would pass 31 of these 57 results; the corrected bar passes 27. This correction applies to each variable's default view specifically — interactively adjusting a chart's time window or switching to a different selectable series reverts that one chart to the flat IPCC standard, since the correction's ranking only holds across the one fixed set of 57 headline results behind it rather than an arbitrary exploration away from it. The magnitude-vs-variability check described above still applies on top of this, independently: a result has to clear both bars to count as a detected change here.

Many of these 72 variables also measure correlated aspects of the same underlying phenomenon (five different drought severity thresholds against the same precipitation record, for instance) rather than fully independent draws. Benjamini-Hochberg's false-discovery guarantee holds under independence or positive dependence between tests, which correlated variables like these satisfy -- stated here rather than assumed away. The Every Variable page lists a still larger number of rows by additionally breaking out every selectable series (severity tier, region, metric) within each of these 72 variables, at the flat, uncorrected threshold -- those rows show alternative views of the same 72 corrected headline tests above rather than additional independent trials to correct for separately.

4 results currently change outcome under this correction -- clearing IPCC's flat 10% example threshold on its own, but not the multiple-comparisons-adjusted bar:

- **Cold Extremes — Frost Days** (Extreme Cold) -- p=0.053, needed p<0.0491 at rank 28 of 57.
- **Agricultural Drought — Soil-Moisture Deficit — Africa** (Root zone 0-100cm, D2+) (Drought) -- p=0.066, needed p<0.0509 at rank 29 of 57.
- **Flooding — River Discharge High-Flow Extent** (Flooding) -- p=0.073, needed p<0.0526 at rank 30 of 57.
- **Extratropical Cyclone Intensity — Minimum Pressure — Asia** (Winter Storms) -- p=0.083, needed p<0.0544 at rank 31 of 57.

The full ranked set, every headline variable's p-value against the threshold it actually has to clear:

RANK	VARIABLE	PHENOMENON	P-VALUE	ADJUSTED TH
1	**Cold Extremes — TN10p (Cold Nights)**	Extreme Cold	0.000	p<0.0018
2	**Heat Waves — TXx (Annual Max Temperature)**	Extreme Heat	0.000	p<0.0035
3	**Flooding — River Discharge — South America**	Flooding	0.000	p<0.0053
4	**Heat Waves — Europe Magnitude Index (HWMId-style)**	Extreme Heat	0.000	p<0.0070
5	**Meteorological Drought — Global Severe-or-Worse Land Area** SPI-style (precipitation only), D2+	Drought	0.000	p<0.0088
6	**Meteorological Drought — Severe-or-Worse Land Area — Africa** SPI-style (precipitation only), D2+	Drought	0.000	p<0.0105
7	**Heat Waves — Europe Heat Wave Index**	Extreme Heat	0.000	p<0.0123
8	**Heat Waves — Magnitude Index (HWMId-style)**	Extreme Heat	0.000	p<0.0140

RANK	VARIABLE	PHENOMENON	P-VALUE	ADJUSTED TH
9	**Cold Extremes — CSDI (Cold Spell Duration Index)**	Extreme Cold	0.000	p<0.0158
10	**Heat Waves — Global Heat Wave Index**	Extreme Heat	0.000	p<0.0175
11	**Convective Instability (CAPE)**	Severe Convective Storms	0.000	p<0.0193
12	**Heat Waves — TN90p (Warm Nights)**	Extreme Heat	0.000	p<0.0211
13	**Agricultural Drought — Soil-Moisture Deficit — South America** Root zone 0-100cm, D2+	Drought	0.000	p<0.0228
14	**Widespread / High-CAPE Days**	Severe Convective Storms	0.000	p<0.0246
15	**Flooding — River Discharge — Africa**	Flooding	0.000	p<0.0263
16	**Meteorological Drought — Severe-or-Worse Land Area — South America** SPI-style (precipitation only), D2+	Drought	0.001	p<0.0281

RANK	VARIABLE	PHENOMENON	P-VALUE	ADJUSTED TH
17	**Heat Waves — North America Heat Wave Index**	Extreme Heat	0.002	p<0.0298
18	**Hydrological Drought — River Low-Flow Extent — South America**	Drought	0.004	p<0.0316
19	**Heat Waves — WSDI (Warm Spell Duration Index)**	Extreme Heat	0.004	p<0.0333
20	**Hydrological Drought — River Low-Flow Extent — Africa**	Drought	0.010	p<0.0351
21	**Agricultural Drought — Global Soil-Moisture Deficit** Root zone 0-100cm, D2+	Drought	0.013	p<0.0368
22	**Hydrological Drought — Global River Low-Flow Extent**	Drought	0.013	p<0.0386
23	**Agricultural Drought — Soil-Moisture Deficit — North America** Root zone 0-100cm, D2+	Drought	0.027	p<0.0404
24	**Tropical Cyclones — Proportion of Hurricanes That Are Major**	Tropical Cyclones	0.030	p<0.0421

RANK	VARIABLE	PHENOMENON	P-VALUE	ADJUSTED TH
25	**Meteorological Drought — Severe-or-Worse Land Area — Asia** SPI-style (precipitation only), D2+	Drought	0.030	p<0.0439
26	**Agricultural Drought — Soil-Moisture Deficit — Asia** Root zone 0-100cm, D2+	Drought	0.033	p<0.0456
27	**Tropical Cyclones — Frequency by Category**	Tropical Cyclones	0.035	p<0.0474
28	**Cold Extremes — Frost Days**	Extreme Cold	0.053	p<0.0491
29	**Agricultural Drought — Soil-Moisture Deficit — Africa** Root zone 0-100cm, D2+	Drought	0.066	p<0.0509
30	**Flooding — River Discharge High-Flow Extent**	Flooding	0.073	p<0.0526
31	**Extratropical Cyclone Intensity — Minimum Pressure — Asia**	Winter Storms	0.083	p<0.0544

RANK	VARIABLE	PHENOMENON	P-VALUE	ADJUSTED TH
32	**Cold Extremes — TNn (Annual Min Temperature)**	Extreme Cold	0.103	p<0.0561
33	**Agricultural Drought — Soil-Moisture Deficit — Oceania** Root zone 0-100cm, D2+	Drought	0.116	p<0.0579
34	**Tropical Cyclones — Accumulated Cyclone Energy (ACE) — Oceania**	Tropical Cyclones	0.118	p<0.0596
35	**Agricultural Drought — Soil-Moisture Deficit — Europe** Root zone 0-100cm, D2+	Drought	0.136	p<0.0614
36	**Tropical Cyclones — Global Landfalls** Cat 1+ landfalls, all basins	Tropical Cyclones	0.170	p<0.0632

RANK	VARIABLE	PHENOMENON	P-VALUE	ADJUSTED TH
37	**Flooding — River Discharge — Oceania**	Flooding	0.208	p<0.0649
38	**Tropical Cyclones — Rapid Intensification**	Tropical Cyclones	0.212	p<0.0667
39	**Tropical Cyclones — Accumulated Cyclone Energy (ACE) — North America**	Tropical Cyclones	0.231	p<0.0684
40	**Flooding — River Discharge — North America**	Flooding	0.288	p<0.0702
41	**Tropical Cyclones — Accumulated Cyclone Energy (ACE) — Africa**	Tropical Cyclones	0.307	p<0.0719

RANK	VARIABLE	PHENOMENON	P-VALUE	ADJUSTED TH
42	**Meteorological Drought — Severe-or-Worse Land Area — Oceania** SPI-style (precipitation only), D2+	Drought	0.317	p<0.0737
43	**Tropical Cyclones — ACE per Storm**	Tropical Cyclones	0.354	p<0.0754
44	**Tropical Cyclones — Accumulated Cyclone Energy (ACE) — Asia**	Tropical Cyclones	0.397	p<0.0772
45	**Tornadoes (United States)**	Severe Convective Storms	0.435	p<0.0789
46	**Extratropical Cyclone Intensity — Minimum Pressure**	Winter Storms	0.488	p<0.0807

RANK	VARIABLE	PHENOMENON	P-VALUE	ADJUSTED TH
47	**Tropical Cyclones — Accumulated Cyclone Energy (ACE)**	Tropical Cyclones	0.580	p<0.0825
48	**Extratropical Cyclone Intensity — Minimum Pressure — Europe**	Winter Storms	0.649	p<0.0842
49	**Flooding — River Discharge — Asia**	Flooding	0.654	p<0.0860
50	**Extratropical Cyclone Intensity — Minimum Pressure — North America**	Winter Storms	0.665	p<0.0877
51	**Hydrological Drought — River Low-Flow Extent — Oceania**	Drought	0.672	p<0.0895

RANK	VARIABLE	PHENOMENON	P-VALUE	ADJUSTED TH
52	**Flooding — River Discharge — Europe**	Flooding	0.752	p<0.0912
53	**Meteorological Drought — Severe-or-Worse Land Area — Europe** SPI-style (precipitation only), D2+	Drought	0.787	p<0.0930
54	**Meteorological Drought — Severe-or-Worse Land Area — North America** SPI-style (precipitation only), D2+	Drought	0.820	p<0.0947
55	**Hydrological Drought — River Low-Flow Extent — North America**	Drought	0.914	p<0.0965
56	**Hydrological Drought — River Low-Flow Extent — Europe**	Drought	0.943	p<0.0982

RANK	VARIABLE	PHENOMENON	P-VALUE	ADJUSTED TH
57	**Hydrological Drought — River Low-Flow Extent — Asia**	Drought	0.967	p<0.1000
—	**Heat Waves — North America Magnitude Index (HWMId-style)**	Extreme Heat	—	—
—	**Wildfire — Burned Area (GWIS) — Africa**	Wildfire	—	—
—	**Wildfire — Burned Area (GWIS) — Asia**	Wildfire	—	—
—	**Wildfire — Burned Area (GWIS) — Europe**	Wildfire	—	—
—	**Wildfire — Burned Area (GWIS) — North America**	Wildfire	—	—

RANK	VARIABLE	PHENOMENON	P-VALUE	ADJUSTED TH
—	**Wildfire — Burned Area (GWIS) — Oceania**	Wildfire	—	—
—	**Wildfire — Burned Area (GWIS) — South America**	Wildfire	—	—
—	**Wildfire — Dry Matter Combusted (GFED5)**	Wildfire	—	—
—	**Wildfire — Dry Matter Combusted (GFED5) — Africa**	Wildfire	—	—
—	**Wildfire — Dry Matter Combusted (GFED5) — Asia**	Wildfire	—	—
—	**Wildfire — Dry Matter Combusted (GFED5) — Europe**	Wildfire	—	—

RANK	VARIABLE	PHENOMENON	P-VALUE	ADJUSTED TH
—	**Wildfire — Dry Matter Combusted (GFED5) — North America**	Wildfire	—	—
—	**Wildfire — Dry Matter Combusted (GFED5) — Oceania**	Wildfire	—	—
—	**Wildfire — Dry Matter Combusted (GFED5) — South America**	Wildfire	—	—
—	**Wildfire — Global Burned Area (GWIS)**	Wildfire	—	—

Reliable trend windows, and excluding the in-progress year

Every chart on this site shows only its reliable-trend-window data — years before a variable's network, model, or satellite record reaches meaningful global coverage drop out entirely, rather than sitting past a default where a widened window control could pull them back into the series. Each variable's reliable-start year rests on a specific basis: a station-count curve crossing a threshold, a documented satellite-era reanalysis-quality break, or an aircraft-reconnaissance-era record's beginning — see each variable's methodology note below for the evidence behind its start year. No chart shows the current, in-progress calendar year as a complete data point either: a partial season or year would otherwise appear as an artificially low final point, so every series ends at the most recently complete year.

Coverage limits — where this site falls short of literally global

Several variables cover less than the whole globe, or measure a related but different quantity from what the name suggests. Each variable page states its coverage limit; this list collects them in one place:

- **Extratropical cyclone intensity** covers the Northern Hemisphere winter season (October–March) only, despite the underlying TRACK catalog's "global climatology" title. The catalog also pre-filters for severity (64% of tracks already qualify as "bomb cyclones," against roughly 7% in an unfiltered climatology), so storm counts serve as description only rather than as a trend metric, and this site does not trend them. Its per-continent breakdown covers North America, Europe, and Asia — 3 of the 6 continents the Northern-Hemisphere-winter catalog reaches; the catalog contains no data for Africa, South America, or Oceania.
- **Flooding** excludes 1979–1981 from both series: GloFAS's documented one-year model spin-up (Harrigan et al. 2020) leaves a residual bias in slow-draining basins, Africa especially, through the record's first three years. See Flooding.
- **Cold extremes** mirrors Heat Waves' scope: it builds only the overnight-low (TMIN) side (TNn, CSDI, TN10p, Frost Days), with no TX10p (cold days by daytime high) companion, matching Heat Waves' construction without a TX90p companion.
- **Convective instability (CAPE)** uses a single 12Z UTC snapshot per day rather than a full diurnal cycle — no single fixed UTC hour matches "local afternoon" everywhere at once, so the metric favors whichever longitudes sit near local afternoon at 12Z.
- **Wildfire** tracks two distinct metrics: GFED5 dry matter combusted (mass burned, by fire type) and GWIS burned area (hectares, MODIS-derived) — each a distinct physical quantity from the US dashboard's MTBS acres-burned metric, and from each other.
- **Tropical cyclones** reuses the companion global-tropical-cyclones.com site's global rollup directly rather than re-deriving it, and refreshes manually rather than on GWX's automated schedule.
- **Tornadoes** covers the United States only (reused directly from the sibling US dashboard) — no unified global tornado database exists beyond Europe's ESWD. The United States accounts for the large majority of the world's tornadoes (NOAA/NSSL's climatology puts the US share near 75%), so this site pairs US tornado counts with CAPE as the best available global proxy, rather than presenting CAPE as a stand-in for a tornado count.

- **A flat global mean can hide opposite regional signals** — this applies to every station-network or grid-based global variable on this site rather than to one alone. Station and grid density varies: a global average weights a well-instrumented region like Europe or the US the same as a sparse one like Africa, South America, or the poles, so an increase in one continent can offset a decrease in another and net out to "no detected change" globally while opposite changes occur underneath. Where a per-continent breakdown exists (see Continents and the coverage table below), it offers a more complete read for this reason — check it before treating a global verdict as the whole picture.

Data currency — how current each variable stands, right now

Each variable page states its currency lag; this table collects them in one place, across all 72 GWX variables. Every month-resolved figure below is read from this build's own data files rather than written into the table, so a variable that stops refreshing shows it here instead of keeping a date that was true when someone last typed it.

VARIABLE	LATEST DATA	TYPICAL LAG
Drought (ERA5)	2026-08	About 1 month — ARCO-ERA5's near-real-time mirror.

VARIABLE	LATEST DATA	TYPICAL LAG
Drought (GPCP observed precipitation)	2026-06	About 2–3 months — NOAA PSL republishes the GPCP file monthly, a step behind ERA5's near-real-time mirror. No credential needed, so this one refreshes on schedule.
Agricultural drought (ERA5 soil moisture)	2026-08	About 1 month — the same ARCO-ERA5 near-real-time mirror as Drought.
Convective instability (CAPE)	2026 (current)	About 1 month — the same ERA5 near-real-time source as Drought.

VARIABLE	LATEST DATA	TYPICAL LAG
Tropical cyclones	2026 season	Reused from global-tropical-cyclones.com; refreshes manually rather than on GWX's automated schedule.
Flooding (GloFAS)	2026-07	GloFAS's own production lag: its consolidated historical product publishes a month or two after the fact, and the pipeline retries a month that is not out yet rather than failing. Currently 1 month behind the ERA5 variables.

VARIABLE	LATEST DATA	TYPICAL LAG
Hydrological drought (GloFAS)	2026-06	The same GloFAS production lag as Flooding, one month further back because a month needs 90% of its days present before it counts. Currently 2 months behind the ERA5 variables.
Heat waves	2025	About 1 year — most non-US GHCN-Daily/GSN stations report roughly a year behind, worse than the sibling dashboard's US-only feed.

VARIABLE	LATEST DATA	TYPICAL LAG
Cold extremes	2025	About 1 year — the same GHCN-Daily/GSN network and lag as Heat Waves.
Tornadoes (US-only)	2025	Standard annual — NCEI Storm Events' most recent complete year; 2026 remains partial and in progress, excluded per the partial-year rule.
Wildfire — GFED5 (dry matter combusted)	2024	About 1.5–2 years — GFED5's summary-table regeneration cadence (files last regenerated 2025-10-07).

VARIABLE	LATEST DATA	TYPICAL LAG
Wildfire — GWIS (burned area)	2024	About 1.5–2 years — Our World in Data's GWIS mirror.
Extratropical cyclone intensity	2022	A fixed endpoint rather than a lag that resolves with time — the TRACK/CEDA source catalog spans 1979–2022 with no newer years published, rather than running a currently updating feed behind.

Per-continent coverage

Drought, both wildfire variables, tropical cyclones (by ocean basin), flooding, and extratropical cyclone intensity (3 of 6 continents) appear per continent — see the nav's "Continents" dropdown for each landing page. Heat waves cover Europe and North America (see below); the table below states the current status for every other variable.

VARIABLE	STATUS	BASIS
Drought	Live	Continent assignment proceeds per 5° grid cell via a point-in-polygon join against Natural Earth's 1:110m country boundaries — both the precipitation-only (SPI-style) and precipitation-minus-AED (SPEI-style) series, matching the global Drought page.
Agricultural drought	Live	The same per-cell Natural Earth join as Drought, on the same 5° grid — live for all 6 continents, both the root-zone (0–100cm) and surface (0–7cm) depths.
Wildfire (GFED5 DM)	Live	Sums GFED5's 14 "basis regions" (NHAF+SHAF for Africa, for example).

VARIABLE	STATUS	BASIS
Wildfire (GWIS burned area)	Live	Our World in Data's GWIS mirror already breaks the data out by continent.
Tropical cyclones	Live	Groups each continent by the ocean basin(s) that border it rather than by a landfall-based reclassification (Africa pairs with the South Indian Ocean; North America with the North Atlantic and Northeast Pacific). Live for 4 of 6 continents; Europe and South America have no bordering basin in this catalog.

VARIABLE	STATUS	BASIS
Extratropical cyclone intensity	Live	Assigns a storm to a continent by proximity (within 500km of its Natural Earth landmass, since most fixes sit over open ocean) rather than a bounding box — live for North America, Europe, and Asia; the underlying Northern-Hemisphere-winter catalog contains no data for Africa, South America, or Oceania.

VARIABLE	STATUS	BASIS
Heat waves / temperature extremes	2 of 6	GSN station density varies by continent (checked directly for all 6, 2026-08-18): Europe clears the global index's ~150-station bar (150+ by 1949); North America stands as a borderline case (peaks at 147, reliable window starts 2000); Asia (121), Africa (37), South America (33), and Oceania (56) all stay well under 100 at their historical peak, too sparse to support an index.
Flooding	Live	GloFAS's pour-point network sits on the same 5° grid Drought uses — live for all 6 continents, both the percentile-based series and GloFAS's Alert/Warning/Severe return-period tiers.

VARIABLE	STATUS	BASIS
Hydrological drought	Live	The same GloFAS pour-point network as Flooding, worked at the low end instead of the high — live for all 6 continents. Each continent's percentiles draw on that continent's cells only, so a continent series matches what a standalone run for it would produce.

Data Sources — Attribution & Licensing

This dashboard computes derived indices (trends, percentiles, detection statistics) from publicly available reanalysis, satellite, and station data produced by national and international agencies — it does not redistribute their raw data. This page credits each source below with its producer, license, and (where the license or agency specifies one) the exact attribution wording it requests, reproduced verbatim rather than paraphrased.

- **ERA5 reanalysis** (Copernicus Climate Data Store, produced by ECMWF for the EU's Copernicus Climate Change Service) — underlies Convective Instability (CAPE), Drought, Agricultural Drought (soil moisture), and, via GloFAS and the CEDA/TRACK catalog below, Flooding, Hydrological Drought and Extratropical Cyclone Intensity. License: Creative Commons Attribution 4.0 International (CC BY 4.0), the Copernicus Climate Change Service licence in effect since 2 July 2025. Required attribution: `"Contains modified Copernicus Climate Change Service information [2026]"`. Neither the European Commission nor ECMWF is responsible for any use made of this information.

- **GloFAS** (Global Flood Awareness System, Copernicus Emergency Management Service, ERA5-forced LISFLOOD reanalysis) — underlies Flooding and Hydrological Drought, which read the high and low tails of the same discharge record. License: CC BY 4.0. Required attribution: `"Contains modified Copernicus Emergency Management Service information [2026]"`. See also Library for Harrigan et al. (2020), the GloFAS-ERA5 methodology paper.
- **Extratropical cyclone tracks** (Gray, Volonté, Martínez-Alvarado & Harvey 2024, TRACK algorithm on ERA5, via the NERC EDS Centre for Environmental Data Analysis (CEDA)) — underlies Extratropical Cyclone Intensity. License: UK Open Government Licence v3.0. Required citation, exactly as CEDA's catalogue record specifies: `"Gray, S.L.; Volonte, A.; Martinez-Alvarado, O.; Harvey, B. (2024): A global climatology of sting-jet cyclones: TRACK files and Sting-Jet Precursor Cut-Outs. NERC EDS Centre for Environmental Data Analysis, 22 October 2024. doi:10.5285/4aac4f8ba15f43e59eb81756b464c9fb."`
- **IBTrACS** (International Best Track Archive for Climate Stewardship, NOAA NCEI) and **HURDAT2** (NOAA National Hurricane Center) — reach this site via the sibling global-tropical-cyclones.com pipeline, which combines both plus real-time supplements. License: public domain (US government work). IBTrACS' recommended citation: Knapp, K.R., Kruk, M.C., Levinson, D.H., Diamond, H.J., Neumann, C.J. (2010): "The International Best Track Archive for Climate Stewardship (IBTrACS): Unifying tropical cyclone best track data." *Bulletin of the American Meteorological Society*, 91, 363–376. HURDAT2 mandates no citation; NOAA's National Hurricane Center takes the conventional credit.
- **climatlas** (Ryan Maue's tropical-cyclone compilation) — reaches this site two ways. Its aggregated current-season best-track feed (NHC working best track for AL/EP/CP, NCAR-RAL open b-decks and JTWC for WP/SH/IO) supplements the sibling global-tropical-cyclones pipeline whenever IBTrACS stalls on a live storm, so every current-season figure on the Tropical Cyclones page depends on it in part. Its independent 1944–2025 global landfall record serves as the external replication of the Global Landfalls variable — see that variable's note below. The site states no license; treat the compilation as Maue's and cite him for it.

- **GHCN-Daily** (Global Historical Climatology Network - Daily, NOAA NCEI) — underlies Heat Waves and Cold Extremes. License: public domain (US government work). Recommended citation: Menne, M.J. et al. (2012): "An Overview of the Global Historical Climatology Network-Daily Database." *Journal of Atmospheric and Oceanic Technology*, 29, 897–910. doi:10.7289/V5D21VHZ.
- **GFED5** (Global Fire Emissions Database, version 5, dry-matter-combusted totals via globalfiredata.org) — underlies Wildfire. License: CC BY 4.0 (per the dataset's Zenodo record, DOI 10.5281/zenodo.16794692). Required attribution: cite the source paper, already in this project's Library — Chen, Y. et al., "Multi-decadal trends and variability in burned area from the fifth version of the Global Fire Emissions Database (GFED5)."
- **GWIS burned area** (Global Wildfire Information System, a Joint Research Centre/European Commission product, MODIS MCD64A1-derived), accessed via Our World in Data's public mirror — a second Wildfire metric alongside GFED5. OWID licenses its processing and presentation as CC BY; OWID states third-party source data it mirrors "are subject to the license terms from the original providers," and does not itself publish a specific license for GWIS's underlying data — this project credits both layers rather than assuming a license GWIS/JRC hasn't stated.
- **Natural Earth** (naturalearthdata.com) — continent boundary polygons, used to assign stations, grid cells, and storm tracks to a continent throughout this site. License: public domain; the authors explicitly state that they require no permission or attribution, though they welcome a citation.
- **NASA EPIC** (Earth Polychromatic Imaging Camera, DSCOVR satellite, epic.gsfc.nasa.gov) — the homepage's full-disk Earth image, refreshed daily. License: freely reusable, including commercially; NASA's EPIC Team requests credit for the original imagery. Displayed here as "Image courtesy of NASA/NOAA."

Per-variable notes

Tropical Cyclones — ACE

Global (all-basin) Accumulated Cyclone Energy, from HURDAT2, IBTrACS, and real-time supplements. The reliable trend window starts in 1980, following Klotzbach & Landsea's published recommendation against pre-1980 data in global TC trend analyses. The 1980 cutoff addresses intensity-estimate accuracy rather than basin coverage — raw storm counts already hold stable well before 1980, but satellites through the 1970s carried only visible-light sensors, and the Dvorak

technique reached global standardization only in the early 1980s. The companion global-tropical-cyclones.com site uses a 1966 start for the same underlying data, a difference in scope between the two sites' trend-reliability standards. An additional, lower-confidence "NATL+WPAC combined" series (selectable from this panel's Series dropdown, with a one-click time-period preset) extends back to 1945: both basins' aircraft-reconnaissance-era records begin then (NATL from 1944; NWPAC/JTWC's best-track record begins 1945), when combined NATL+NWPAC storm counts jump from 3–14/year pre-1944 to a stable 35–45+/year from 1945. These two basins track global activity closely: measured over the 1980–2025 global reliable window, NATL+WPAC combined account for about 52% of global ACE (WPAC alone about 37%, NATL alone about 15% — WPAC ranks as the single most active basin), about 45% of named-storm count, about 48% of hurricane and major-hurricane counts, and about 74% of Category 5 storms specifically (WPAC's warm pool produces most of the planet's strongest storms) — roughly half of global activity by every measure, and the majority of the most extreme events. The extended view adds caveats the 1980+ window escapes: NOAA's ongoing Atlantic Hurricane Reanalysis Project documents intensity biases even in the aircraft-recon era (Cat 1–2 systematically about 5kt high, the most intense storms undersampled), and WPAC's aircraft-fix record has documented gaps (1952 missing entirely, 1955 limited).

Tropical Cyclones — Category Frequency, ACE per Storm, % Major, Rapid Intensification

Category frequency and ACE-per-storm reuse GTC's per-storm peak-intensity-tier and lifetime-ACE table directly — category frequency counts each storm's exact peak tier rather than the cumulative "Cat 3+ or stronger" counts the ACE panel's levels show; Cat 1 and Cat 2 share one band (both fall in the 64–95kt "H" range, GTC's HURDAT2/IBTrACS convention). % major measures the major-hurricane share of hurricanes specifically rather than of all named storms. Rapid intensification (a 30kt-or-greater increase in maximum wind within 24 hours, the standard NHC definition) draws on GTC's 6-hourly best-track fixes, comparing each fix only against the same storm's fix exactly 24 hours earlier, so a storm's first day, or any fix following a data gap, correctly registers no RI event. Hurricane Otis (2023) recorded a computed 24-hour wind increase of 90kt (55kt to 145kt) under this method, matching its documented record as one of the fastest tropical cyclone intensifications observed. All four metrics share the 1980 reliable window (Klotzbach & Landsea) and the same manual-refresh schedule.

ACE-per-storm shows no detected change (Mann-Kendall p=0.35, nominally decreasing, 18% of the 90% historical range) over the same 1980–2025 window where % Major Hurricanes shows a detected change (p=0.030, +2.1 points/decade, 34% of the 90% range) — the two panels answer different questions rather than disagreeing. Comparing 1980–2002 to 2003–2025, Cat 1–3 storm counts have declined (Cat 1–2 hurricanes, for example, 25.8→21.1/season) while Cat 4–5 counts have risen (10.9→12.9 and 3.7→6.0/season). % major captures that compositional shift directly; ACE-per-storm averages across all named storms, most of them weak systems, so the ACE lost from fewer moderate hurricanes roughly offsets the ACE gained from the rarer, more extreme ones. Over the 1980–2025 global window, every one of the 5 category-frequency levels above individually clears detection (p between 0.03 and 0.0004 across NS/H/MH/IH/C5; magnitude 35–56% of the 90% historical range).

Both panels also offer NATL+WPAC-only levels (reliable back to 1945, versus 1980 for global), computed over both the matching 1980–2025 window and the full 1945–2025 extended window, with mixed results that bear on how confidently the %major finding in particular should be read: NS and MH hold up as detected changes at every window length checked. H's decline and %major's increase do not survive the full 1945–2025 window — both flip to not-detected (%major's magnitude falls from 34% of the 90% range over 1980–2025 alone to 6% over the full record). IH's global-level increase never clears detection in this 2-basin subset at any window length, which places that increase in the basins NATL+WPAC excludes. C5's increase survives but weakens over the longer window (p=0.008 narrows to p=0.08, at the significance edge this site applies). None of this overturns the global 1980–2025 findings — the pre-1980 portion of the extended record has documented intensity biases (see the ACE panel above), which could mask a recent trend as easily as reveal that one lacks durability — but the %major finding in particular remains open.

Tropical Cyclones — Global Landfalls

Landfalls per season at hurricane strength or above, all basins, 1980–2025 on the same reliable window every other tropical-cyclone panel here uses. GTC detects each landfall geometrically from the storm's 6-hourly fix positions, following the method of Weinkle, Maue and Pielke Jr. (2012), rather than reading any source's own landfall flag — HURDAT2's "L" record, IBTrACS's DIST2LAND field and real-time ATCF disagree about what a landfall means, and ATCF carries no flag at all. Landfall intensity takes the greater of the landfall fix and the fix immediately before it, which captures the storm's strength before land-induced weakening sets in. The count runs per landfall rather than per storm, so a system crossing Cuba and then Florida contributes two. That choice differs deliberately from Weinkle et al., who collapse each storm to its most intense landfall for loss-normalization purposes; climatology, not loss consistency, governs the choice here. The underlying `landfall_h/mh/ih/c5` fields have shipped in GTC's published season summary from the start, and this site left them unread until September 2026.

The four intensity levels split over the 1980–2025 window. Cat 1+ landfalls show no detected change (p=0.170). Cat 3+ (+1.36/decade, p=0.036), Cat 4+ (+0.91/decade, p=0.043) and Cat 5 (+0.26/decade, p=0.021) each clear both the significance and magnitude bars. Three separate checks then cut against reading those three as a climate signal, and this section states them because the panel's default level shows the null while three of its four levels do not.

First, start date. Holding the end at 2025 and moving the start walks both headline levels straight across the detection threshold, in the same direction, at the same place.

WINDOW	CAT 1+ LANDFALLS	CAT 3+ LANDFALLS
1950–2025	+0.83/decade, p=0.070 (detected)	+0.70/decade, p=0.011 (detected)

WINDOW	CAT 1+ LANDFALLS	CAT 3+ LANDFALLS
1966–2025	+1.19/decade, p=0.052 (detected)	+1.22/decade, p=0.003 (detected)
1970–2025	p=0.111 (not detected)	+1.25/decade, p=0.004 (detected)
1980–2025 (site default)	p=0.170 (not detected)	+1.36/decade, p=0.036 (detected)
1990–2025	p=0.679 (not detected)	p=0.342 (not detected)

Every landfall level here loses detection once the window begins in 1990. A result that depends on including the 1980s rests on the decade whose intensity estimates the ACE panel above already flags as the weakest part of the modern record.

Second, the landfall share. Dividing landfalls by the basin-wide storm counts that produced them asks whether storms reach land more often, and the answer over 1980–2025 comes back yes: the hurricane landfall share climbs +3.40 percentage points per decade (p=0.013) and the major-hurricane landfall share +4.89 points per decade (p=0.024). No physical mechanism makes a fixed population of storms find coastlines more frequently, so a rising landfall fraction points at the observing system. Best-track position accuracy improved sharply across the 1980s, and a track placed more accurately crosses a coastline more reliably in a geometric test. Both shares also stop climbing from 1990 (p=0.327 and p=0.219), matching the counts.

Third, the extended record. The NATL+WPAC combined series, selectable from this panel and reaching back to 1945, detects nothing at any intensity over its full span: Cat 1+ p=0.557, Cat 3+ p=0.169, Cat 4+ p=0.105. Cat 5 clears the significance bar at p=0.031 but returns a Sen slope of exactly zero, so the site records it as flat rather than as a direction. The same pre-1980 intensity biases the ACE panel describes apply to this window, so it cannot settle the question either — it simply declines to reproduce the global result.

Independent replication, and an acknowledgment

Ryan Maue compiles an independent global landfall record at climatlas.com/tropical/landfalls, and this site fetches his per-storm table (1851–2025, built from a JTWC+NHC+Neumann merged best

track) on every pipeline run so the comparison below re-runs rather than sitting here as a dated claim. The two compilations share the Weinkle–Maue–Pielke landfall definition and diverge on two implementation choices: climatlas admits any island above 50 km² where GTC works from a Natural Earth land polygon, and climatlas records one flag per storm where GTC counts every crossing, which puts its levels lower by construction. Over the 46 seasons from 1980 to 2025 the two agree at r=0.89 on hurricane landfalls and r=0.93 on major landfalls, and they return the same verdicts: his major-landfall count runs +0.88/decade (p=0.038) against this site's +1.36/decade (p=0.036). Both fall to no-detected-change from 1990 (p=0.568 there, p=0.342 here). The one disagreement sits at Cat 1+, where his series clears the flat 10% bar (p=0.090) and this one does not (p=0.170) — close enough to the threshold that the convention difference accounts for it. Maue's page reaches the same conclusion in his words: a null that holds. Agreement between two independent compilations confirms that the processing works; it says nothing about whether the best-track record underneath them holds steady, which the start-date and landfall-share checks above address instead.

The debt runs further than a cross-check. GTC's real-time pipeline reads Maue's aggregated best-track feed directly (besttrack.csv), which supplements the Western Pacific and Southern Hemisphere whenever IBTrACS stalls — in August 2026 that feed carried Typhoon Dolphin's entire Category 5 phase, which IBTrACS's live copy had dropped. Every current-season figure on this page therefore depends in part on his compilation. He also publishes a per-storm table back to 1851 and a plain-text season digest, and the landfall replication above draws on the first of those. Weinkle, Maue and Pielke Jr. (2012) supplies the method both records apply.

One further result of his bears directly on every intensity-based metric this page carries. Maue's power-dissipation work integrates observed wind fields rather than peak wind alone, and finds that dissipation area shrinks as intensity grows, which makes the cubed-peak-wind Power Dissipation Index a poor stand-in for the physical quantity: storm size carries more of the interannual variance than intensity does, and adding the 34-knot wind radius changes the answer materially. Over 2002–2025, the window with analysed wind radii, none of PD, IKE, ACE or PDI carries a significant trend. His size and structure database also reports that splicing an ERA5 reconstruction onto the observed radii produces large significant trends running opposite to the observations — the same reanalysis-versus- observation split this site's drought audit found between ERA5 and GPCP. ACE, category counts, %major and landfalls on this page all read peak wind, so none of them measures the term his work identifies as the largest. That limit applies to the panels above as stated, and closing it needs a size record this site does not yet carry.

Heat Waves

GHCN-Daily's GCOS Surface Network (GSN, about 991 stations across 164 countries), the global analog of the US HCN network. Station-relative detection (a trailing 4-day mean temperature above each station's 90th-percentile-of-record threshold) makes this well-posed globally across every hemisphere and season, the same principle behind global-mean-temperature-anomaly products. The reliable trend window starts in 1949 (station count crosses the same ~300-station bar the US network's 1895 window used, later here since WMO international cooperation only began in 1950). 2024 and 2023 rank as the two highest years in the 2006–2025 window,

matching the established finding that 2024 and 2023 rank as the two hottest years on record globally (NASA GISS, NOAA, Copernicus, and Berkeley Earth all agree). GSN's international reporting lag exceeds than the US-only feed the sibling dashboard uses — most non-US stations report roughly a year behind, visible in this variable's falling station count over its most recent 1–2 years. The qualifying station count drops by roughly a third between 2018 and 2019 (from about 400–480 down to about 270–330) and stays down through 2025, a permanent contraction in the network's post-2018 completeness rather than ordinary year-to-year reporting lag; the pattern matches a systemic change in how a batch of international station reports flow into GHCN-Daily. A separate Europe-only index applies the same method to GSN stations within Europe (Russia included, per Natural Earth's continent boundaries), the one continent with a GSN network dense enough (150+ stations by 1949) to support its index.

Three companion metrics extend the headline index. The **magnitude index**(HWMId-style, Russo et al. 2014/2015) scores each qualifying station's most severe heat wave of the year by summing every day's magnitude — (a day's 4-day mean temperature minus the station's 25th-percentile annual maximum) divided by (the 90th-percentile minus the 25th-percentile annual maximum, the index's detection threshold) — both anchors drawn from the same station-relative annual-max distribution the event-count index uses, a simplification of Russo et al.'s original construction, which uses a separate calendar-day threshold and a 25th/75th-percentile scale. 2010 ranks as the single highest year in the record (1.78, more than 4 times the 1949–2025 mean), matching the documented 2010 Russian heat wave, Russia's worst on record; that same year ranks outside the top 5 on the bare event-count index (0.43), illustrating the distinction between one severe event and many mild ones this metric captures. **TXx** (IPCC AR6/ETCCDI standard) reports the single hottest daily high temperature observed each year at each qualifying station, averaged across stations, with no percentile threshold or base period. 2024 posts the highest TXx of the displayed window (35.6°C), matching 2024's status as the hottest year on record globally.**WSDI** (ETCCDI/CLIMDEX, Zhang et al. 2005) counts days in a run of 6 or more consecutive days above a station's fixed-base-period (1961–1990) 90th percentile.**TN90p** (ETCCDI/CLIMDEX) reports the percentage of days with an overnight low above the same fixed-base-period 90th percentile — NCA5 flags nighttime-low warming as a distinct, high-confidence signal rather than a restatement of TXx. TXx, WSDI, and TN90p all share the 1949 reliable trend window.

Convective Instability (CAPE)

ARCO-ERA5, the same global reanalysis store as the US dashboard's CAPE variable. The reliable trend window starts in 1979, marking ERA5's documented post-TOVS-satellite reanalysis-quality improvement. A single 12Z UTC snapshot per day stands in for a full diurnal cycle — no single fixed UTC hour matches "local afternoon" everywhere at once, and correcting for that would cost roughly 24 times more to assemble, the same cost as pulling all 24 hours. The day-count metrics (widespread and high-CAPE days) use the 90th percentile of the record's distribution, computed fresh each run, rather than a fixed absolute threshold: the US dashboard's fixed thresholds (10% of CONUS at moderate CAPE; 2500 J/kg for extreme) produce no signal at global scale, since global %-area-moderate never approaches 10% (ocean, desert and polar ice cover most of the planet at any instant) while global max CAPE exceeds 2500 J/kg on nearly every day (a thunderstorm occurs somewhere in the tropics on most days). Both metrics instead use percentile-

relative thresholds, the same approach as the Heat Waves variable. "Widespread instability days" counts days in the top decile of global %-area-at-moderate-CAPE; "high-CAPE days" counts days in the top decile of the single most unstable grid cell on Earth that day.

Wildfire

Global Fire Emissions Database (GFED5), dry-matter-combusted totals by fire type, via its pre-aggregated summary tables. Coverage spans 1997–2024, the full available record. GFED5's authors state that 1997–2000 uses coarser ATSR/VIRS-scaled estimates rather than the MODIS burned-area retrieval every year from 2001 on uses, and describe 1997–2000 as "not on par with data from the MODIS era"; the reliable trend window accordingly starts in 2001. Canada's boreal-forest DM for 2023 stands as the record in the series, 2.5 times the next-highest year, matching Canada's documented 2023 wildfire season. **A second metric** — GWIS burned area (hectares, MODIS MCD64A1-derived), via Our World in Data's public mirror of the JRC's GWIS dataset — covers 2002–2024. Africa averages about 67% of the global burned-area total, matching known savanna-fire dominance, and the global total declined about 18% from 2002–2012 to 2013–2024, matching Andela et al. 2017's documented decline in global burned area.

Extratropical Cyclone Intensity

CEDA/TRACK catalog (Gray, Volonte, Martínez-Alvarado, Harvey 2024), ERA5-driven — the same source and algorithm the US dashboard's Northeast-focused ETC intensity variable uses, here computed over each storm's whole track rather than a US-coast bounding box, an extension the already Northern-Hemisphere-wide underlying catalog supports directly. The reliable trend window starts in 1979. The single lowest minimum-pressure storm in the 1979–2022 record (genesis 1993-01-10, minimum MSLP 914.87 hPa) matches the Braer Storm, both in date and pressure, against the widely cited (about 914–916 hPa) historical record of that event. A per-continent breakdown covers North America, Europe, and Asia. Since most ETC fixes sit over open ocean rather than land, a strict landfall test would miss nearly every storm — this site instead assigns a storm to a continent when its track comes within 500km of that continent's Natural Earth landmass, and a storm can count toward more than one continent (one North Atlantic storm affecting both eastern North America and western Europe in sequence, for example). The Braer Storm reproduces in Europe's continent-filtered subset at effectively the same pressure.

Drought

A live index built directly from ARCO-ERA5 precipitation, in place of SPEIbase (the standard global-gridded-SPEI source), which has published no release since July 2024, breaking its roughly annual release cadence. Each 5°-coarsened land grid cell's 3-month trailing precipitation enters a percentile rank against that cell's same-calendar-month history, never against an absolute precipitation normal, and classifies into USDM-equivalent D0–D4 categories, the same convention as the US dashboard's drought variable. The reliable trend window spans the full 1979–2026 record. Each cell enters the aggregation weighted by its spherical area times its land fraction, so a 5° cell at 60° of latitude counts for about half an equatorial one, and "global" spans 60°S–90°N — the same land the six continental indices cover between them. At the precipitation-only D2+ level the five worst years are 2023, 2024, 2021, 2025 and 2022: the Amazon and Panama Canal

droughts, the Horn of Africa's worst drought in 40 years, and the Yangtze and European drought of 2022. **A second, AED-inclusive companion series** subtracts atmospheric evaporative demand (AED, estimated via the FAO-56 Hargreaves method from ERA5 temperature, a simplification of the source paper's full Penman-Monteith calculation) from precipitation before ranking, following Vicente-Serrano et al. 2022 ("Global drought trends and future projections," *Phil. Trans. R. Soc. A* 380: 20210285), the paper that motivated this second series. Comparing 1980–2002 with 2003–2025, the precipitation-only series rises +3.01 percentage points and the AED-inclusive series +6.06, about twice as far. Two of that paper's choices match the ones here: a three-month timescale, and AED taken from ERA5.

Where this site now diverges from that source paper, and the site states the divergence. Vicente-Serrano et al. report that meteorological drought shows no substantial global change across at least 120 years, and that on a 12-month SPI over 1950–2020 the percentage of land area in drought *declines* significantly in both the CRU and GPCC precipitation datasets. Their AED-inclusive signal stays regional — significant drying in western North America, Australia, southern Europe, eastern, central and southern Africa and parts of South America — together with a rise in global drought area over the last decade. This site's precipitation-only series now shows a detected global *increase*, the opposite sign to their SPI result, and its AED-inclusive series detects globally rather than only regionally. Until 15 September 2026 the two agreed, because an unweighted grid-cell average held the precipitation-only series below this site's detection bar until area weighting lifted it past that bar. Several differences bear on the comparison: gauge-based CRU and GPCC precipitation against ERA5 reanalysis, a 12-month index against three months, 1950–2020 against 1979–2026, and their zero-threshold drought definition against the USDM percentile ladder used here. This site leaves the divergence standing rather than resolving it by picking a favourite dataset. Their future-projection component stays out of scope here. See theLibrary.

A retracted citation, removed from the evidence and named in this note. This page previously cited Gebrechorkos et al. 2025 (*Nature* 642, 628–635), co-authored by Vicente-Serrano, as a newer and independent confirmation that AED had raised global drought severity by about 40%. ***Nature* retracted that paper on 2 September 2026**(doi:10.1038/s41586-026-11027-z). The retraction notice lists four problems: study-wide averages taken without area weighting of grid cells, GLEAM v3 results presented as GLEAM4, a date-parsing error that misassigned months where the authors split 1981–2017 from 2018–2022, and an arid-region mask (mean annual precipitation under 180mm) applied to one figure and omitted from the drought-area percentages. A retracted paper supports nothing, so it no longer stands behind any statement on this site, and the mechanism the AED-inclusive series measures rests on the Vicente-Serrano et al. 2022 entry. Two of those four problems — area weighting and the arid mask — prompted a full audit of this site's drought index, whose findings appear in the next two paragraphs.

A third series, on observed precipitation rather than on reanalysis. ERA5 is a physical model constrained by whatever observations its assimilation could reach. Where a rain-gauge network is dense that constraint is tight; where it is sparse the model supplies what the observations do not, and a precipitation trend there is the model's as much as the weather's. So this index also runs on **GPCP v2.3** (NASA/GSFC's Global Precipitation Climatology Project, NOAA PSL's mirror): satellite

retrievals merged onto the GPCC gauge analysis, monthly at 2.5° from 1979. Every other choice matches the ERA5 series exactly — the same 5° blocks, land mask, 60°S–90°N scope, three-month window, percentile rank, D0–D4 ladder and area weights — so selecting one against the other isolates the precipitation record and nothing else. GPCP's own limits: NOAA PSL's file carries "interim" status from November 2021 onward, so the recent years lean on GPCC's monitoring analysis rather than its full one, and 2.5° resolves less inside a 5° block than ERA5's native 0.25°.

The two records disagree about the trend, and this site publishes both rather than choosing. Over the full record the ERA5 series gives +1.36 percentage points per decade ($p < 0.001$), a detected increase; the GPCP series gives −0.26 per decade ($p = 0.195$), no detected change. An audit in September 2026 found the disagreement concentrated where the gauges are thin: across Europe, North America and Oceania the two records agree and neither detects a rise, while Africa and South America supply 85% of the ERA5 increase and only South America's appears in the observations. A gauge-only record, GPCC's full analysis, covers 1979–2019 and returns a detected *decrease* over that window where ERA5 returns a detected increase. ERA5's global land precipitation also steps down about 5% at 2000–2001, a break neither observational record shows. Which record is right is not settled here. Read the meteorological drought trend as a property of ERA5 until an observational record corroborates it, and note that the soil-moisture and streamflow series on the Drought page descend from that same ERA5 precipitation — GloFAS is a hydrological model forced by ERA5, and ERA5's soil moisture is ERA5's own land surface — so they are not independent of it.

A limit on the Hargreaves estimate of evaporative demand, and the fix it prompted. The equation $ET0 = 0.0023 \cdot Ra \cdot (Tmean + 17.8) \cdot \sqrt{(Tmax - Tmin)}$ turns negative below a mean temperature of −17.8 °C. This pipeline applied it without a floor until 15 September 2026, and 21.9% of land cell-months came back negative — 54.8% of those south of 60°S, 23.3% north of 60°N and 4.9% between 30°N and 60°N. A negative term lifts a cell's water balance above its precipitation, and a warming trend there then lowers the balance by shrinking that term rather than by drying anything. The equation now floors at zero, and the same audit narrowed this index to 60°S–90°N, which together leave 7.6% of the cell-months now in scope touched by the floor at all. The correction moved the AED-inclusive period change by about 0.3%, so it mattered for the reasoning rather than for the number.

The choice of evaporative-demand formula moves the AED-inclusive trend more than any other methodological choice on this page, and the literature points toward a smaller slope. Sheffield, Wood and Roderick (2012, *Nature* 491:435) found that temperature-based estimates overstate drying in dry regions relative to the full Penman-Monteith equation. Xu et al. 2026 (*Communications Earth & Environment* 7:726) go further and argue that Penman-Monteith itself overstates it, because Penman-type formulations neglect the land–atmosphere coupling that limits evaporative demand as a surface dries. Applying six formulations to SPEI over 1981–2024, they report Penman-type drying trends **at least six times** those of energy-constrained formulations, drought-area trends **7.8 times** larger, and the share of the drought trend attributable to evaporative demand falling from **47.5% to 25%** once the constraint applies — leaving precipitation the dominant driver at 75%. The Hargreaves method used here applies no coupling constraint, so it sits among the estimators both papers criticise rather than among the energy-based ones. Read

the AED-inclusive series as an upper bound on the drying signal, and the precipitation-only series as the one least exposed to this choice.

Two further formulations, now measured rather than argued about. A full FAO-56 Penman-Monteith series and the energy-only formulation Xu et al. adopt (Milly and Dunne 2016, *PET = 0.8 × net radiation / latent heat*) were built from the same ARCO-ERA5 fetch, at a measured 4.6 TB and about eight hours, then run through this index over the 571 months all three share. Swapping only the evaporative-demand term and holding every other choice fixed, **Penman-Monteith returns 0.91 times the period change plotted above and the energy-only formulation 0.47 times**, against this series' own +6.06 percentage points at D2+.

Three things follow. The upper-bound label above holds, and the bound is tight: Hargreaves exceeds Penman-Monteith by 11% at D0, narrowing to 1% at D4. No verdict turns on the choice — all three formulations detect an increase at every severity level, the largest p-value across the sixty series tested reaching 0.00025. And Xu et al.'s sixfold gap does not reproduce here: on this index Penman-Monteith runs **1.95 times**the energy-constrained series rather than six, holding between 1.84 and 1.95 at every severity level. Their figures come from a different index over a different window on gauge-based precipitation, so this measures the gap on this site's construction rather than contradicting theirs — but the sixfold and 7.8-fold figures quoted above describe their setup and not this one. One distinction worth keeping straight: Xu et al.'s headline concerns*acceleration*, a second-order trend, and their first-order result still shows a statistically significant global drying trend under both families of formulation.

Arid-cell behaviour, measured rather than assumed. A percentile rank against a near-zero precipitation history invites the objection that evaporative demand alone decides an arid cell's drought class. On this grid the objection has little force: a 5°-coarsened block mean of a monthly total reaches exactly zero over three months in 0.03% of land cell-months and 0.5% of hyperarid ones, and those months classify as D2 or worse 72% of the time. Hyperarid cells cover 7.0% of the land area and supply 6.0% of the AED-inclusive increase and −2.5% of the precipitation-only increase, so masking them widens both trends rather than narrowing them. Random tie-breaking and the standard SPI zero-precipitation adjustment each move the global D2+ period change by 0.03 points or less. Humid land, 59.9% of the area, supplies 55% of the AED-inclusive increase.

Percentiles rank against the whole record, which re-ranks on every update.A new month enters every cell's same-calendar-month reference pool, so historical percentiles shift slightly as the record grows. That choice takes the conservative side: ranking against a fixed 1981–2010 base instead gives a period change of +3.84 points precipitation-only and +7.46 points AED-inclusive, against +2.60 and +5.58 on the full record.

Agricultural Drought (Soil Moisture)

ERA5 volumetric soil water on the same 5°-coarsened land grid Drought uses, on the same 3-month trailing window, percentile-ranked against each cell's same-calendar-month history and classified into the same USDM-equivalent D0–D4 categories — the same modeled-soil-moisture-percentile approach the US Drought Monitor uses as one of its standing inputs, rather than a metric invented here. A rainfall deficit becomes an agricultural drought only once the soil store

draws down, which depends on antecedent storage, evaporative demand and soil depth, so soil moisture lags and damps precipitation rather than tracking it.

Two depths appear alongside each other, mirroring the SPI/SPEI pairing. Root zone (0–100cm) is the depth-weighted mean of ERA5 layers 1–3, weighted by their real thicknesses (7, 21 and 72cm rather than equal weights, which would triple-count the thin surface layer relative to its actual water volume) — the water a crop can reach, and the headline series. Surface (0–7cm) is layer 1 alone, which responds to a rainfall deficit within days rather than weeks and is the layer satellite soil-moisture products such as ESA CCI and SMAP observe, so a reader can cross-check it against an independent observational source. Sampling covers 4 synoptic hours a day (00/06/12/18Z), matching the temperature convention the AED series uses rather than Drought's every-hour precipitation fetch: rainfall spikes quasi-randomly within a day, while soil moisture is a storage term that varies smoothly, so a synoptic subsample recovers the monthly mean.

Disclosed limitation. ERA5 models soil moisture rather than observing it, and the assimilation of screen-level temperature and humidity nudges its upper layers, which damps long-term trends. This series therefore reads as a record of interannual drought events rather than as a precise measure of a century-scale drying rate. That note appears under each soil-moisture figure on the site as well as here, since the limitation bears on how the trend line itself should be read rather than only on how the data was built. The root-zone mean omits layer 4 (100–289cm) — below the rooting depth of nearly all annual crops, and slow enough to act as a groundwater store, which Hydrological Drought already covers.

Result. A detected global increase in the root-zone series (D2+: +2.05 points/decade, p=0.013), and at every severity level D0 through D4. Per continent, a detected increase in South America (+3.51 points/decade), North America (+1.78) and Asia (+1.61), with Africa a borderline case that clears the flat 10% significance bar (p=0.066) but not the multiple-comparisons-adjusted one; nothing detected in Europe or Oceania. The surface (0–7cm) series climbs more steeply than the root zone at every level, the expected behaviour of a faster-responding shallow layer, and every one of its five levels clears both detection bars. Taken with the other two drought types, South America shows a detected increase on all three independent measures, Africa on rainfall and river flow, Asia and North America on soil moisture alone, and Europe and Oceania on none.

These results changed on 15 September 2026, and the reason sits in the aggregation rather than in the data. Until then this index and both meteorological ones averaged their 5° grid cells equally, which yields no global average: a 5° cell at 60° of latitude covers about half the area of an equatorial one. Of the 867 land cells in the grid, 263 sat south of 60°S — 30.3% of the cell count against 9.8% of the land area — so Antarctica held 3.08 times its area's weight while Africa held 0.55 times, South America 0.57, Asia 0.66 and Oceania 0.61 of theirs. The count discounted the continents carrying the signal. Weighting each cell by its spherical area times its land fraction moved the global root-zone series from no detected change (p=0.40) to a detected increase, took North America's from no detected change to a detected increase, and did the same to the precipitation-only meteorological series at every severity level. The audit behind this sits in the repository under `audit/drought/`, with every figure traceable to a CSV.

Hydrological Drought

The low-flow counterpart to Flooding, from the same GloFAS discharge record and the same 1,074 pour-point cells — a river-flow deficit rather than a rainfall deficit, and the drought type that closes navigation, empties reservoirs and curtails hydropower. Each cell's monthly mean discharge enters a 3-month trailing window (the Standardized Streamflow Index convention, and the same timescale Drought's SPI-3/SPEI-3 indices use), percentile-ranked against that cell's same-calendar-month history and classified into the same USDM-equivalent D0–D4 categories, so the three drought panels compare directly. Monthly rather than daily, unlike Flooding's high-flow index: a hydrological drought accumulates over a season, where a flood peaks in a day. The pipeline drops months with fewer than 90% of their days present, so a partial final month cannot enter the ranking as though it were a full one.

The record starts in 1982, reusing Flooding's `FLOOD_INDEX_RELIABLE_START_YEAR` rather than declaring a second cutoff — the same spin-up artifact underlies both, and it matters more here than it does for floods: artificially high early flow suppresses early drought, which would manufacture a drying trend out of a model artifact, the direction that would flatter a "drought is worsening" reading. The cutoff does not produce the trend. Recomputing the percentiles from scratch at start years of 1979, 1982, 1985, 1990 and 1995 moves Sen's slope on the global D2+ series only between +0.55 and +0.87 points per decade — same sign and order of magnitude throughout. The index also recovers independently documented events without any tuning toward them: its highest years are 2023, 2024, 2022 and 2025 (the Amazon and Panama Canal droughts, the 2022 Yangtze and European drought), then 2015 and 1983, the two strongest El Niños of the later 20th century. The series ends a few months earlier than the ERA5-based drought indices, since the GloFAS consolidated reanalysis publishes on a lag.

Cold Extremes

The structural counterpart to Heat Waves: four standard ETCCDI/CLIMDEX cold-side indices (TNn, CSDI, TN10p, Frost Days) built from the same GHCN-Daily GSN network and station data, using the same pooled-percentile-window and spell-duration-run logic as TXx/WSDI/TN90p, generalized to the cold side. Frost Days counts days below a fixed freezing point — an absolute TMIN<0°C count. The reliable trend window starts in 1949, matching Heat Waves' station-count threshold. San Antonio's station record shows TNn of −12.7°C and CSDI of 7 days in 2021 (against 0 CSDI days in each neighboring year), matching the documented February 2021 Winter Storm Uri cold wave (NWS-recorded low of −12.8°C).

Flooding

GloFAS (Global Flood Awareness System), ERA5-forced LISFLOOD reanalysis, subsampled to 1,074 "pour point" cells (the highest-upstream-area grid cell in each of the same 5° blocks Drought uses) — river discharge moves as a channelized quantity, so this site applies the standard gridded-hydrology "pour point" technique rather than Drought's block-mean approach. Two distinct series appear alongside each other: an invented-here 90th-percentile-of-its-history "high flow" metric (continuous, about 10% of days qualify at any cell by construction), and GloFAS's published 2/5/20-year return-period discharge thresholds, classified into the same Alert/Warning/Severe

tiers GloFAS's operational forecasting system uses (cumulative — a Severe day also counts as Warning and Alert). Both series exclude 1979–1981: GloFAS-ERA5's documented one-year model spin-up (Harrigan et al. 2020) leaves a longer residual bias in at least one region — Africa's pour-point cells averaged about 56% above their 1985–2025 baseline discharge in 1979, elevated fairly uniformly across all 12 months and fading only gradually through 1980–1981, consistent with a slow-draining-groundwater spin-up artifact rather than an actual flood event (other continents' 1979 values show no comparable anomaly). A single cutoff, `FLOOD_INDEX_RELIABLE_START_YEAR = 1982`, applies to every region and both series. Each region's highest-flood months line up with documented events: 1998 (El Niño East Africa and Yangtze River floods), 1982–83 (one of the 20th century's strongest El Niños, catastrophic South American flooding), 1988 (the Khartoum/Sudan flood), 2010 (the Pakistan floods) and 2010–11 (La Niña Queensland floods), 2019 (US Midwest flooding), and 2022–2024 (eastern Australia, Greece/Balkans, and West/Central Africa flood events). See `docs/FLOODING_METHODOLOGY.md` for the full construction.

Tornadoes (United States) & Severe Convective Storms

Tornado counts reuse the sibling US Extreme Weather Dashboard's pipeline directly, sourced from the NCEI Storm Events Database (reconstructed tornado tracks). The reliable trend window starts where NEXRAD-era radar and spotter coverage began detecting far more weak tornadoes than earlier decades could — an observing-network change rather than a climate signal in the counts before then. The United States records the large majority of the world's known tornadoes: NOAA/NSSL's international tornado climatology puts the US share near 75% of the global total (Canada adds about 5% more, so North America accounts for about 80%), a consequence of the Great Plains and Midwest's combination of moist Gulf air, dry continental air, and jet-stream shear. This concentration explains why the Tornadoes page pairs US tornado counts with global CAPE as a proxy for severe-thunderstorm-favorable conditions, rather than presenting CAPE alone as a tornado count. See Convective Instability (CAPE) above for that variable's construction.

Loss Normalization

Not a live GWX pipeline like the variables above — a curated literature page (built on Pielke 2020's full 53-study normalization review) plus two separately sourced pie charts covering economic losses and loss of life, 1980–2025. Economic-by-phenomenon comes directly from EM-DAT's published dollar totals; economic-by-continent required reconstructing dollar figures from a %-of-GDP series (World Bank nominal GDP, current US$), since no ready-made continent-level dollar total exists — summing the reconstruction back up by phenomenon reproduces EM-DAT's totals within 1–3%. Loss-of-life comes from a separate source (the economic paper makes no fatality claims): North America accounts for over half of economic losses but under 4% of the weather-related death toll over the same window, while Africa and Asia together account for about 74% of deaths, each dominated by a different cause (African drought, Asian tropical cyclones).

Full per-variable technical detail (data sources, cost estimates, validation checks) lives in each variable's methodology document in this project's source repository (`docs/*_METHODOLOGY.md`).

Appendix A: Variable & Data Source Directory

Every headline variable on this site (25 global variables plus 47 continent-scoped tiles, 72 total), its data source, unit, and reliable trend window.

VARIABLE	PHENOMENON	SOURCE	UNIT	WINDOW
Agricultural Drought — Global Soil-Moisture Deficit	Drought	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Monthly	% of land area	1979–2026
Agricultural Drought — Soil-Moisture Deficit — Africa	Drought	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Monthly	% of land area	1979–2026
Agricultural Drought — Soil-Moisture Deficit — Asia	Drought	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Monthly	% of land area	1979–2026
Agricultural Drought — Soil-Moisture Deficit — Europe	Drought	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Monthly	% of land area	1979–2026
Agricultural Drought — Soil-Moisture Deficit — North America	Drought	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Monthly	% of land area	1979–2026

VARIABLE	PHENOMENON	SOURCE	UNIT	WINDOW
Agricultural Drought — Soil-Moisture Deficit — Oceania	Drought	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Monthly	% of land area	1979–2026
Agricultural Drought — Soil-Moisture Deficit — South America	Drought	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Monthly	% of land area	1979–2026
Hydrological Drought — Global River Low-Flow Extent	Drought	GloFAS v4.0 (Copernicus CEMS Global Flood Awareness System) Monthly	% of pour-point cells	1982–2026
Hydrological Drought — River Low-Flow Extent — Africa	Drought	GloFAS v4.0 (Copernicus CEMS Global Flood Awareness System) Monthly	% of pour-point cells	1982–2026
Hydrological Drought — River Low-Flow Extent — Asia	Drought	GloFAS v4.0 (Copernicus CEMS Global Flood Awareness System) Monthly	% of pour-point cells	1982–2026
Hydrological Drought — River Low-Flow Extent — Europe	Drought	GloFAS v4.0 (Copernicus CEMS Global Flood Awareness System) Monthly	% of pour-point cells	1982–2026

VARIABLE	PHENOMENON	SOURCE	UNIT	WINDOW
Hydrological Drought — River Low-Flow Extent — North America	Drought	GloFAS v4.0 (Copernicus CEMS Global Flood Awareness System) Monthly	% of pour-point cells	1982–2026
Hydrological Drought — River Low-Flow Extent — Oceania	Drought	GloFAS v4.0 (Copernicus CEMS Global Flood Awareness System) Monthly	% of pour-point cells	1982–2026
Hydrological Drought — River Low-Flow Extent — South America	Drought	GloFAS v4.0 (Copernicus CEMS Global Flood Awareness System) Monthly	% of pour-point cells	1982–2026
Meteorological Drought — Global Severe-or-Worse Land Area	Drought	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Monthly	% of land area	1979–2026
Meteorological Drought — Severe-or-Worse Land Area — Africa	Drought	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Monthly	% of land area	1979–2026
Meteorological Drought — Severe-or-Worse Land Area — Asia	Drought	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Monthly	% of land area	1979–2026

VARIABLE	PHENOMENON	SOURCE	UNIT	WINDOW
Meteorological Drought — Severe-or-Worse Land Area — Europe	Drought	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Monthly	% of land area	1979–2026
Meteorological Drought — Severe-or-Worse Land Area — North America	Drought	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Monthly	% of land area	1979–2026
Meteorological Drought — Severe-or-Worse Land Area — Oceania	Drought	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Monthly	% of land area	1979–2026
Meteorological Drought — Severe-or-Worse Land Area — South America	Drought	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Monthly	% of land area	1979–2026
Cold Extremes — CSDI (Cold Spell Duration Index)	Extreme Cold	NOAA GHCN-Daily, GCOS Surface Network (GSN) stations Annual	days per year	1949–2025
Cold Extremes — Frost Days	Extreme Cold	NOAA GHCN-Daily, GCOS Surface Network (GSN) stations Annual	days per year	1949–2025

VARIABLE	PHENOMENON	SOURCE	UNIT	WINDOW
Cold Extremes — TN10p (Cold Nights)	Extreme Cold	NOAA GHCN-Daily, GCOS Surface Network (GSN) stations Annual	% of valid days	1949–2025
Cold Extremes — TNn (Annual Min Temperature)	Extreme Cold	NOAA GHCN-Daily, GCOS Surface Network (GSN) stations Annual	°C (annual min daily low)	1949–2025
Heat Waves — Europe Heat Wave Index	Extreme Heat	NOAA GHCN-Daily, GCOS Surface Network (GSN) stations, Europe subset Annual	events per station per year	1949–2025
Heat Waves — Europe Magnitude Index (HWMId-style)	Extreme Heat	NOAA GHCN-Daily, GCOS Surface Network (GSN) stations, Europe subset Annual	magnitude index (dimensionless)	1949–2025
Heat Waves — Global Heat Wave Index	Extreme Heat	NOAA GHCN-Daily, GCOS Surface Network (GSN) stations Annual	events per station per year	1949–2025
Heat Waves — Magnitude Index (HWMId-style)	Extreme Heat	NOAA GHCN-Daily, GCOS Surface Network (GSN) stations Annual	magnitude index (dimensionless)	1949–2025

VARIABLE	PHENOMENON	SOURCE	UNIT	WINDOW
Heat Waves — North America Heat Wave Index	Extreme Heat	NOAA NCEI nClimGrid-Daily (homogenized), via the sibling US Extreme Weather Dashboard Annual	days per year	1951–2025
Heat Waves — North America Magnitude Index (HWMId-style)	Extreme Heat	NOAA GHCN-Daily, GCOS Surface Network (GSN) stations, North America subset Annual	magnitude index (dimensionless)	2000–2025
Heat Waves — TN90p (Warm Nights)	Extreme Heat	NOAA GHCN-Daily, GCOS Surface Network (GSN) stations Annual	% of valid days	1949–2025
Heat Waves — TXx (Annual Max Temperature)	Extreme Heat	NOAA GHCN-Daily, GCOS Surface Network (GSN) stations Annual	°C (annual max daily high)	1949–2025
Heat Waves — WSDI (Warm Spell Duration Index)	Extreme Heat	NOAA GHCN-Daily, GCOS Surface Network (GSN) stations Annual	days per year	1949–2025
Flooding — River Discharge — Africa	Flooding	GloFAS (Global Flood Awareness System), Copernicus Early Warning Data Store Monthly	% of pour-point cells	1982–2026

VARIABLE	PHENOMENON	SOURCE	UNIT	WINDOW
Flooding — River Discharge — Asia	Flooding	GloFAS (Global Flood Awareness System), Copernicus Early Warning Data Store Monthly	% of pour-point cells	1982–2026
Flooding — River Discharge — Europe	Flooding	GloFAS (Global Flood Awareness System), Copernicus Early Warning Data Store Monthly	% of pour-point cells	1982–2026
Flooding — River Discharge — North America	Flooding	GloFAS (Global Flood Awareness System), Copernicus Early Warning Data Store Monthly	% of pour-point cells	1982–2026
Flooding — River Discharge — Oceania	Flooding	GloFAS (Global Flood Awareness System), Copernicus Early Warning Data Store Monthly	% of pour-point cells	1982–2026
Flooding — River Discharge — South America	Flooding	GloFAS (Global Flood Awareness System), Copernicus Early Warning Data Store Monthly	% of pour-point cells	1982–2026
Flooding — River Discharge High-Flow Extent	Flooding	GloFAS (Global Flood Awareness System), Copernicus Early Warning Data Store Monthly	% of pour-point cells	1982–2026

VARIABLE	PHENOMENON	SOURCE	UNIT	WINDOW
Convective Instability (CAPE)	Severe Convective Storms	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Annual	J/kg, global 12Z mean	1979 – 2025
Tornadoes (United States)	Severe Convective Storms	NCEI Storm Events Database (reconstructed tornado tracks) Annual	tornadoes per year	1980 – 2025
Widespread / High-CAPE Days	Severe Convective Storms	ARCO-ERA5 (ECMWF ERA5 reanalysis, Google Cloud mirror) Annual	days per year	1979 – 2025
Tropical Cyclones — Accumulated Cyclone Energy (ACE)	Tropical Cyclones	global-tropical-cyclones.com (HURDAT2 + IBTrACS + real-time) Annual	ACE units (10^4 kt²)	1980 – 2025
Tropical Cyclones — Accumulated Cyclone Energy (ACE) — Africa	Tropical Cyclones	global-tropical-cyclones.com (HURDAT2 + IBTrACS + real-time) Annual	ACE units (10^4 kt²)	1980 – 2025
Tropical Cyclones — Accumulated Cyclone Energy (ACE) — Asia	Tropical Cyclones	global-tropical-cyclones.com (HURDAT2 + IBTrACS + real-time) Annual	ACE units (10^4 kt²)	1980 – 2025

VARIABLE	PHENOMENON	SOURCE	UNIT	WINDOW
Tropical Cyclones — Accumulated Cyclone Energy (ACE) — North America	Tropical Cyclones	global-tropical-cyclones.com (HURDAT2 + IBTrACS + real-time) Annual	ACE units (10^4 kt²)	1980–2025
Tropical Cyclones — Accumulated Cyclone Energy (ACE) — Oceania	Tropical Cyclones	global-tropical-cyclones.com (HURDAT2 + IBTrACS + real-time) Annual	ACE units (10^4 kt²)	1980–2025
Tropical Cyclones — ACE per Storm	Tropical Cyclones	global-tropical-cyclones.com (HURDAT2 + IBTrACS + real-time) Annual	ACE units (10^4 kt²) per storm	1980–2025
Tropical Cyclones — Frequency by Category	Tropical Cyclones	global-tropical-cyclones.com (HURDAT2 + IBTrACS + real-time) Annual	storms per season	1980–2025
Tropical Cyclones — Global Landfalls	Tropical Cyclones	global-tropical-cyclones.com (HURDAT2 + IBTrACS + real-time) Annual	landfalls per season	1980–2025
Tropical Cyclones — Proportion of Hurricanes That Are Major	Tropical Cyclones	global-tropical-cyclones.com (HURDAT2 + IBTrACS + real-time) Annual	% of hurricanes	1980–2025

VARIABLE	PHENOMENON	SOURCE	UNIT	WINDOW
Tropical Cyclones — Rapid Intensification	Tropical Cyclones	global-tropical-cyclones.com (HURDAT2 + IBTrACS + real-time) Annual	% of named storms	1980–2025
Wildfire — Burned Area (GWIS) — Africa	Wildfire	Global Wildfire Information System (GWIS/JRC), via Our World in Data Annual	hectares	2002–2024
Wildfire — Burned Area (GWIS) — Asia	Wildfire	Global Wildfire Information System (GWIS/JRC), via Our World in Data Annual	hectares	2002–2024
Wildfire — Burned Area (GWIS) — Europe	Wildfire	Global Wildfire Information System (GWIS/JRC), via Our World in Data Annual	hectares	2002–2024
Wildfire — Burned Area (GWIS) — North America	Wildfire	Global Wildfire Information System (GWIS/JRC), via Our World in Data Annual	hectares	2002–2024
Wildfire — Burned Area (GWIS) — Oceania	Wildfire	Global Wildfire Information System (GWIS/JRC), via Our World in Data Annual	hectares	2002–2024

VARIABLE	PHENOMENON	SOURCE	UNIT	WINDOW
Wildfire — Burned Area (GWIS) — South America	Wildfire	Global Wildfire Information System (GWIS/JRC), via Our World in Data Annual	hectares	2002–2024
Wildfire — Dry Matter Combusted (GFED5)	Wildfire	Global Fire Emissions Database (GFED5) Annual	1e12 g/year (DM)	2001–2024
Wildfire — Dry Matter Combusted (GFED5) — Africa	Wildfire	Global Fire Emissions Database (GFED5) Annual	1e12 g/year (DM)	2001–2024
Wildfire — Dry Matter Combusted (GFED5) — Asia	Wildfire	Global Fire Emissions Database (GFED5) Annual	1e12 g/year (DM)	2001–2024
Wildfire — Dry Matter Combusted (GFED5) — Europe	Wildfire	Global Fire Emissions Database (GFED5) Annual	1e12 g/year (DM)	2001–2024
Wildfire — Dry Matter Combusted (GFED5) — North America	Wildfire	Global Fire Emissions Database (GFED5) Annual	1e12 g/year (DM)	2001–2024

VARIABLE	PHENOMENON	SOURCE	UNIT	WINDOW
Wildfire — Dry Matter Combusted (GFED5) — Oceania	Wildfire	Global Fire Emissions Database (GFED5) Annual	1e12 g/year (DM)	2001–2024
Wildfire — Dry Matter Combusted (GFED5) — South America	Wildfire	Global Fire Emissions Database (GFED5) Annual	1e12 g/year (DM)	2001–2024
Wildfire — Global Burned Area (GWIS)	Wildfire	Global Wildfire Information System (GWIS/JRC), via Our World in Data Annual	hectares	2002–2024
Extratropical Cyclone Intensity — Minimum Pressure	Winter Storms	CEDA / TRACK catalog (Gray, Volonte, Martinez-Alvarado, Harvey 2024) Annual	hPa (lower = more intense)	1980–2021
Extratropical Cyclone Intensity — Minimum Pressure — Asia	Winter Storms	CEDA / TRACK catalog (Gray, Volonte, Martinez-Alvarado, Harvey 2024) Annual	hPa (lower = more intense)	1980–2021

VARIABLE	PHENOMENON	SOURCE	UNIT	WINDOW
Extratropical Cyclone Intensity — Minimum Pressure — Europe	Winter Storms	CEDA / TRACK catalog (Gray, Volonte, Martinez-Alvarado, Harvey 2024) Annual	hPa (lower = more intense)	1980 – 2021
Extratropical Cyclone Intensity — Minimum Pressure — North America	Winter Storms	CEDA / TRACK catalog (Gray, Volonte, Martinez-Alvarado, Harvey 2024) Annual	hPa (lower = more intense)	1980 – 2021

Appendix B: Full Bibliography

The complete citation list backing the GWX dashboard's methods and findings, grouped by topic — identical to the Library page.

Tropical Cyclones

- Kossin, J.P., Knapp, K.R., Olander, T.L., Velden, C.S. (2020). Global increase in major tropical cyclone exceedance probability over the past four decades. *Proceedings of the National Academy of Sciences, 117(22), 11975–11980*. The finding behind AR6 SPM statement A.3.4. See the Detection & Attribution page for a documented critique of how it reached AR6, and the Kossin et al. correction entry.
- Kossin, J.P., Knapp, K.R., Olander, T.L., Velden, C.S. (2020). Correction for Kossin et al., Global increase in major tropical cyclone exceedance probability over the past four decades. *Proceedings of the National Academy of Sciences, 117(45), 28532*. Published before AR6's citation deadline; narrows the statistically significant result from global to two basins.
- Klotzbach, P.J., Landsea, C.W. (2015). Extremely intense hurricanes: Revisiting Webster et al. (2005) after 10 years. *Journal of Climate, 28(19), 7621–7629*. Basis for the 1980 reliable-trend-window start used here (pre-1980s satellite intensity estimates predate the standardized Dvorak technique).
- Klotzbach, P.J., Bell, M.M., Bowen, S.G., Gibney, E.J., Knapp, K.R., Schreck III, C.J. (2022). Trends in global tropical cyclone activity: 1990–2021. *Geophysical Research Letters, 49, e2021GL095774*.
- Bhatia, K.T., Vecchi, G.A., Knutson, T.R., Murakami, H., Kossin, J., Dixon, K.W., Whitlock, C.E. (2022). A potential explanation for the global increase in tropical cyclone rapid intensification. *Nature Communications, 13, 6626*. Post-AR6. A candidate physical mechanism (a warming ocean, more favorable environments) for the global rapid-intensification-rate increase the Detection & Attribution page discusses via the Kossin et al. 2020 finding.
- Maue, R.E. (2011). Recent historically low global tropical cyclone activity. *Geophysical Research Letters, 38, L14803*.

- Weinkle, J., Maue, R., Pielke Jr., R. (2012). Historical global tropical cyclone landfalls. *Journal of Climate, 25(13), 4729–4735*. Supplies the landfall definition the Global Landfalls variable applies -- the storm center crossing a coastline, detected from fix positions rather than from a source's landfall flag. Ryan Maue's independent compilation at climatlas.com applies the same method and replicates that variable's findings; see the Methodology page.
- Balaguru, K., Chang, C.-C., Leung, L.R., Foltz, G.R., Hagos, S.M., Wehner, M.F., Kossin, J.P., Ting, M., Xu, W. (2024). A global increase in nearshore tropical cyclone intensification. *Earth's Future, 12(5), e2023EF004230*. Post-AR6. Rapid intensification events within 400 km of a coastline tripled globally from 1980 to 2020 -- a coastal-landfall-focused complement to Bhatia et al. (2022)'s basin-wide mechanism finding.
- Knutson, T., Camargo, S.J., Chan, J.C.L., Emanuel, K., Ho, C.-H., Kossin, J., Mohapatra, M., Satoh, M., Sugi, M., Walsh, K., Wu, L. (2019). Tropical cyclones and climate change assessment: Part I. Detection and attribution. *Bulletin of the American Meteorological Society, 100(10), 1987–2007*. The World Meteorological Organization expert-team consensus assessment of which global and basin-scale tropical cyclone trends are detectable in the observational record, the multi-decade synthesis alongside the detection standard here.

Heat & Cold Extremes

- Zhang, X., Hegerl, G., Zwiers, F.W., Kenyon, J. (2005). Avoiding inhomogeneity in percentile-based indices of temperature extremes. *Journal of Climate, 18(11), 1641–1651*. The ETCCDI/CLIMDEX standard definitions (fixed 1961-1990 base period, bootstrap-corrected percentile thresholds) the Heat Waves (TXx/WSDI/TN90p) and Cold Extremes (TNn/CSDI/TN10p) pages both implement directly rather than a project-specific choice.
- Zhang, X., Alexander, L., Hegerl, G.C., Jones, P., Klein Tank, A., Peterson, T.C., Trewin, B., Zwiers, F.W. (2011). Indices for monitoring changes in extremes based on daily temperature and precipitation data. *WIREs Climate Change, 2(6), 851–870*. The source of the TXx/WSDI/TN90p/TNn/CSDI/TN10p/FD indices here: a broader ETCCDI index-set review.

- Seneviratne, S.I., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Di Luca, A., Ghosh, S., Iskandar, I., Kossin, J., Lewis, S., Otto, F., Pinto, I., Satoh, M., Vicente-Serrano, S.M., Wehner, M., Zhou, B. (2021). Weather and climate extreme events in a changing climate. *In: Climate Change 2021: The Physical Science Basis (IPCC AR6 WGI, Chapter 11), Cambridge University Press*. AR6's chapter-length assessment of temperature and precipitation extremes globally, covering both the Heat Waves and Cold Extremes pages.
- McKinnon, K.A., Simpson, I.R., Williams, A.P. (2024). The pace of change of summertime temperature extremes. *Proceedings of the National Academy of Sciences, 121(42), e2406143121*. Post-AR6. Ninety years of station data (1959–2023): the hottest summer days have warmed at essentially the same rate as the seasonal median, with the observed widening of the warm tail driven by the cold tail warming more slowly rather than the hot tail accelerating.

Drought

- Vicente-Serrano, S.M., Peña-Angulo, D., Beguería, S., Domínguez-Castro, F., Tomás-Burguera, M., Noguera, I., Gimeno-Sotelo, L., El Kenawy, A. (2022). Global drought trends and future projections. *Philosophical Transactions of the Royal Society A, 380, 20210285*. The paper that motivated the Drought page's AED-inclusive series, and two of its choices match the ones here: a three-month timescale, and AED from ERA5. It uses the full FAO-56 Penman-Monteith equation where this site uses Hargreaves. The results now DIVERGE, and the Drought section of the Methodology page says so: the paper reports no substantial global change in meteorological drought over at least 120 years and a statistically significant DECLINE in 12-month-SPI drought area over 1950-2020 in both CRU and GPCC, with its AED-inclusive drying signal regional rather than global. This site's precipitation-only series shows a detected global increase, the opposite sign, and its AED-inclusive series detects globally. The two agreed until 15 September 2026, when correcting an unweighted grid-cell average lifted the precipitation-only series above the detection bar. Gauge-based precipitation against ERA5 reanalysis, 12 months against three, and 1950-2020 against 1979-2026 all bear on the comparison, which this site leaves standing rather than resolved.

- Allen, R.G., Pereira, L.S., Raes, D., Smith, M. (1998). Crop evapotranspiration: Guidelines for computing crop water requirements. *FAO Irrigation and Drainage Paper No. 56, Food and Agriculture Organization of the United Nations, Rome*. Source of the Hargreaves-Samani method this site uses to estimate atmospheric evaporative demand from ERA5 temperature; verified against the paper's worked example (Example 8) to within 0.1%.
- Xu, J., Zhang, X., McColl, K.A., Berg, A., Zhou, S., Yang, J., Dong, Z., Luo, Y., Fan, Y. (2026). Global drought shows no detectable recent acceleration under climate warming. *Communications Earth & Environment, 7, 726*. Post-AR6, and it cuts against the magnitude of this site's AED-inclusive series rather than supporting it, and so earns a place here. Applying six potential-evapotranspiration formulations to SPEI over 1981-2024, the authors report that Penman-type PET produces drying trends at least six times stronger than energy-constrained formulations (drought-area trends 7.8x), because Penman-type estimates neglect the land-atmosphere coupling that limits evaporative demand. The share of the drought trend attributable to PET falls from 47.5% to 25% once that constraint applies, leaving precipitation as the dominant driver at 75%. Their first-order finding still shows a statistically significant global drying trend under both PET families; they find no evidence for ACCELERATION, a second-order trend this site does not measure or claim. The Hargreaves method this site uses sits among the unconstrained estimators rather than the energy-based ones, so the Methodology page's caveat quotes this paper's figures. Their target is Gebrechorkos et al. 2025 below, which Nature retracted nine days before this paper appeared.
- Milly, P.C.D., Dunne, K.A. (2016). Potential evapotranspiration and continental drying. *Nature Climate Change, 6, 946-949*. The energy-only potential-evapotranspiration formulation (PET = 0.8 x net radiation / latent heat of vaporisation) that Xu et al. 2026 above adopt as their principal alternative to Penman-type estimates. This site computes it alongside Penman-Monteith from the same ARCO-ERA5 radiation fetch, since it requires only net radiation.

- Gebrechorkos, S.H., Sheffield, J., Vicente-Serrano, S.M., Funk, C., Miralles, D.G., Peng, J., Dyer, E., Talib, J., Beck, H.E., Singer, M.B., Dadson, S.J. (2025). Warming accelerates global drought severity [RETRACTED]. *Nature, 642, 628–635 — RETRACTED 2 September 2026*. RETRACTED by Nature on 2 September 2026 (doi:10.1038/s41586-026-11027-z). The retraction notice lists four problems: study-wide averages taken without area weighting of grid cells, GLEAM v3 results presented as GLEAM4, a date-parsing error that misassigned months where the authors split 1981-2017 from 2018-2022, and an arid-region mask (mean annual precipitation under 180mm) applied to one figure and omitted from the drought-area percentages. The paper had reported a ~40% AED-driven increase in global drought severity, and this Library cited it until 15 September 2026 as post-AR6 confirmation of the mechanism the SPEI-style series measures. A retracted paper supports nothing: the entry stays for the record, and that mechanism now rests on the Vicente-Serrano et al. 2022 entry. Two of the four problems, area weighting and the arid mask, prompted a full audit of this site's drought index (see the Drought section of the Methodology page).
- Balsamo, G., Beljaars, A., Scipal, K., Viterbo, P., van den Hurk, B., Hirschi, M., Betts, A.K. (2009). A Revised Hydrology for the ECMWF Model: Verification from Field Site to Terrestrial Water Storage and Impact in the Integrated Forecast System. *Journal of Hydrometeorology, 10(3), 623–643*. Describes HTESSEL, the ECMWF land-surface scheme whose four soil layers ERA5 reports. The agricultural-drought series here depth-weights layers 1-3 by their real thicknesses (7, 21 and 72cm) into a 0-100cm root-zone value rather than averaging them equally, and reports layer 1 alone as the 0-7cm surface series; this paper supplies the source for those depths.

Wildfire

- Andela, N., Morton, D.C., Giglio, L., Chen, Y., van der Werf, G.R., Kasibhatla, P.S., DeFries, R.S., Collatz, G.J., Hantson, S., Kloster, S., Bachelet, D., Forrest, M., Lasslop, G., Li, F., Mangeon, S., Melton, J.R., Yue, C., Randerson, J.T. (2017). A human-driven decline in global burned area. *Science, 356(6345), 1356–1362*. The Wildfire page's GWIS/land-cover series confirms this paper's finding directly: global burned area has declined roughly 18% from 2002–2012 to 2013–2024.

- Chen, Y., Hall, J., van Wees, D., Andela, N., Hantson, S., Giglio, L., van der Werf, G.R., Morton, D.C., Randerson, J.T. (2023). Multi-decadal trends and variability in burned area from the fifth version of the Global Fire Emissions Database (GFED5). *Earth System Science Data, 15, 5227–5259*.
- Jones, M.W., Abatzoglou, J.T., Veraverbeke, S., Andela, N., Lasslop, G., Forkel, M., Smith, A.J.P., Burton, C., Betts, R.A., van der Werf, G.R., Sitch, S., Canadell, J.G., Santín, C., Kolden, C., Doerr, S.H., Le Quéré, C. (2022). Global and regional trends and drivers of fire under climate change. *Reviews of Geophysics, 60(3), e2020RG000726*. Post-AR6. A synthesis of 500+ studies and satellite/model reanalysis: burned area declines globally even as fire weather severity and human exposure both rise, the same divergence the Wildfire page tracks via the GWIS/land-cover series.
- Kelley, D.I., Burton, C., Di Giuseppe, F., Jones, M.W., Barbosa, M.L.F., et al. (2025). State of Wildfires 2024–2025. *Earth System Science Data, 17(10), 5377–5488*. Post-AR6. The most recent edition of this annual assessment: global burned area stayed below average through the March 2024-February 2025 fire season even as individual events (Los Angeles, January 2025; Canada's boreal forests; South American rainforest and wetland fires) grew more extreme and costly -- the exact declining-area-vs-costlier-extremes divergence Jones et al. (2022) above first documented, now current through the most recent fire season.

Tornadoes & Severe Convective Storms

- Brooks, H.E., Doswell III, C.A. (2001). Some aspects of the international climatology of tornadoes by damage classification. *Atmospheric Research, 56(1-4), 191–201*. Source of the ~75%-of-world's-known-tornadoes-in-the-US figure the Tornadoes page cites as the basis for using US counts as a global severe-convective-storm indicator.
- Taszarek, M., Allen, J.T., Marchio, M., Brooks, H.E. (2021). Global climatology and trends in convective environments from ERA5 and rawinsonde data. *npj Climate and Atmospheric Science, 4, 35*. Source of the global CAPE climatology and trend methodology the Tornadoes page's CAPE series (ARCO-ERA5) rests on -- finds mixed-direction regional CAPE/shear trends, consistent with this site's mixed-direction detected changes across its three CAPE-derived series.

Extratropical Cyclones

- Gray, S.L., Volonté, A., Martínez-Alvarado, O., Harvey, B.J. (2024). A global climatology of sting-jet extratropical cyclones. *Weather and Climate Dynamics, 5, 1523–1544*. Source of the TRACK-catalog extratropical cyclone intensity series used here.
- Sanders, F., Gyakum, J.R. (1980). Synoptic-dynamic climatology of the "bomb". *Monthly Weather Review, 108(10), 1589–1606*. The original "bomb cyclone" (explosive cyclogenesis) definition -- the latitude-adjusted Bergeron threshold the bomb-cyclone classification here (n_bomb_cyclones, and now the Cold Extremes/CSDI page's methodology) rests on directly.
- Keates, O., et al. (2024). Storm Ciarán — synoptic evolution and warning strategy of the intense mid-latitude windstorm affecting parts of Northwest Europe on 1/2 November 2023. *Weather, 79(4)*. Post-AR6. A recent, extreme European windstorm (one of the most intense North Atlantic extratropical cyclones on record) -- a natural future validation check for the Europe-continent ETC intensity series here, the same role the already-validated Braer Storm (1993) plays for the global series.

Flooding

- Gudmundsson, L., Boulange, J., Do, H.X., Gosling, S.N., Grillakis, M.G., Koutroulis, A.G., Leonard, M., Liu, J., Müller Schmied, H., Papadimitriou, L., Pokhrel, Y., Seneviratne, S.I., Satoh, Y., Thiery, W., Westra, S., Zhang, X., Zhao, F. (2021). Globally observed trends in mean and extreme river flow attributed to climate change. *Science, 371(6534), 1159–1162*. A global streamflow-trend detection study feeding directly into AR6 Ch.11's river-flood assessment: observed trends are real but not spatially coherent in one direction, the same patchy, no-single-global-signal pattern as this site's GloFAS-based continent series.
- Harrigan, S., Zsoter, E., Alfieri, L., Prudhomme, C., Salamon, P., Wetterhall, F., Barnard, C., Cloke, H., Pappenberger, F. (2020). GloFAS-ERA5 operational global river discharge reanalysis 1979–present. *Earth System Science Data, 12, 2043–2060*. Primary source for the Flooding page (both the percentile-based and GloFAS-return-period-based series). The paper's documented 1-year model spin-up procedure leaves a residual bias in slow-draining basins through 1981, the basis for the flooding reliable-trend-window start year used here.

- Wasko, C., Sharma, A. (2017). Global assessment of flood and storm extremes with increased temperatures. *Scientific Reports, 7, 7945*.
- Wasko, C., Nathan, R. (2019). Influence of changes in rainfall and soil moisture on trends in flooding. *Journal of Hydrology, 575, 432–441*.
- Ho, M., Nathan, R., Wasko, C., Vogel, E., Sharma, A. (2022). Projecting changes in flood event runoff coefficients under climate change. *Journal of Hydrology, 615, 128689*. Basis for the Flooding page's north/south-Australia divergence note.
- Tramblay, Y., Villarini, G., El Khalki, M.E., Gründemann, G., Hughes, D. (2021). Evaluation of the drivers responsible for flooding in Africa. *Water Resources Research, 57(6), e2021WR029595*. Basis for the Africa continent-page flooding note: 399 African gauges, 1981-2018, found flood magnitude more strongly driven by soil moisture than by rainfall extremes.
- Blöschl, G., Hall, J., Viglione, A., Perdigão, R.A.P., Parajka, J., Merz, B., et al. (2019). Changing climate both increases and decreases European river floods. *Nature, 573, 108–111*. Basis for the Europe continent-page flooding note: opposite-signed regional flood trends (increasing NW Europe, decreasing S/E Europe) rather than a single continent-wide direction.
- Hodgkins, G.A., Whitfield, P.H., Burn, D.H., Hannaford, J., Renard, B., Stahl, K., Fleig, A.K., Madsen, H., Mediero, L., Korhonen, J., Murphy, C., Wilson, D. (2017). Climate-driven variability in the occurrence of major floods across North America and Europe. *Journal of Hydrology, 552, 704–717*. Basis for the North America continent-page flooding note: no widespread significant trend in major-flood occurrence (1961-2010), dominated by multidecadal variability rather than a directional trend.
- Barichivich, J., Gloor, E., Peylin, P., Brienen, R.J.W., Schöngart, J., Espinoza, J.C., Pattnayak, K.C. (2018). Recent intensification of Amazon flooding extremes driven by strengthened Walker circulation. *Science Advances, 4(9), eaat8785*. Basis for the South America continent-page flooding note: a fivefold increase in severe Amazon floods at Manaus since the early 2000s.

- Do, H.X., Westra, S., Leonard, M. (2017). A global-scale investigation of trends in annual maximum streamflow. *Journal of Hydrology, 552, 28–43*. Basis for the Asia continent-page flooding note: Asia's average streamflow gauge record length (~17 years) falls short of a defensible long-term trend claim -- a data-coverage gap rather than an absence of interest.

Loss Normalization

- Pielke Jr., R. (2020). Economic 'normalisation' of disaster losses 1998–2020: a literature review and assessment. *Environmental Hazards*. Source of the full Table 1 (53 weather/climate-related normalization studies) on the Loss Normalization page.
- Pielke Jr., R. (2019). Tracking progress on the economic costs of disasters under the indicators of the sustainable development goals. *Environmental Hazards, 18(1), 1–6*. Finds weather/climate disaster losses declined as a share of global GDP from 1990, even as absolute losses rose -- the indicator the Loss Normalization page's top chart extends through 2025.
- Mohleji, S., Pielke Jr., R. (2014). Reconciliation of trends in global and regional economic losses from weather events: 1980–2008. *Natural Hazards Review, 15(4), 04014009*. Source of the Loss Normalization page's economic-loss-by-phenomenon-and-continent pie charts (extended through 2025 with fresher EM-DAT data, replacing the paper's rate-of-increase framing).
- Centre for Research on the Epidemiology of Disasters (CRED), UCLouvain (2026). EM-DAT: The International Disaster Database. *emdat.be*. Source (via Our World in Data's public mirror) of the Loss Normalization page's economic-loss and fatality data, and the Flooding/Wildfire economic-context figures on this dashboard.
- Zhang, J., Trück, S., Truong, C., Pitt, D. (2023). Time trends in losses from major tornadoes in the United States. *Weather and Climate Extremes, 41, 100579*. Added to the Loss Normalization page's study table: a significant national decline in normalized US tornado losses, 1954-2018.

- Willoughby, H.E., Hernandez, J.I., Pinnock, A. (2024). Trends in U.S. Atlantic tropical cyclone damage, 1900–2022. *Journal of Applied Meteorology and Climatology, 63(12), 1499–1510*. Uses the ICAT Damage Estimator dataset (flagged in the study table's ICAT/BDD column); reports a detected increase in normalized US Atlantic hurricane damage. See Pielke (2025) below and this same author team's 2025 reply.
- Muller, J., Mooney, K., Bowen, S.G., Klotzbach, P.J., Martin, T., Philp, T.J., Bhatt, D., Dixon, R.S., Girimurugan, S.B. (2025). Normalized hurricane damage in the United States: 1900–2022. *Bulletin of the American Meteorological Society, 106(1), E51–E67*. Also uses the ICAT/combined dataset; finds no detected trend in normalized US hurricane damage over the full record.
- Pielke Jr., R. (2025). Do not use the ICAT hurricane loss "dataset": An opportunity for course correction in climate science. *Journal of Applied Meteorology and Climatology, 64(4)*. A direct critique of the ICAT Damage Estimator dataset's reliability as a basis for trend detection, aimed at Willoughby et al. (2024) and Muller et al. (2025) above -- see Willoughby et al.'s (2025) direct reply.
- Willoughby, H.E., Hernandez, J.I., Pinnock, A. (2025). Reply to Pielke (2025). *Journal of Applied Meteorology and Climatology, 64(4)*. Direct reply to the critique above; revises the authors' 2024 trend finding down to a weaker, not-statistically-significant 0.6%/year result.
- Paprotny, D., Tilloy, A., Treu, S., Buch, A., Vousdoukas, M.I., Feyen, L., Kreibich, H., Merz, B., Frieler, K., Mengel, M. (2025). Attribution of flood impacts shows strong benefits of adaptation in Europe since 1950. *Science Advances, 11, eadt7068*. Added to the study table: a detected decrease in normalized European flood losses, attributed to adaptation.
- Paprotny, D., Terefenko, P., Śledziowski, J. (2024). HANZE v2.1: An improved database of flood impacts in Europe from 1870 to 2020. *Earth System Science Data, 16, 5145–5170*. The underlying European flood-impact database Paprotny et al. (2025) above draws on; this paper finds reporting completeness rather than a trend dominates the raw 1870-2020 record's apparent pattern.
- Vessey, A.F., Baker, A.J., Marcellin-Honore, V., Michelin, J. (2026). Combining hazard, exposure and vulnerability data to predict historical United States hurricane losses. *Natural Hazards and Earth System Sciences, 26, 2133–2150*. Primarily a loss-prediction methodology paper; an upward fit in US hurricane losses (1979-2024) appears incidentally rather than as a tested detection claim.

- Botzen, W.J.W., Estrada, F., Tol, R.S.J. (2021). Methodological issues in natural disaster loss normalisation studies. *Environmental Hazards, 20(2), 112–115*. A methods-focused commentary on normalization studies generally, added to the study table as a methods row (no empirical detection/attribution result).

Statistical Methodology

- Mann, H.B. (1945). Nonparametric tests against trend. *Econometrica, 13(3), 245–259*. The Mann-Kendall trend test itself -- the significance test lib/trend.ts applies to every variable on this site.
- Sen, P.K. (1968). Estimates of the regression coefficient based on Kendall's tau. *Journal of the American Statistical Association, 63(324), 1379–1389*. Sen's slope estimator -- the trend-magnitude (per-decade rate) figure shown on every chart's assessment text.
- Weatherhead, E.C., Reinsel, G.C., Tiao, G.C., Meng, X.-L., Choi, D., Cheang, W.-K., Keller, T., DeLuisi, J., Wuebbles, D.J., Kerr, J.B., Miller, A.J., Oltmans, S.J., Frederick, J.E. (1998). Factors affecting the detection of trends: Statistical considerations and applications to environmental data. *Journal of Geophysical Research, 103(D14), 17149–17161*. The standard formula for how many years of record a trend of a given magnitude and noise level needs for reliable detection. lib/trend.ts computes it for every variable on every build. This site does NOT publish the result, and the Detection and Time of Emergence page says why: fed the slope estimated from the record under test, it becomes post-hoc power (Hoenig & Heisey below), which cannot be used to explain away that same record's null result. Fed a projected signal assessed independently of the record, the same formula gives an emergence timescale in the sense of Crompton et al. below.
- Hamed, K.H., Rao, A.R. (1998). A modified Mann-Kendall trend test for autocorrelated data. *Journal of Hydrology, 204(1-4), 182–196*. Basis for the lag-1-autocorrelation effective-sample-size correction in lib/trend.ts -- a simplification of this paper's full multi-lag method, a GWX-specific enhancement not yet on the US dashboard.
- Benjamini, Y., Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society, Series B, 57(1), 289–300*. The false-discovery-rate correction lib/bhCorrection.ts applies across the headline variables tracked here -- see the Methodology page's multiple-comparisons section.

- Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences. *2nd edition, Routledge*. Reference point (Cohen's d ≈ 0.2/0.5/0.8 for small/medium/large effect) informing the magnitude-vs-natural-variability detection tier used here.
- Hoenig, J.M., Heisey, D.M. (2001). The abuse of power: The pervasive fallacy of power calculations for data analysis. *The American Statistician, 55(1), 19–24*. Why this site declines to publish a years-to-detection figure computed from the observed slope. Power calculated after the fact from an effect size the same data produced adds nothing beyond the p-value already reported, and reliably understates how long detection would take for any result that happened to come out null.
- Hawkins, E., Sutton, R. (2012). Time of emergence of climate signals. *Geophysical Research Letters, 39(1), L01702*. The signal-to-noise formulation of time of emergence, and the convention AR6 WG1 Chapter 12 adopts by default -- a signal-to-noise ratio above 1 against a pre-industrial baseline and interannual variability. Chapter 12 states that it assesses across multiple methods and adopts this one only where a study does not specify otherwise.
- Chadwick, C., Gironás, J., Vicuña, S., Meza, F. (2019). Estimating the local time of emergence of climatic variables using an unbiased mapping of GCMs: An application in semiarid and Mediterranean Chile. *Journal of Hydrometeorology, 20(8), 1635–1647*. The second definition of emergence named in AR6 WG1 Chapter 12's opening sentence on the subject: a signal emerges when an indicator's probability distribution becomes significantly different from its distribution over a reference period, rather than when a ratio crosses a threshold.
- Crompton, R.P., Pielke Jr, R.A., McAneney, K.J. (2011). Emergence timescales for detection of anthropogenic climate change in US tropical cyclone loss data. *Environmental Research Letters, 6(1), 014003*. A third family of emergence method, and the design the Detection and Time of Emergence page describes: take the projected signal from a source independent of the record, take the noise from the record, and solve for the years required. Applied to normalized US tropical cyclone losses the answer ran 120 to 550 years across models, and 260 years for the 18-model ensemble.

IPCC Assessment Reports

- IPCC (2021). Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. *Cambridge University Press*. The Sixth Assessment Report itself -- the comparison point for the Detection & Attribution page.