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Why observed tropical-cyclone inner-core rain trends oppose model projections: perspectives from ERA5

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The disparity between observed and projected trends in tropical cyclone (TC) inner-core rain rates remains a fundamental challenge in climate science. Over the past two decades, satellite observations show a decline in inner-core rain rates, whereas climate models and the ERA5 reanalysis project increases under warming. Here we investigate the mechanisms governing this discrepancy. We find that under the transient warming of the recent two decades ($\sim 0.4^{\circ}\text{C}$), moisture-driven rain rate increases have not materialized. Instead, the observed decline reflects falling TC intensity and an expanding radius of maximum wind, with atmospheric stability providing a robust suppressing effect. Conversely, the ERA5 increase is driven by rising reanalyzed intensity and a shrinking radius of maximum wind. Prior model-based studies typically simulate larger warming ($>1^{\circ}\text{C}$), where moisture increases dominate over suppressing effects to produce net rain rate increases. These findings validate current physical frameworks, building essential confidence in TC inner-core rainfall projections.

Introduction

Tropical cyclones (TCs) are among the most destructive natural hazards, serving as a dominant driver of extreme precipitation in coastal regions (1–4). Within these storms, the inner core harbors the most intense convective updrafts, delivering torrential rainfall over short durations that can trigger catastrophic flash flooding and landslides (5). Under a warming climate, numerical simulations, including cloud-resolving models and global climate models, consistently project increases in TC inner-core rain rates (6–14). These projected increases stem primarily from two factors: higher atmospheric moisture and greater TC intensity. Warmer sea surface temperatures enable higher TC intensity, while a warmer troposphere can hold more moisture, as described by the Clausius–Clapeyron relationship ($\sim 7\% \text{ }^{\circ}\text{C}^{-1}$).

Over the past two decades (1999–2020), multi-satellite precipitation products consistently indicate a decline in global TC inner-core rain rates (15–18). Despite the societal importance of these opposing trends, the mechanisms behind the observed decline and its relationship to model projected increases remain unresolved.

ERA5 reanalysis (19) serves as a cornerstone of modern climate science, blending millions of historical weather observations with an advanced numerical weather prediction model. It provides a spatially uniform, hourly global record of the earth’s atmosphere, serving as a flagship reanalysis and a key benchmark for diagnosing atmospheric structure and precipitation trends (20, 21). Although its 0.25-degree horizontal grid resolution limits the explicit representation of TC inner-core dynamics, ERA5 remains an essential reference for investigating long-term TC rainfall trends (16). Over the modern satellite period, ERA5 indicates rising inner-core rainfall rates, consistent with the direction projected by climate models (16). Unravelling this ERA5–satellite divergence can not only help improve future reanalysis systems such as ERA6 but also provide crucial insight into the processes driving broader model–observation disagreements.

TC intensity and environmental moisture are well-established positive controls on TC rain rate (9, 13, 22, 23). Two thermodynamic factors may further shape the inner-core rain-rate response. Atmospheric stability (AS), defined as the upper–lower tropospheric potential-temperature difference, measures resistance to vertical motion (24). The observed decline has been attributed to increased AS in recent decades (16). However, why ERA5 TC inner-core rain rate increases under

a similarly stabilizing atmosphere remains poorly understood. A later reexamination of this AS role suggested that the raw AS–TC inner-core rain-rate relationship may be trend-driven rather than a direct physical sensitivity (18). Neither study, however, controlled for confounding factors such as TC intensity, leaving the intrinsic effect of AS on inner-core rain rate unclear. Column saturation deficit (CSD), a vertically integrated measure of absolute atmospheric dryness, is another candidate control on inner-core rain rate. CSD has been shown to suppress storm-scale TC precipitation by reducing the fraction of converged moisture that reaches the surface as rain (10), although that work was restricted to the full storm footprint. Whether CSD constrains TC inner-core rain rate remains unresolved. Inner-core rain rate also depends on storm structure (18, 23, 25). For a given $V_{\max}$, the radius of maximum wind (RMW) shapes the radial wind gradient and low-level frictional convergence near the eyewall (18). A larger RMW broadens the vortex, which weakens the radial wind gradient and near-core ascent, ultimately reducing the inner-core rain rates (18, 23). A recent attribution demonstrated that the observed decline in inner-core rain rate is primarily driven by an increasing RMW and a decreasing TC intensity (18).

In this study, we begin by documenting the opposing trends between satellite observations and ERA5 in TC inner-core rain rate. Next, we ask how AS, CSD, and RMW govern inner-core rain rate. We then attribute the divergent annual trends to the trends of these drivers. Finally, we discuss the broader implications of these results for the model–observation discrepancy.

Results

Divergent observed and reanalysis inner-core rain-rate trends

Throughout, the inner-core rain rate (R_{IC}) is the storm-centered area-mean rain rate over a disk around the storm center (Materials and Methods). The disk radius follows ref. 16 for the satellite observations (100 or 125 km, set by basin and intensity category) and is fixed at 100 km for ERA5. Over the 1999–2018 period, the annual-mean TC inner-core rain rate derived from TMPA satellite observations exhibits a significant decreasing trend of $-0.65 \text{ mm h}^{-1}/\text{decade}$ (Mann–Kendall $p < 0.001$). In contrast, the ERA5 reanalysis indicates an opposing upward trend of $+0.53 \text{ mm h}^{-1}/\text{decade}$ ($p = 0.005$; Fig. 1A). The decline has been attributed to increasing AS (16),

but ERA5 rises under the same stabilization. To establish clear causality between AS and inner-core rain rate, we re-examine AS as a storm-relative environmental quantity, averaged over the surroundings of each storm rather than the vortex itself (Materials and Methods). Our storm-relative environmental AS increases at $+0.44$ K/decade ($p = 0.047$; Fig. 1B), consistent in direction with an earlier estimate of $+0.29$ K/decade in basin-averaged AS from ERA-Interim (16).

Crucially, the relationship between AS and satellite-observed inner-core rain rate is scale-dependent. At the annual-mean level, annual AS and annual TMPA inner-core rain rate are negatively correlated (Fig. 1C). Conversely, at the six-hourly snapshot level, the raw correlation between AS and TMPA inner-core rain rate is weakly positive (Fig. 1D). This contrast implies that the apparent negative relationship at the annual scale is primarily driven by co-occurring multi-decadal trends rather than a direct, storm-scale physical constraint. In addition, raw bivariate correlations can be misleading when assessing direct thermodynamic controls. A robust test of AS's impact on TC inner-core rainfall requires controlling for confounding drivers, including storm intensity and structural changes.

To evaluate whether ERA5's rain-rate increase is tied to storm dynamics, we examine storm intensity, quantified as the 10-m maximum wind speed ($V_{\max}$) along the storm tracks. Although ERA5 systematically underestimates TC intensity compared with best-track observations due to limited model resolution, it exhibits a robust increasing intensity trend of $+0.92$ m s^{-1} /decade ($p = 0.005$; Fig. 1E). In contrast, the observed $V_{\max}$ decreased at -1.87 m s^{-1} /decade over the observed analysis window ($p = 0.109$; not significant). Discrepancies also emerge in storm structure: observed RMW shows a tendency toward expansion ($+3.15$ km/decade, $p = 0.151$), whereas ERA5 depicts an inner-core contraction (-19.05 km/decade, $p < 0.001$; Fig. 1F). RMW is also markedly overestimated in ERA5 compared with observations. Notably, although ERA5 cannot fully resolve fine-scale eyewall and inner-core structures, the trends in these metrics remain meaningful, as they still reflect changes in storm dynamics.

Reexamining impact of AS, CSD, and RMW

To test whether atmospheric stability directly suppresses inner-core rain rate once co-varying drivers are accounted for, we fitted a five-predictor partial regression at the six-hourly snapshot scale. Inner-

core rain rate was regressed on the environmental AS, column saturation deficit (CSD), and total column water vapor (TCWV), together with storm intensity ($V_{\max}$) and radius of maximum wind (RMW):

$$R_{\text{IC}} = C + \beta_{\text{AS}} \cdot \text{AS} + \beta_{\text{CSD}} \cdot \text{CSD} + \beta_{\text{RMW}} \cdot \text{RMW} + \beta_{\text{TCWV}} \cdot \text{TCWV} + \beta_{V_{\max}} \cdot V_{\max} \quad (1)$$

All environmental predictors are storm-relative and derived from ERA5 (Materials and Methods). Each coefficient is a partial regression coefficient, isolating a predictor's association with inner-core rain rate while holding the other four predictors constant. We fitted the model in two configurations: an observational one, in which TMPA inner-core rain rate (2002–2018) was regressed on observed $V_{\max}$ and observed RMW together with ERA5 environmental fields, and a reanalysis one, in which the rain rate and all five predictors were taken from ERA5 (1999–2018). The observational configuration starts in 2002, because observed RMW is available only from 2002. To compare relative importance across predictors, all coefficients are standardized and reported in mm h^{-1} per predictor standard deviation (s.d.), with ordinary least-squares 95% confidence intervals.

After all other factors are controlled, the global partial regression coefficient of AS on inner-core rain rate is negative in both the reanalysis and the observations: ERA5 $-0.722 \text{ mm h}^{-1}/\text{s.d.}$ and TMPA $-0.312 \text{ mm h}^{-1}/\text{s.d.}$ (Fig. 2A). The ERA5-based suppression is statistically significant across all basins. In comparison, the observational estimate is significantly negative in the western North Pacific (-0.628), South Indian (-0.259), South Pacific (-0.337), and eastern North Pacific (-0.213), while the estimates for the North Atlantic (-0.051) and North Indian (-0.179) are negative but not statistically significant. Although ERA5 parameterizes rather than explicitly resolves eyewall deep convection, it reproduces the negative conditional AS association. This suggests that ERA5 captures the large-scale thermodynamic coupling between environmental stability and inner-core precipitation.

By contrast, the free-tropospheric moisture deficit (CSD) shows no evidence of suppressing inner-core rain rate, despite its well-documented suppression of storm-total TC rainfall (10). The global partial regression coefficient for CSD is significantly positive in ERA5 ($+0.334 \text{ mm h}^{-1}/\text{s.d.}$; 95% CI: $[+0.298, +0.370]$) and statistically indistinguishable from zero in TMPA ($+0.050 \text{ mm h}^{-1}/\text{s.d.}$; 95% CI: $[-0.006, +0.106]$) (Fig. 2B). The absence of a significant

negative association indicates that CSD exerts negligible direct suppression on the convective core. This null result is physically consistent because intense eyewall updrafts and the surrounding moist envelope within the inner core effectively decouple inner-core precipitation processes from ambient CSD.

In addition to thermodynamic stability, the radius of maximum wind exerts a prominent control on inner-core rain rate. Globally, the partial regression coefficient for RMW is negative in both datasets: TMPA yields $-0.152 \text{ mm h}^{-1}/\text{s.d.}$ (95% CI: $[-0.196, -0.108]$) and ERA5 $-0.540 \text{ mm h}^{-1}/\text{s.d.}$ (95% CI: $[-0.569, -0.511]$) (Fig. 2C), a response about three and a half times stronger in the reanalysis than in the observations. Basin-scale estimates mirror the AS pattern: the TMPA coefficient is significantly negative in the Western North Pacific (-0.194), North Atlantic (-0.334), and South Indian Ocean (-0.142), and non-significant in the South Pacific (-0.014) and North Indian Ocean ($+0.140$), whereas ERA5 is negative with confidence intervals excluding zero in all six basins. The Eastern North Pacific is the exception, where the TMPA coefficient is significantly positive ($+0.084$; 95% CI: $[+0.013, +0.156]$). Physically, these negative partial associations indicate that, for a given storm intensity, a larger RMW broadens the vortex, shallows the radial wind gradient, and weakens near-core ascent, thereby reducing inner-core rain rates.

Scale dependence of the AS and CSD associations

We next asked whether the associations of AS and CSD with TC rain rate depend on the spatial scale over which precipitation is averaged. We refit the five-predictor partial regression model across nine averaging radii, from 100 km to 500 km at 50 km intervals. The two thermodynamic controls display opposite radial dependencies: AS suppression is strongest within the inner core and weakens outward, whereas CSD suppression emerges only at broader scales (Fig. 3).

For AS, the negative association is strongest within the inner core and systematically weakens outward with increasing radius (Fig. 3A and B). At a 100 km averaging radius, the global AS regression coefficient is $-0.722 \text{ mm h}^{-1}/\text{s.d.}$ (95% CI: $[-0.757, -0.686]$) for ERA5 and $-0.458 \text{ mm h}^{-1}/\text{s.d.}$ (95% CI: $[-0.512, -0.404]$) for TMPA. All basin estimates are negative. As the averaging radius expands, the suppressive effect of AS diminishes and the coefficient crosses zero near 250 km in ERA5 and 200 km in TMPA. By 500 km, negative suppression vanishes and

flips to positive. This radial attenuation demonstrates that AS suppression is confined primarily to the TC inner core rather than broader spatial scales. The positive AS–TC rain rate relationship at broader scales is interesting but not interpreted here, as our analysis targets inner-core rain rate. The reason for this relationship remains unclear and is an open question for future studies.

CSD displays the opposing radial dependence (Fig. 3C and D). At 100 km, the global CSD coefficient is $+0.334 \text{ mm h}^{-1}/\text{s.d.}$ for ERA5 and $+0.081 \text{ mm h}^{-1}/\text{s.d.}$ for TMPA. CSD therefore provides no negative control on inner-core rain rate in either product. However, as the domain expands, both ERA5 and observations converge toward a robust negative association. By 500 km, the global CSD coefficient becomes significantly negative in both products, reaching $-0.160 \text{ mm h}^{-1}/\text{s.d.}$ (95% CI: $[-0.167, -0.152]$) for ERA5 and $-0.178 \text{ mm h}^{-1}/\text{s.d.}$ (95% CI: $[-0.192, -0.165]$) for TMPA, with all six ocean basins exhibiting negative coefficients in both datasets.

These contrasting radial dependencies highlight fundamental differences in how thermodynamic variables interact with storm dynamics across spatial scales. High inertial stability has been used to explain the insensitivity of inner-core rain rate to AS (18). While high inertial stability in the vortex core acts as a stiff dynamical barrier that insulates the inner core against lateral entrainment of mid-level dry air, static stability operates as a vertical constraint on convective updrafts. Because AS directly regulates vertical core updraft intensity without requiring cross-eyewall lateral mixing, its suppressive impact is felt most acutely within the inner core. Conversely, CSD suppression emerges primarily at larger spatial scales (200–300 km and beyond), where lower inertial stability permits dry-air entrainment to modulate precipitation (10) in outer rainbands and broader stratiform regions. This is also consistent with evidence that evaporation and entrainment processes occur primarily in the outer-core region rather than in the inner core (26).

Trend attribution

We next asked whether the snapshot-scale associations identified above, combined with the observed changes in the predictors, can account for the opposing trends of inner-core rain rates. Because CSD exerts negligible direct influence on inner-core rain rate (Fig. 3C and D), we omitted it and formulated a reduced four-predictor model:

$$R_{IC} = C + \beta_{AS} \cdot AS + \beta_{RMW} \cdot RMW + \beta_{TCWV} \cdot TCWV + \beta_{V_{max}} \cdot V_{max} \quad (2)$$

We fitted this model to six-hourly oceanic snapshots within each basin to capture the distinct predictor relationships, then aggregated the fitted values to annual means to attribute the inner-core rain rate trends (Materials and Methods).

For ERA5, the annual inner-core rain rate increased significantly by $+0.525 \text{ mm h}^{-1} \text{ decade}^{-1}$ (95% CI: $[+0.210, +1.013]$). The per-basin snapshot model reproduces this increasing trend, yielding a fitted Theil–Sen trend of $+0.452 \text{ mm h}^{-1} \text{ decade}^{-1}$. The residual trend is small and statistically indistinguishable from zero ($+0.137 \text{ mm h}^{-1} \text{ decade}^{-1}$; 95% CI: $[-0.047, +0.272]$). Trend decomposition reveals that storm intensity is the primary positive driver, contributing $+0.464 \text{ mm h}^{-1} \text{ decade}^{-1}$. Notably, RMW provides the second-largest positive contribution ($+0.113 \text{ mm h}^{-1} \text{ decade}^{-1}$), surpassing the positive thermodynamic contribution from TCWV ($+0.067 \text{ mm h}^{-1} \text{ decade}^{-1}$). Conversely, AS exerted a suppressive effect, contributing $-0.167 \text{ mm h}^{-1} \text{ decade}^{-1}$.

The observed TMPA annual inner-core rain rate in the RMW-matched sample (2002–2018) declined steeply, with a trend of $-0.830 \text{ mm h}^{-1} \text{ decade}^{-1}$. The per-basin snapshot attribution model reproduced the direction of this decline, yielding a fitted global trend that was negative ($-0.228 \text{ mm h}^{-1} \text{ decade}^{-1}$). Among the individual predictors, V_{max} made the largest negative contribution ($-0.103 \text{ mm h}^{-1} \text{ decade}^{-1}$; 95% CI: $[-0.278, +0.072]$) but was not statistically significant, whereas RMW contributed $-0.031 \text{ mm h}^{-1} \text{ decade}^{-1}$, alongside the stabilizing influence of AS ($-0.051 \text{ mm h}^{-1} \text{ decade}^{-1}$). The TCWV contribution was positive but negligible ($+0.010 \text{ mm h}^{-1} \text{ decade}^{-1}$), consistent with the near-zero trend in environmental TCWV over this period ($-0.08 \text{ kg m}^{-2} \text{ decade}^{-1}$; $p = 0.90$; fig. S1).

This contrast highlights fundamentally different drivers of trends in ERA5 versus observations. The observed decline reflects decreasing TC intensity and an expanding radius of maximum wind, with atmospheric stability providing a robust suppressing effect. In contrast, the ERA5 increase is driven by simulated storm intensification and vortex shrinkage, which together overwhelm the suppressing effect of increasing atmospheric stability. Notably, the linear attribution model reproduces the observed decline in direction but not in magnitude. The unexplained component is itself a significant decline, with a residual trend of $-0.544 \text{ mm h}^{-1} \text{ decade}^{-1}$. This residual

may reflect unidentified constraints, observational uncertainty, or nonlinear interactions that a linear additive model cannot capture. To test whether this attribution depends on the choice of precipitation product, we repeated it using two additional precipitation products, MSWEP and IMERG (Materials and Methods). Both agree that the fitted trends remain negative and that the TCWV contribution remains negligible relative to those of $V_{\max}$ and RMW (fig. S2).

Implications for model–observation discrepancy

Model-based studies of TC inner-core rain-rate response to warming span a range of model types, resolutions, and warming protocols (9, 22, 23, 27, 28). To create a sufficiently large forced physical response of inner-core rain rate, they typically consider at least 1°C of warming, which is substantially more than what has been observed in the recent two decades. The annual-mean environmental SST (see Materials and Methods) increased by +0.20°C per decade over 1999–2018 (95% CI [−0.09, +0.36]; $p = 0.26$; fig. S3). The modest increase of SST has not translated to stable increase of TCWV (fig. S1). As a result, trends in inner-core rain rate in both the observational record and ERA5 are not primarily driven by increases in TCWV. In the scenarios considered by model experiments, by contrast, the moisture increase is broadly regarded as the dominant driver of increased inner-core rain rate (9, 12, 22, 28).

In the trend attribution (Fig. 4B), TCWV contributes positively in both datasets, +0.067 mm h^{−1}/decade in ERA5 and +0.010 mm h^{−1}/decade in TMPA. AS contributes negatively, −0.167 mm h^{−1}/decade in ERA5 and −0.051 mm h^{−1}/decade in TMPA. In both datasets the stability term exceeds the moisture term in magnitude, so the moisture-driven enhancement projected by models has not yet emerged under the modest warming of recent decades. Given that both atmospheric moisture and stability are projected to increase with very high confidence under continued warming (29, 30), it is essential to quantify their relative importance on inner-core rain rate. To roughly estimate this, we combined the snapshot-level coupling of environmental fields to SST with the partial-regression sensitivities of inner-core rain rate (Fig. 2). Per 1°C of environmental SST, TCWV increases by 5.7% (near the Clausius–Clapeyron expectation of ~7%), whereas AS increases by only 0.6% (fig. S4). Through the ERA5 partial-regression sensitivities, these couplings imply inner-core rain-rate changes of +9.0% and −2.3% per °C, respectively.

The stability suppression is real but remains smaller than the moisture enhancement. Under 1–2°C of warming, and assuming the present-day AS and TCWV sensitivities to SST persist, the moisture-driven enhancement can therefore dominate over stability suppression. Notably, the model-based studies typically project increased intensity and shrinking RMW (9, 23, 28). These intensity and structure changes reinforce rather than offset the moisture-driven enhancement. Model-based studies therefore project enhanced inner-core rain rate.

Discussion

Over the recent two decades, satellite observations show a declining TC inner-core rain rate, whereas climate models project increases under warming and the ERA5 reanalysis shows an increasing trend. This divergence matters beyond the trend itself, because a declining record invites the inference that warming poses less of a rainfall threat than models project. That inference would understate the hazard, and whether the recent record can be used to discount future TC rainfall risk depends on how the two trends are reconciled. We show that the discrepancy is reconcilable within a single physical framework. The same four predictors account for the ERA5 increase and for the direction of the observed decline. The divergence therefore reflects opposing trends in storm intensity and vortex structure rather than conflicting physics. Observed TC intensity shows no increasing trend over the past two decades, yet the ERA5 reanalysis simulates an intensifying TC population under only modest warming. One possibility is that the underlying model’s response to climate change is itself biased, so that ERA5 overestimates the TC intensity response to warming.

Reanalyses and climate models, despite their coarse resolution, remain indispensable for investigating TC inner-core rain rates. Investigating the inner-core rain rate trends in long-term climate contexts is a great challenge currently. Accurately resolving eyewall convection and mesoscale vortex structures requires kilometre-scale horizontal grid spacing (31). While such ultra-high-resolution global simulations are increasingly feasible, their prohibitive expense precludes their use in multidecadal climate runs (5). However, our findings demonstrate that even at a coarse horizontal resolution of 0.25°, where the radius of maximum wind, peak convective updrafts, and exact eyewall geometry are not explicitly resolved, the model underlying ERA5 can still capture fundamental thermodynamic constraints. After isolating confounding factors, the AS sensitivity is negative in

every basin in both satellite observations and ERA5, supporting a suppressive AS role (16, 18). The two datasets agree even on the scale dependence of this suppression, which suggests that coarse general circulation models may still retain large-scale environmental-to-vortex coupling. They can therefore help to evaluate inner-core precipitation responses in multidecadal climate records.

Notably, we stress that this study offers a perspective on the model–observation discrepancy in inner-core rain rate rather than a resolution of it. Model-based studies of the inner-core response span a wide range of model types, grid resolutions, and warming protocols. This breadth prevents us from diagnosing the mechanism behind the rain-rate increase in each configuration. The same increase may therefore arise from different causes in different models, and our result does not adjudicate among them. Although our study does not resolve the model–observation discrepancy, it expands the conventional paradigm of TC inner-core rain-rate change attribution. Whereas prior studies (12, 13, 22, 23, 28) have predominantly focused on dynamic intensity ($V_{\max}$) and thermodynamic moisture, we demonstrate that inner-core rain-rate changes also include contributions from RMW and AS. The updraft strength in the inner core is not determined solely by TC intensity.

Lastly, our radial scale analysis reveals a clear spatial partitioning that offers direct applications for parametric TC rainfall modelling (2, 32). While inner-core rain rate is governed by $V_{\max}$, RMW, and AS, outer-core precipitation is robustly suppressed by CSD. Given that outer-core rain-rate mechanisms remain far less understood than those of the inner core, CSD represents a critical, previously underutilized thermodynamic constraint. Future iterations of operational parametric models, such as R-CLIPER (33), could substantially improve their physical fidelity by parameterizing the inner core using AS and RMW while incorporating CSD to govern outer-core rain rates.

Materials and Methods

Observational data

Historical TC tracks are taken from IBTrACS best tracks (34), using the track set of ref. 16. For observed intensity, we use the U.S. agency-reported 10-m maximum sustained wind speed (USA WIND). The observed radius of maximum wind (RMW) is obtained from the agency-specific

IBTrACS v04r01 RMW fields, with 87% of matched RMW values originating from USA reports. We take RMW preferentially from the agency that reported the snapshot’s intensity. When that agency’s RMW is missing, we fall back to any other available agency field, preferring USA reports. Owing to sparse RMW reporting, annual-mean observed RMW is shown only for years with $\geq 50\%$ coverage (Fig. 1F).

We retain only six-hourly synoptic time points (00:00, 06:00, 12:00, and 18:00 UTC). Following ref. 16, snapshots are included if they meet four criteria: (i) $V_{\max} \geq 17.5 \text{ m s}^{-1}$ (tropical-storm strength or greater), (ii) absolute latitude $< 40^\circ$, (iii) occurrence within basin-specific peak seasons, and (iv) location in one of six basins: Western North Pacific (WP), Eastern North Pacific (EP), North Atlantic (NA), South Indian (SI), South Pacific (SP), and North Indian (NI). To isolate oceanic environmental controls, we define an open-ocean subsample (land distance $> 300 \text{ km}$). This threshold excludes coastal and landfalling cases, where inner-core rainfall is modulated by surface friction and topography, thereby isolating the large-scale environment–precipitation coupling over open water. Because observed RMW fields are available only from 2002, the observed analysis spans 2002–2018.

Satellite precipitation is taken from the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) 3B42 research product, version 7 (35) (0.25° , 3-hourly, 1998–2019). The observed inner-core rain rate follows the definition of ref. 16. The rainfall metric in this study is the TC inner-core rain rate, denoted R_{IC} . We use the all-pixel mean inner-core rain rate, where non-rainy pixels are treated as zero in the average. This approach differs from a “rainy-pixels-only” average that excludes non-rainy areas. Our results are not sensitive to the two averaging approaches.

To test whether the trend attribution depends on the precipitation product, we repeated the analysis with two additional products over the same 2002–2018 period: IMERG Final Run version 07 (36), which provides half-hourly precipitation on a 0.1° grid and MSWEP v2.8 (37), which provides 3-hourly precipitation on a 0.1° grid.

Reanalysis data

We analyse ERA5 reanalysis fields (19) over 1999–2018. ERA5 is a flagship reanalysis with relatively high resolution among reanalysis products, yet its 0.25° grid spacing cannot fully resolve fine-scale eyewall and inner-core structures. TC center positions in ERA5 can differ from observed best-track positions (10). We therefore relocate the ERA5 center for each snapshot. We use the IBTrACS best-track position as a first guess, and then we search for the minimum ERA5 sea-level pressure within a $\pm 2^\circ$ radius of the best-track location and adopt that grid point as the reanalysis TC center (10). ERA5 intensity is the maximum 10-m wind speed within 500 km of the relocated center, and the ERA5 wind-maximum radius is the distance from the center to that maximum. The inner-core rain rate for ERA5 is defined as the rain rate within a 100-km averaging radius.

Environmental variables

All environmental variables are derived from ERA5 and referenced to the relocated storm centre described above. To characterize the unperturbed background synoptic environment while limiting contamination from the storm itself, each variable is averaged over the annulus corresponding to the scale at which its association with inner-core rain rate is expressed. Atmospheric stability, whose suppressive association is more local and vertically oriented, is averaged over a 200–400 km annulus, whereas CSD and TCWV, whose associations emerge at broader scales related to horizontal transport, are averaged over a 600–800 km annulus. In addition, the ERA5 fields are sampled 6 h earlier ($t - 6$). This temporal offset is not redundant with the spatial offset: the annulus excludes the inner-core vortex at the snapshot time, whereas the 6 h lead samples the pre-storm environment, so that the predictors describe the background the storm is embedded in rather than one that has already co-evolved with the rain rate. Retaining both spatial and temporal offsets helps ensure that the sampled air is more representative of the unperturbed background. The offset is also short relative to synoptic evolution, and the results are insensitive to its exact value: sampling at t or $t - 12$ h leaves all coefficients and attributions qualitatively unchanged.

Atmospheric stability (AS) is defined as $\theta_{300} - \theta_{850}$, where $\theta = T(p_0/p)^\kappa$ is the potential temperature computed from ERA5 temperature at 300 and 850 hPa, with $p_0 = 1000$ hPa and $\kappa = R_d/c_p$. Column saturation deficit (CSD) is the 850–100 hPa vertical integral of the specific-

humidity saturation deficit, $\int_{100}^{850} (q_{\text{sat}} - q) dp/g$, where q_{sat} is the saturation specific humidity and q is the specific humidity; it is expressed in kg m^{-2} . Total column water vapor (TCWV) is the ERA5 column-integrated water vapor. Environmental sea surface temperature (SST) is the mean ERA5 SST over a 600–800 km annulus at $t - 6$ h, taken from the global ERA5 SST archive (0.25° , six-hourly); land points and sea-ice points are excluded.

Trend estimation and attribution

We fit the four-predictor snapshot regression (AS, RMW, TCWV, and V_{max}) separately within each of the six ocean basins because the predictor associations differ substantially across basins (Fig. 2). Fitting at the snapshot scale rather than directly on annual means leverages the full six-hourly record and avoids the spatial and temporal aggregation biases that can mask snapshot-level physical relationships. Then, we aggregate the actual values, fitted values, residuals, and per-term component contributions to calendar-year means. Basin annual series are then combined into the global annual series shown in Fig. 4 by weighting each basin-year mean by its snapshot count. The fitted annual values represent the part of the annual trend implied by snapshot-scale associations, and the residual is actual minus fitted.

Annual trends in the actual, fitted, and residual series are estimated using Theil–Sen slopes and reported per decade with Theil–Sen confidence intervals. We use Mann–Kendall tests to provide nominal significance levels for these trends. To quantify the contribution of each fitted term, we use ordinary least-squares slopes on the annual component series and report ordinary least-squares confidence intervals. These component slopes sum exactly to the ordinary least-squares trend in annual fitted inner-core rain rate, but do not decompose the Theil–Sen slope.

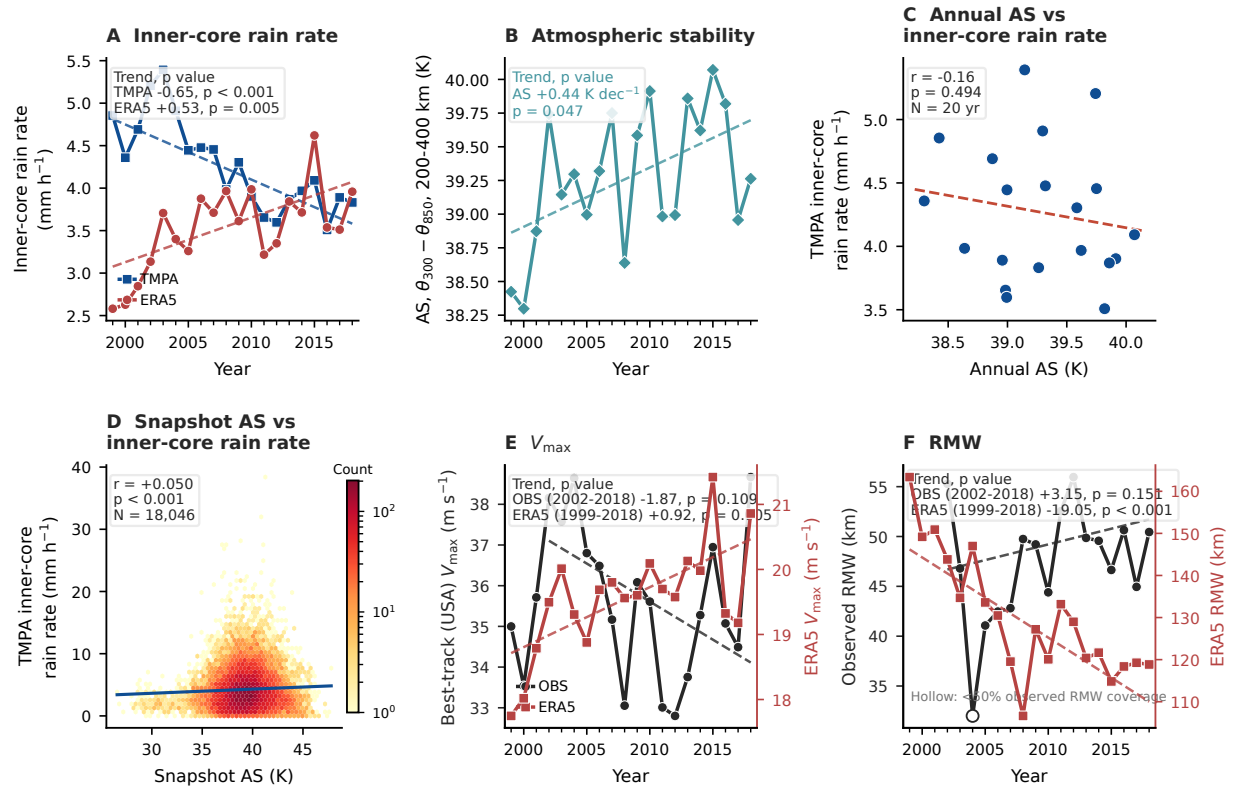


Figure 1: Satellite and ERA5 disagree in sign for inner-core rain rate, intensity, and storm structure over 1999–2018. (A) Annual-mean inner-core rain rate from TMPA (blue squares) and ERA5 (red circles). (B) Annual-mean storm-relative environmental atmospheric stability (AS). (C) Raw bivariate relationship between annual-mean AS and TMPA inner-core rain rate, one point per year. (D) Raw bivariate relationship between AS and TMPA inner-core rain rate at the six-hourly snapshot level; hexagonal bins show snapshot density. (E) TC maximum wind speed: best-track on the left y-axis (black, no significant trend over 2002–2018) and ERA5 on the right y-axis (red, increasing). (F) Radius of maximum wind (RMW) from 2002, when observed coverage first becomes reliable: observed best-track RMW (left axis) and ERA5 wind-maximum radius (right axis, 1999–2018). Hollow symbols denote years with $<50\%$ observed RMW coverage.

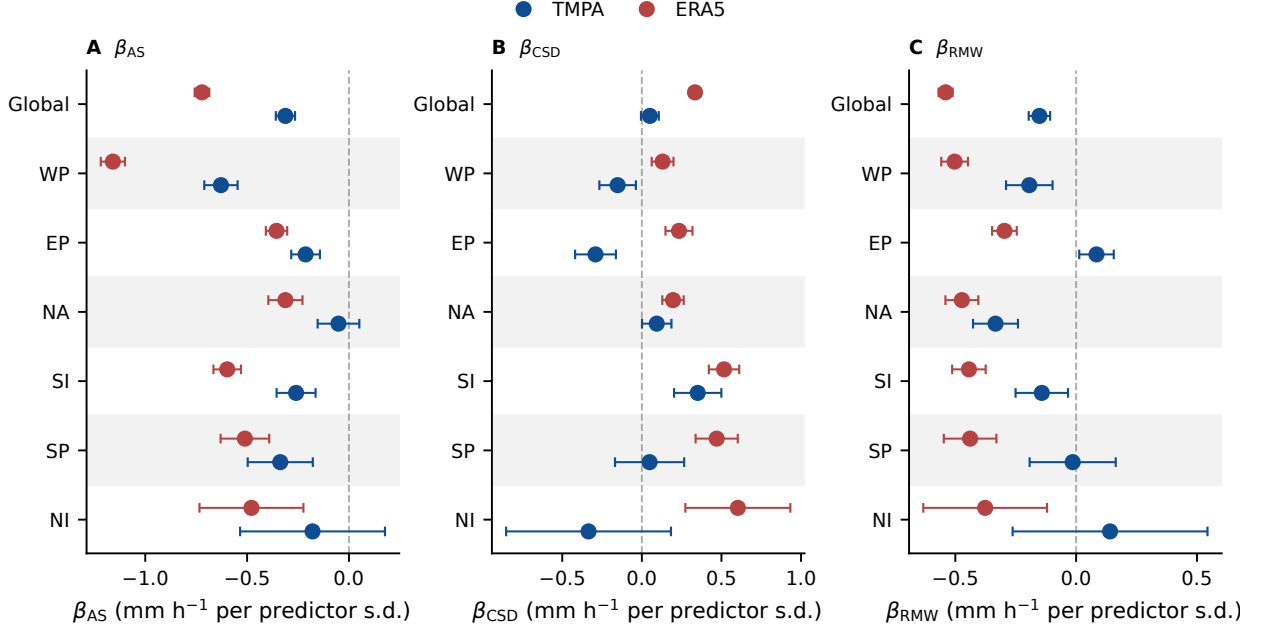


Figure 2: Atmospheric stability and radius of maximum wind negatively associate with inner-core rain rate, whereas column saturation deficit does not suppress the inner core. (A) Atmospheric stability (AS) coefficient; (B) column saturation deficit (CSD) coefficient; (C) radius of maximum wind (RMW) coefficient. Coefficients are from the five-predictor partial regression (Eq. 1), so each coefficient controls for the other four predictors. Blue (TMPA) circles show the regression of observed TMPA inner-core rain rate and red (ERA5) circles the regression of ERA5 inner-core rain rate, with error bars giving ordinary least-squares 95% confidence intervals. Predictors are standardized separately within each basin and data source (Materials and Methods), and coefficients are reported in mm h⁻¹ per predictor s.d..

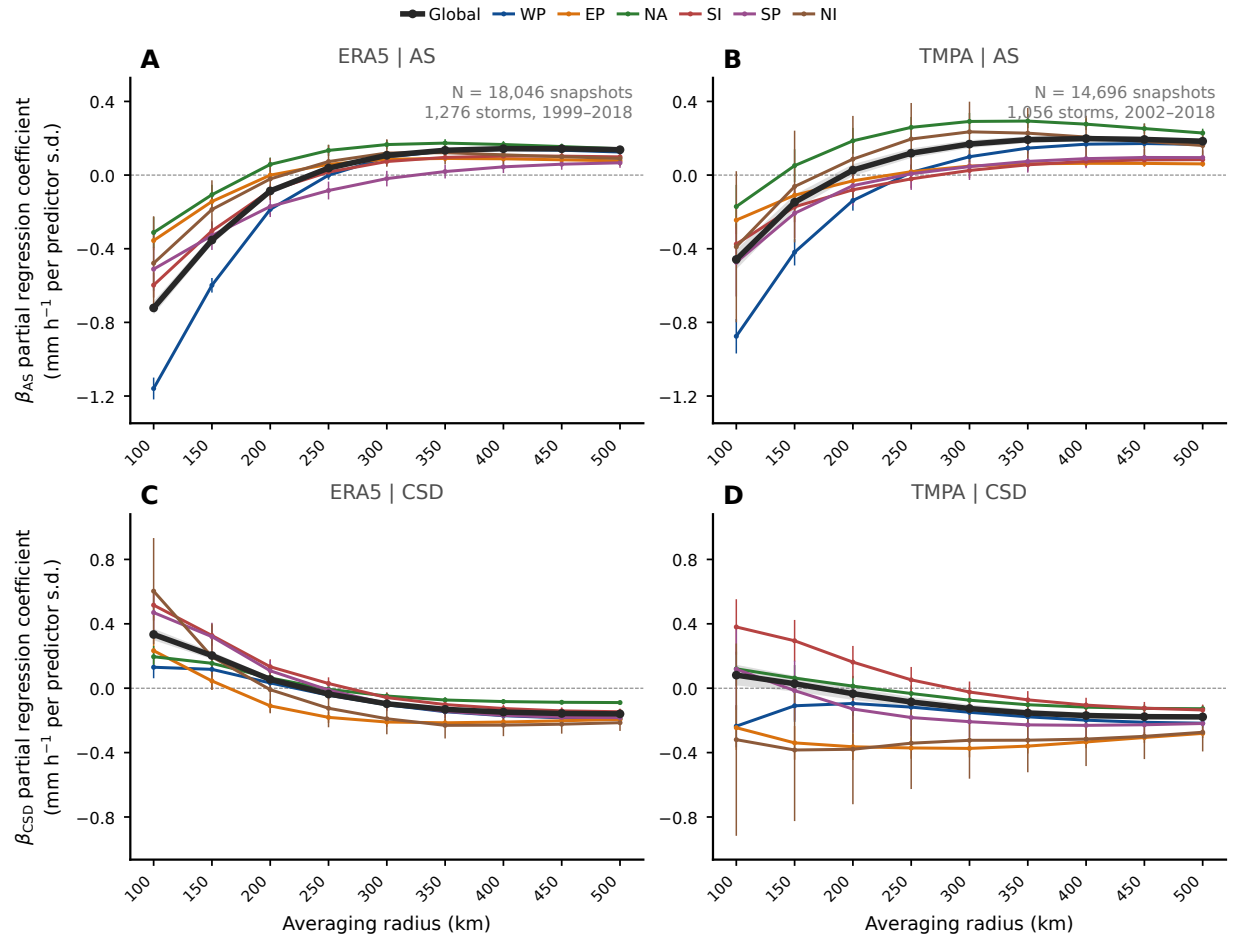


Figure 3: Stability suppression is confined to the inner core, while saturation-deficit suppression emerges only at broad scales. Coefficients are from the five-predictor partial regression (Eq. 1), so each coefficient controls for the other four predictors. Left panels regress ERA5 near-storm rain rate on ERA5-represented intensity and RMW. Right panels regress observed TMPA near-storm rain rate on observed intensity and RMW. Near-storm rain rate is computed at nine averaging radii, from 100 to 500 km at 50 km intervals. Predictors are population-standardized within each basin–radius fit, and coefficients are reported in mm h^{-1} per predictor s.d.. The thick black line shows the global estimate with its ordinary least-squares (OLS) 95% confidence interval (CI) shaded. Thin colored lines show six basin-level estimates with OLS 95% CI error bars.

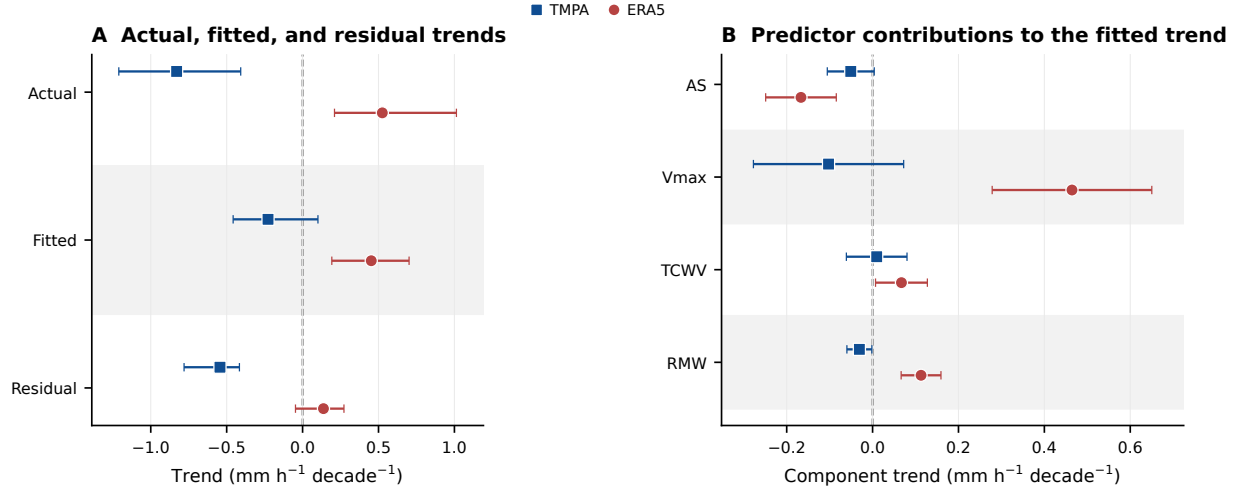


Figure 4: Trend attribution for observed and ERA5 rain rates. (A) Annual Theil–Sen trends ($\text{mm h}^{-1} \text{ decade}^{-1}$) of the actual, fitted, and residual series. (B) Predictor contributions to the fitted trend, as ordinary least-squares (OLS) slopes of the annual component series. Bars are 95% confidence intervals (Theil–Sen in A, OLS in B). Confidence intervals in A are order-statistic bounds on the Theil–Sen pairwise-slope distribution and therefore need not be symmetric about the estimated point. A snapshot regression of the inner-core rain rate on V_{max} , AS, TCWV, and RMW was fitted per basin and aggregated to annual series (Materials and Methods). All series use oceanic snapshots: TMPA 2002–2018 (14,702 snapshots from 1,056 storms, blue squares) and ERA5 1999–2018 (18,046 snapshots from 1,276 storms, red circles).

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Author contributions: J.C. conceived the study, conducted the primary data analysis, led the interpretation of results and wrote the original draft of the paper. S.T. and D.X. contributed to the interpretation and analysis of results. D.X. supervised the study. All authors contributed to writing, reviewing and editing the paper and approved the submitted version.

Competing interests: The authors declare no competing interests.

Data, code and materials availability: IBTrACS data are available from NOAA NCEI (<https://www.ncei.noaa.gov/data/international-best-track-archive-for-climate-stewardship-ibtracs/>). TMPA 3B42 data are from NASA GES DISC. ERA5 data are from the Copernicus Climate Data Store (<https://cds.climate.copernicus.eu/>). The analysis code and the processed source data used to generate the figures in this study will be made publicly available via Zenodo upon acceptance. No physical materials were generated in this work.

Supplementary materials

Figs. S1 to S4

Supplementary Materials for
Why observed tropical-cyclone inner-core rain trends oppose
model projections: perspectives from ERA5

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*Corresponding author. Email: dazhixi@hku.hk

This PDF file includes:

Figs. S1 to S4

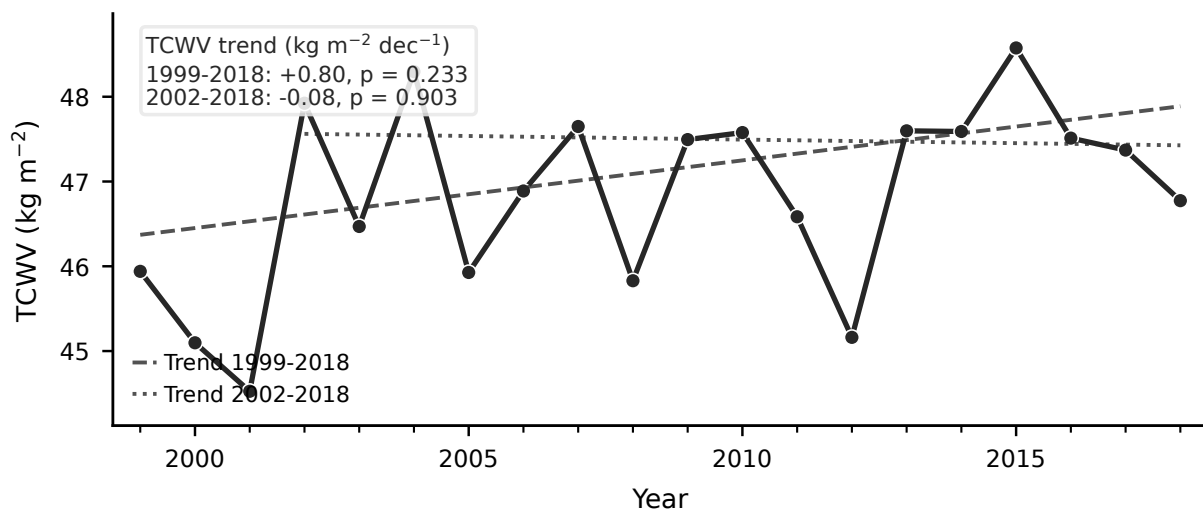


Figure S1: Environmental TCWV trend. Annual means of the environmental total column water vapour (ERA5, 600–800 km annulus, sampled 6 h before each snapshot) over the oceanic snapshots used in the trend attribution, 1999–2018. Dashed and dotted lines are Theil–Sen fits over 1999–2018 and 2002–2018, respectively.

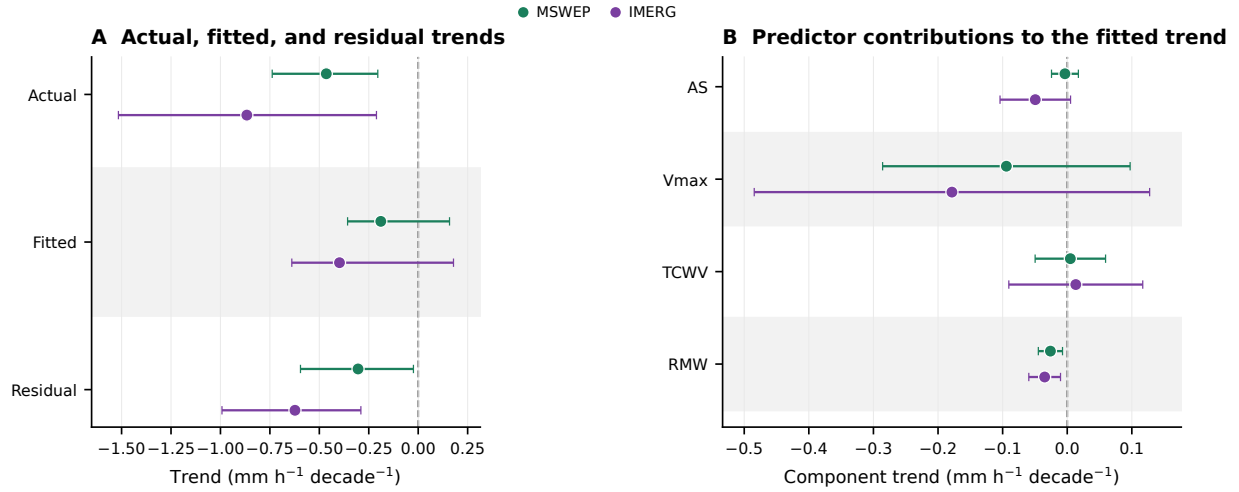


Figure S2: The observed decline and its negligible moisture contribution are reproduced by two independent precipitation products. (A) Annual Theil–Sen trends of the actual, fitted, and residual inner-core rain rate. **(B)** Ordinary least-squares trend contributions of atmospheric stability (AS), $V_{\max}$, total column water vapour (TCWV), and radius of maximum wind (RMW). MSWEP (teal) and IMERG (purple) circles show estimates with 95% confidence intervals. Both products are regressed with the same four-predictor snapshot model used for the TMPA attribution, fitted separately within each basin and aggregated to a global annual series. Both use the same oceanic 2002–2018 snapshot sample as the TMPA leg (14,702 snapshots, 1,056 storms), with matched observed RMW and USA 1-min $V_{\max}$; only the rain-rate response differs.

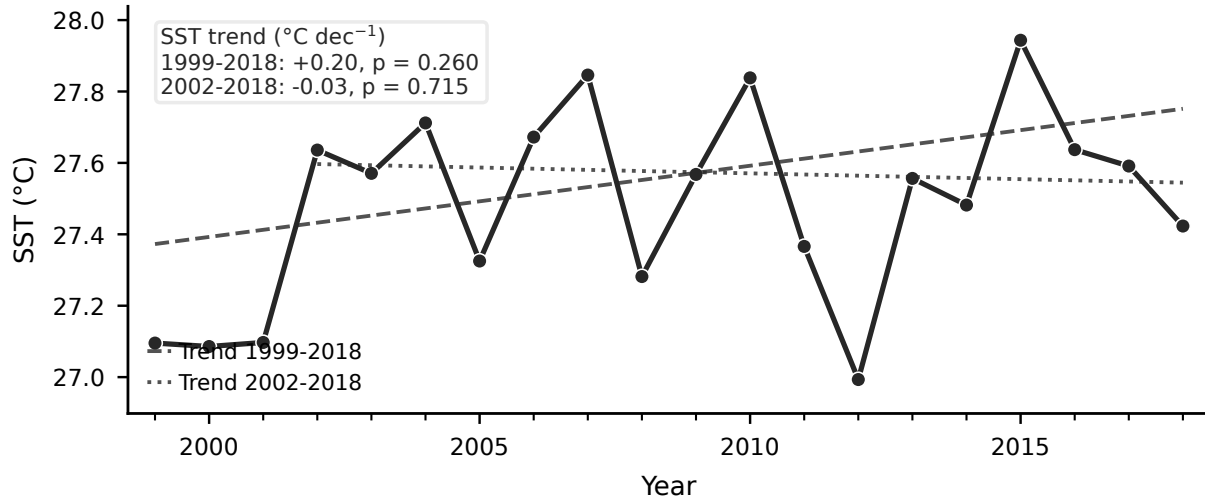


Figure S3: Environmental SST trend. Annual means of the environmental sea surface temperature (ERA5, 600–800 km annulus, sampled 6 h before each snapshot, land and sea-ice points excluded) over the oceanic snapshots used in the trend attribution, 1999–2018. Dashed and dotted lines are Theil–Sen fits over 1999–2018 and 2002–2018, respectively.

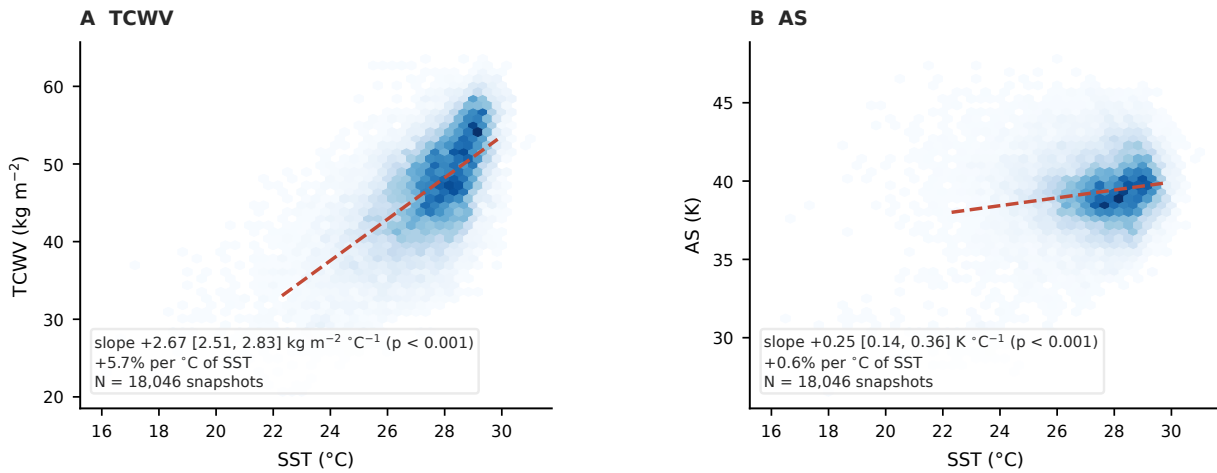


Figure S4: Environmental TCWV increases near the Clausius–Clapeyron rate with SST, whereas AS increases weakly. Snapshot-level coupling of the (A) environmental total column water vapour (TCWV) and (B) static stability (AS; $\theta_{300} - \theta_{850}$) to environmental sea surface temperature (SST). Dashed lines are pooled OLS fits with storm-clustered standard errors. TCWV increases by +5.7% per °C (near the Clausius–Clapeyron expectation of $\sim 7\%$), whereas AS increases by only +0.5% per °C.