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Research Article

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Posted Date: October 16th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10918403/v1>

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Recurrence compression of post-monsoon rainfall hazard under Indian Ocean Dipole and ENSO variability: implications for flood risk and infrastructure reliability in Bangladesh

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Abstract

The post-monsoon season (October–December, OND) concentrates a disproportionate share of flood hazard in the Ganges–Brahmaputra–Meghna delta, coinciding with the principal Bay of Bengal cyclone season, with elevated antecedent soil moisture and river stages, and with the period in which polders, embankments, and urban drainage in Bangladesh are most exposed to compound surge–rainfall loading. The frequency of the extreme rainfall driving that hazard is conventionally treated as fixed in time. This study quantifies how observable interannual ocean–atmosphere variability—the Indian Ocean Dipole (IOD) and the El Niño–Southern Oscillation (ENSO)—modulates it. Nonstationary generalized extreme value (GEV) models conditioned on climate indices were fitted to regional annual maximum monthly rainfall over Bangladesh (1950–2013),

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with a focused hazard analysis of Central Bangladesh for the homogeneous 1982–2013 window. Both indices are significant covariates, with cool and negative ocean states amplifying extremes; ENSO is the more consistent driver across the full record, while the IOD signal strengthens after 1982, although an interaction test cannot formally confirm regime dependence. The principal consequence is *recurrence compression*: depending on calibration period, the depth of the nominal 100-year event behaves as an approximately 36- to 54-year event under strongly negative IOD states, a 1.9- to 2.8-fold compression that is robust across leave-one-out, rolling-window, fixed-panel, and cross-model audits and confirmed by four independent distribution-free tests. Lifetime exceedance probability for a 50-year-service structure is near the stationary value under climatological weighting of states but rises substantially when service life coincides with negative-phase conditions, so the practical significance is the temporal clustering of risk rather than a uniform bias. Because these are rainfall-only estimates, they are lower bounds on true compound surge and river-stage risk. The results support an implementable risk-management framework—a climate surcharge factor, seasonal operational triggers, climate-weighted lifetime-reliability assessment, and asset-portfolio prioritization—that augments existing practice without speculative trend extrapolation.

Keywords: Flood hazard; Extreme rainfall; Climate variability; Indian Ocean Dipole; ENSO; Risk assessment; Nonstationary frequency analysis; Infrastructure reliability; Bangladesh

1 Introduction

1.1 Post-monsoon flood hazard in the Bengal delta

Bangladesh, situated at the head of the Bay of Bengal within the Ganges–Brahmaputra–Meghna delta, is among the most flood-exposed countries in the world (Mirza 2003). Although the southwest monsoon (June–September) supplies roughly 71% of annual rainfall (Shahid 2010), the post-monsoon season (October–December, OND) carries a disproportionate share of hydrologic risk: it coincides with the principal Bay of Bengal cyclone season

(Islam and Peterson 2009), with elevated antecedent soil moisture and river stages inherited from the monsoon, and with the operational period in which polders, embankments, and urban drainage systems in the delta are most vulnerable to compound surge–rainfall loading (Karim and Mimura 2008; Ikeuchi et al. 2017)—a class of compound hydrometeorological hazard in which the joint occurrence of interacting drivers produces risk that single-driver analyses systematically understate (Zscheischler et al. 2018). Rainfall in Bangladesh exhibits significant variability and documented changes in wet and dry spells and extreme events (Shahid 2010, 2011; Chowdhury 2003), and the destructive 2024 transboundary floods have renewed attention on the interaction between extreme rainfall, antecedent conditions, and infrastructure performance in the delta (Das et al. 2026).

The hazard is therefore not a single-driver phenomenon, and its design-relevant expression is not a single storm. What governs drainage congestion, embankment loading, and polder performance in the OND season is the accumulated multi-day rainfall of the wettest post-monsoon month, arriving on a catchment already saturated and into rivers already running high. It is the frequency of that loading, and its stability in time, that this paper examines.

1.2 Stationary treatment of a non-stationary hazard

Design standards for drainage systems, embankments, flood-control structures, and water-resources infrastructure are conventionally derived from frequency analysis of historical extremes under the assumption of stationarity: the premise that the probability distribution of annual maxima is invariant in time (Katz et al. 2002; Khaliq et al. 2006). In Bangladesh this premise is embedded throughout statutory practice: flood-control, drainage, and irrigation (FCDI) structures are designed to fixed return-period standards under the Bangladesh Water Development Board’s design manuals (Bangladesh Water Development Board 2013b; Government of Bangladesh 2000), coastal polder embankments to return-period surge and wave levels (Bangladesh Water Development Board 2013a), national water planning to the return-period inundation framework established by the Master Plan Organization (Master

Plan Organization 1986; Water Resources Planning Organization 2004), and urban drainage to the rainfall-intensity provisions of the Bangladesh National Building Code (Housing and Building Research Institute 2020)—in every case from a stationary frequency analysis of the historical record, with no provision for the interannual ocean-state modulation quantified below.

The limitations of this premise are now widely recognized (Milly et al. 2008), and a substantial body of work has developed nonstationary alternatives in which distribution parameters vary with time or with physically meaningful covariates (El Adlouni et al. 2007; Villarini et al. 2009; Cheng et al. 2014). A parallel literature has reformulated the concepts of return period, reliability, and design life for nonstationary conditions (Cooley 2013; Rootzén and Katz 2013; Salas and Obeysekera 2014; Read and Vogel 2015), while cautioning that nonstationary models must be deployed with restraint because parameter uncertainty can dominate when records are short (Serinaldi and Kilsby 2015), and out-of-sample testing has found that the predictive advantage of nonstationary over stationary models is frequently modest or absent when the nonstationarity is extrapolated as an open-ended trend rather than tied to an observable, recurrent covariate (Luke et al. 2017).

Most applications of this framework use time as the covariate, implicitly attributing nonstationarity to secular trends. An alternative, and in many respects more physically defensible, approach is to condition extreme-value distributions on observable modes of climate variability (Katz et al. 2002; Gilleland and Katz 2016). This distinction has become central to recent methodological work: several studies now argue explicitly that a time covariate lacks physical significance and that physically meaningful covariates such as temperature, ENSO, and the IOD yield more defensible nonstationary estimates (Yan et al. 2023; Vinarasi and Dhanya 2022; Agilan and Umamahesh 2017). When extremes are conditioned on a climate state rather than on calendar time, the resulting model does not extrapolate an open-ended trend; it instead quantifies how risk is redistributed among recurring, observable states of the ocean–atmosphere system. This matters for practice: climate-state covariates

can be monitored and, increasingly, forecast at seasonal lead times, so a state-conditioned model translates directly into operational risk information.

Recent Bangladesh-specific extreme-value work has begun to relax the stationarity assumption. Dey and Patwary (2025) fitted nonstationary GEV models to daily rainfall in Dhaka and Chattogram using atmospheric temperature as a covariate, finding materially higher extreme-rainfall probabilities in Chattogram; and CMIP6-based projections indicate substantial changes in extreme-precipitation indices over Bangladesh through mid-century (Islam et al. 2025). These studies establish that nonstationarity is detectable and design-relevant for Bangladesh, but they either use time or local temperature as the covariate, or operate at the scale of seasonal projections; the question of how much the effective frequency of the design event is modulated by observable, in-season ocean states has received little attention.

1.3 Ocean drivers of post-monsoon rainfall variability

Two coupled ocean–atmosphere modes plausibly modulate OND rainfall extremes over Bangladesh. The El Niño–Southern Oscillation (ENSO) is the canonical driver of interannual variability in South Asian rainfall (Rasmusson and Carpenter 1983; Webster et al. 1998; Kumar et al. 1999), operating through shifts in the Walker circulation and associated changes in convection and moisture convergence over the Bay of Bengal. The Indian Ocean Dipole (IOD), an east–west gradient of equatorial Indian Ocean sea surface temperature that peaks in boreal autumn (Saji et al. 1999; Webster et al. 1999), modifies convection over the eastern Indian Ocean and the strength of moisture transport into the northern Bay of Bengal precisely during the OND season (Saji and Yamagata 2003; Schott et al. 2009). The two modes interact: the IOD can modify the ENSO–monsoon relationship (Ashok et al. 2001), ENSO diversity produces distinct teleconnections (Ashok et al. 2007), and the Indian Ocean acts as a capacitor that delays and reshapes ENSO impacts (Xie et al. 2009).

For Bangladesh specifically, statistical evidence links ENSO to seasonal rainfall and tem-

perature anomalies (Wahiduzzaman and Luo 2021), and long-term regional trend analyses report ENSO and IOD teleconnections that vary by season and sub-region (Rahman and Islam 2019). Across the broader Indian monsoon region, the IOD and ENSO exert a non-stationary and nonlinear influence on the frequency of extreme-rainfall events, with the IOD contribution strengthening over recent decades even as the ENSO–monsoon relationship has weakened (Krishnaswamy et al. 2015). There is, moreover, growing evidence that extreme IOD events themselves are becoming more frequent under greenhouse warming (Cai et al. 2014; Abram et al. 2020), and that unprecedented IOD states can drive rainfall extremes well outside the historically sampled range (MacLeod et al. 2024). Whether this regional tendency extends to design-relevant extremes over Bangladesh, as opposed to seasonal means, has nonetheless received little attention.

1.4 Objectives and framing of this study

This paper addresses the flood hazard posed by post-monsoon rainfall extremes, and asks how far the frequency of that hazard—the quantity on which exposure and reliability assessments depend—is modulated by observable states of the ocean–atmosphere system. The question is not which ocean mode dominates Bangladesh rainfall, which the available record cannot settle definitively, but the more practical one: by how much does observable climate-state variability alter the reliability of stationary hazard estimates, and is that alteration robust to reasonable choices of covariate and model structure?

Accordingly, the analysis (i) fits stationary and climate-conditioned GEV models to regional OND annual maximum rainfall using both the IOD (Dipole Mode Index, DMI) and ENSO (Niño 3.4) as competing covariates; (ii) subjects the fitted models to a sequence of robustness audits, including leave-one-out sensitivity to extreme years, multi-start optimization checks, formal interaction tests for temporal regime dependence, and cross-model comparison; (iii) translates only the audited, surviving results into hazard and risk metrics—namely climate-state-dependent return levels, equivalent return periods of the nominal design event

(recurrence compression), and lifetime failure probabilities under climate-state cycling—and (iv) distils these metrics into a four-component risk-management framework, comprising a design-stage verification surcharge, seasonal operational triggers, lifetime reliability assessment, and asset-portfolio prioritization, that can be adopted within existing practice. Throughout, ENSO and the IOD are treated as competing but complementary covariates, and conclusions are stated at the level of robustness the data support.

2 Study area and data

2.1 Rainfall observations and regionalization

Monthly rainfall totals were compiled from quality-controlled daily records of 34 Bangladesh Meteorological Department (BMD) stations for 1948–2014, with stations screened for data completeness (>95% complete months). Stations were grouped into five hydrologic regions: Central (Dhaka, Faridpur, Madaripur, Tangail, Barisal, Khulna, Mongla, Jessore, Satkhira, Bhola), Northeastern (Sylhet, Srimangal, Comilla, Mymensingh, Chandpur, Feni, Maijdee Court), Coastal (Chittagong, Cox’s Bazar, Hatiya, Sandwip, Kutubdia, Sitakunda, Patenga, Teknaf), Northwestern (Rajshahi, Bogra, Dinajpur, Rangpur, Thakurgaon), and Southwestern (Patuakhali, Khepupara).

For each region and year, the analysis variable is the OND annual maximum monthly rainfall, computed as the station-mean of the maximum monthly total over October–December. Monthly block maxima were used in preference to daily maxima because monthly totals during OND integrate the multi-day rainfall episodes, frequently of cyclonic origin, that govern drainage-congestion and embankment loading in the delta, and because they are less sensitive to station-level daily gaps in the early record. The resulting variable, the regional mean of each station’s wettest post-monsoon month, is to be understood as a regional index of seasonal flood loading rather than as a point design storm. The regional grouping pools hydrologically comparable stations in the spirit of regional frequency analysis (Hosk-

ing and Wallis 1997), while deliberately adopting a simple station-mean index in place of formal L-moment regional pooling; it characterizes the saturation, drainage-congestion, and embankment-loading environment of the season, and the quantities derived from it in Section 5 are protection-level statements for that loading environment, not direct inputs to the sizing of individual hydraulic structures, which respond to shorter-duration point or areal depths.

The Southwestern region was excluded from the regional comparison on methodological grounds. Its two constituent stations begin substantially later than the rest of the network (1973 for Patuakhali, 1974 for Khepupara, versus 1950 for the four analyzed regions), yielding a shorter and non-overlapping record ($n = 39\text{--}40$ years) that cannot be directly compared against the 64-year window used elsewhere. A two-station region also falls below the station density conventionally recommended for a stable regional index (Hosking and Wallis 1997). For these reasons, and independent of the fitted coefficients themselves, the Southwestern region is reported separately rather than pooled into the primary four-region comparison. All regional results below therefore refer to the four remaining regions, each with complete 1950–2013 coverage ($n = 64$ years).

The primary hazard analysis focuses on Central Bangladesh, the region with the densest station coverage and the most populous exposure (including metropolitan Dhaka). Station locations and the regionalization are shown in Fig. 1. Station records within the region begin at different dates: five of the ten Central stations report continuously from 1948–1953, while the remainder commence later (Bhola 1966, Madaripur 1977, Tangail 1987, Mongla 1991). The regional OND maximum is computed as the mean of available station maxima in each year, so the number of contributing stations rises from five in 1950 to eight by 1982 and ten by 2000. This increasing station density is a further reason, beyond the satellite-era improvement in sea-surface-temperature observation, for basing the primary analysis on the post-1982 period, during which at least eight of the ten stations contribute throughout.

Fig. 1. BMD stations used in this study, by analysis region

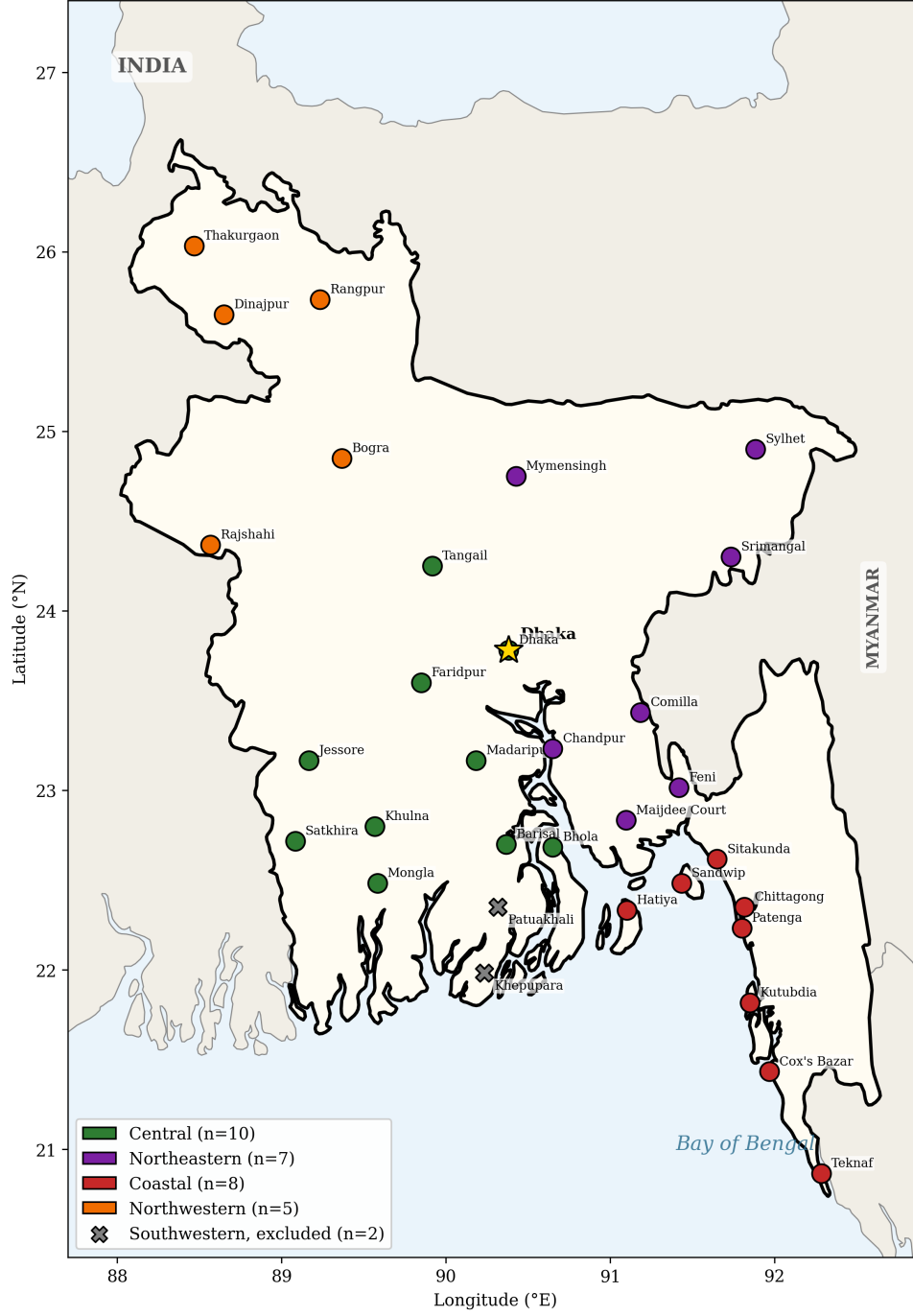


Figure 1: Bangladesh Meteorological Department stations used in this study, grouped into the four analysis regions; Southwestern stations (crosses) are reported separately (Section 5). The national border is drawn from Natural Earth 1:10m vector data; station positions are plotted at town coordinates.

2.2 Climate indices

The IOD state is represented by the Dipole Mode Index (DMI), the difference in sea surface temperature anomaly between the western (50°E–70°E, 10°S–10°N) and southeastern (90°E–110°E, 10°S–0°) equatorial Indian Ocean, computed from HadISST (Rayner et al. 2003) following Saji et al. (1999). The ENSO state is represented by the Niño 3.4 sea surface temperature anomaly from ERSSTv5 (Huang et al. 2017). Both indices were averaged over October–December to align with the rainfall season, and were standardized (zero mean, unit variance) over the analysis period so that regression coefficients are expressed in millimetres per standard deviation ($\text{mm } \sigma^{-1}$) of the index. One standard deviation of OND DMI corresponds to approximately 0.21 °C in the 1982–2013 sample. Two candidate Niño 3.4 products were cross-checked over their 1982–2013 overlap ($r = 0.987$; median absolute difference 0.17 °C); the ERSSTv5 series was adopted because it spans the full 1950–2013 period.

3 Methods

3.1 Stationary and climate-conditioned GEV models

Annual maxima were modeled with the generalized extreme value (GEV) distribution (Coles 2001). Because each annual maximum is the largest of only three monthly totals, the asymptotic extreme-value argument does not by itself justify the GEV here; the distribution is instead used as a flexible three-parameter family for block maxima, in line with common hydrologic practice for seasonal maxima (Katz et al. 2002), and its adequacy is established empirically through the goodness-of-fit testing described below rather than asserted theoretically. The stationary model M_0 has constant location μ , scale σ , and shape ξ . Climate conditioning was introduced through the location parameter: M_1 , $\mu(t) = \beta_0 + \beta_1 \text{DMI}(t)$; M_2 , $\mu(t) = \beta_0 + \beta_1 \text{NINO34}(t)$; and M_3 , $\mu(t) = \beta_0 + \beta_1 \text{DMI}(t) + \beta_2 \text{NINO34}(t)$, with σ and

ξ held constant. Location-only conditioning was retained after preliminary testing because the short record does not support stable estimation of covariate effects in σ or ξ (Serinaldi and Kilsby 2015). Parameters were estimated by maximum likelihood using Nelder–Mead optimization initialized from a grid of starting values for each covariate coefficient, which guards against convergence to local optima. Nested models were compared by likelihood-ratio tests (LRT) and non-nested alternatives by the Akaike information criterion (Akaike 1974). Distributional adequacy of fitted models was verified with Kolmogorov–Smirnov and Anderson–Darling tests on transformed residuals; no model considered here was rejected at the 5% level.

3.2 Temporal regime analysis

Because the ENSO–monsoon relationship is known to have weakened after the late 1970s (Kumar et al. 1999) and IOD variability and SST observation density both increase in the satellite era, the 64-year record was split at 1982 into two equal 32-year regimes. The breakpoint was specified a priori on these physical and observational grounds, at the start of the satellite SST era, and was not selected by searching over candidate breakpoints for fit quality. Covariate models were refitted within each regime, and regime dependence was tested formally with interaction models: M_5 adds a regime indicator and a $\text{DMI} \times \text{regime}$ term to M_3 . The interaction coefficient was further examined with a nonparametric bootstrap to obtain a confidence interval that does not rely on asymptotic likelihood theory at this sample size.

3.3 Robustness audits

Three audits were applied before any result was carried into the hazard analysis. First, leave-one-out (LOO) sensitivity: the years containing the most influential extremes within 1982–2013 (1988, 1998, 2004, 2007) were removed one at a time, covariates were re-standardized, models were refitted, and the resulting spread of β_1 was compared with the full-sample

estimate. Second, optimization stability: all headline coefficients were reproduced from substantially broader starting-value grids. Third, formula verification: every quantity reported in Section 5 was checked against closed-form anchors (e.g., a T -year level must satisfy a round-trip $T \rightarrow \text{quantile} \rightarrow T$ identity, and a 100-year design must yield a 39.5% exceedance probability over a 50-year life under stationarity). Quantities that failed audit—in particular confidence intervals on long return levels, which proved unstable under both bootstrap and profile-likelihood construction at $n = 32$ —are reported as point estimates only, with uncertainty characterized through the LOO and cross-model analyses instead (Section 5.4).

3.4 Hazard and reliability metrics

Let $F_s(x)$ denote the GEV distribution function conditional on climate state s (a specified standardized value of the covariate). Three metrics translate the fitted models into risk-relevant terms. (i) Climate-state return levels: the T -year level under state s is the quantile of F_s at probability $1 - 1/T$. (ii) Equivalent return period (recurrence compression): for the design depth x_{100} defined by the stationary 100-year event, the effective return period under state s is $T_e(s) = 1/[1 - F_s(x_{100})]$; values below 100 years indicate compression (the design event is exceeded more often than its nominal frequency) and values above 100 years indicate dilation. (iii) Lifetime failure probability: for a structure with L -year service life, the probability of at least one exceedance of the design depth is $1 - \prod_s [F_s(x_{100})]^{L_s}$, where L_s is the time spent in state s . Three cases are reported: a single persistent state ($L_s = L$); a climatological weighting in which the standardized state is redrawn annually from its observed (approximately standard normal) distribution; and an equal-time stress cycling among strongly negative, neutral, and strongly positive states ($L_s = L/3$), which deliberately over-weights extreme phases relative to their climatological frequency and therefore serves as a bounding scenario rather than an expectation (Salas and Obeysekera 2014; Read and Vogel 2015). All reliability formulas operate on exceedance probabilities $p_s = 1 - F_s(x_{100})$, and each reported value was verified against the stationary anchor $1 - (1 - 1/100)^{50} = 0.395$.

4 Climate-conditioned extreme value analysis

4.1 Competing covariates over the full record (1950–2013)

Table 1 compares the candidate models for Central Bangladesh over the full 64-year record. Both indices are individually significant covariates of OND extreme rainfall, with negative coefficients in all cases: warm ENSO states and positive IOD states are associated with suppressed extremes, and cool/negative states with amplified extremes. Over the full record ENSO is marginally the stronger single covariate ($\Delta\text{AIC} = -10.8$ relative to stationarity; $p < 0.001$), with the IOD close behind ($\Delta\text{AIC} = -10.4$; $p < 0.001$), and the dual-covariate model M_3 attains the lowest AIC overall, indicating that the two indices carry partially independent information.

Table 1: Model comparison for Central Bangladesh OND annual maximum rainfall, 1950–2013 ($n = 64$). ΔAIC is relative to the stationary model M_0 ; p -values are from likelihood-ratio tests against M_0 .

Model	Location structure	AIC	ΔAIC	β (mm σ^{-1})	LRT p
M_0 Stationary	μ	752.5	0	—	—
M_1 DMI	$\mu + \beta_1\text{DMI}$	742.1	-10.4	-22.0	< 0.001
M_2 ENSO	$\mu + \beta_1\text{NINO34}$	741.7	-10.8	-25.1	< 0.001
M_3 DMI+ENSO	$\mu + \beta_1\text{DMI} + \beta_2\text{NINO34}$	738.9	-13.6	-15.7 / -16.1	—

4.2 Temporal regime structure

Splitting the record at 1982 reveals an asymmetry between the two indices. The ENSO coefficient is significant in both sub-periods and a formal ENSO $\times$ regime interaction is not significant, indicating a stable ENSO influence throughout the record. The DMI coefficient, by contrast, is weak and non-significant before 1982 but strong afterwards ($\beta = -33.5$ mm σ^{-1} , $p < 0.01$ in the analysis window). The corresponding DMI $\times$ regime interaction has a negative point estimate ($\beta_4 \approx -12$ mm σ^{-1}) but does not reach significance (LRT $p = 0.41$), and its bootstrap 95% confidence interval includes zero. The data are therefore directionally

consistent with an intensified post-1982 IOD influence, possibly reflecting improved SST observation in the pre-satellite era as much as genuine regime change, but with 32 years per regime the test is underpowered and no formal claim of regime dependence is made.

Two conservative conclusions follow: ENSO is a persistent covariate over the full record, and the post-1982 period provides the cleanest, most homogeneous window for quantifying the joint climate-state influence. The hazard analysis of Section 5 is therefore based on 1982–2013, within which both covariates are significant and of comparable magnitude. Because the full-record DMI coefficient is smaller ($-22.0 \text{ mm } \sigma^{-1}$), and the regime difference cannot be formally confirmed, the headline quantities of Section 5.2 are additionally reported under the full-record coefficient as an explicit lower-bound sensitivity, so that no conclusion depends on accepting the post-1982 window as the correct characterization.

4.3 Leave-one-out sensitivity and formal influence diagnostics

Because $n = 32$ annual maxima could in principle be dominated by a handful of exceptional seasons, two complementary influence analyses were performed. A leave-one-out (LOO) refit was carried out for every year in the record, and the change in the DMI coefficient was quantified formally by its standardized DFBETA (Table 2 reports the most influential years). No single year exceeds standard influence thresholds by enough to alter the conclusion: the largest single-year effect is the exclusion of 1984, which moves the coefficient from -33.5 to $-39.5 \text{ mm } \sigma^{-1}$ (an 18% change), followed by 1992 (-39.3); the year with the most extreme covariate value, and hence the highest formal leverage, is 1997, the record super-IOD event, whose removal actually weakens the coefficient to -28.7 . Critically, across all 32 leave-one-out refits the DMI coefficient remains between -27.9 and $-39.5 \text{ mm } \sigma^{-1}$ —negative, of the same order of magnitude, and statistically significant in every case—and the ENSO coefficient varies by no more than 16%. The fitted climate sensitivity is therefore a property of the full distribution of OND extremes rather than an artifact of any single season; individual high-leverage years affect the coefficient’s precise magnitude but never its sign, order of

318 magnitude, or significance.

Table 2: Leave-one-out sensitivity of the DMI coefficient, Central Bangladesh, 1982–2013, showing the five most influential years ranked by standardized DFBETA. Full-sample $\beta_{\text{DMI}} = -33.46 \text{ mm } \sigma^{-1}$. The sign and significance of the effect are preserved in all 32 refits.

Year excluded	$\beta_{\text{DMI}} \text{ (mm } \sigma^{-1})$	DFBETA _{std}	Note
1984	−39.51	+2.47	largest influence
1992	−39.28	+2.37	
1996	−27.87	−2.27	
1997	−28.72	−1.92	highest leverage (super-IOD)
1998	−37.64	+1.70	

Range over all 32 refits: −39.51 to −27.87; sign and $p < 0.05$ significance retained throughout.

319 The fitted covariate relationship and the distributional adequacy of the conditional model
320 are shown directly in Fig. 2. The upper panel plots the observed OND annual maxima against
321 the standardized DMI together with the 50- and 100-year conditional return-level curves;
322 both curves decline with increasing DMI, so the negative climate effect is expressed directly
323 as a downward shift of the hazard quantiles. The lower panels are the nonstationary quantile–
324 quantile and probability plots of the probability-integral-transformed maxima against the
325 standard Gumbel: points fall close to the identity line across the full range, and neither the
326 Kolmogorov–Smirnov nor the Anderson–Darling test rejects the conditional GEV at the 5%
327 level.

328 One structured feature is nonetheless visible in the scatter that the location-only model
329 does not capture: the spread of observed maxima narrows as the DMI increases, indicating
330 a scale dependence on climate state in addition to the location shift. Because the largest
331 dispersion occurs at strongly negative DMI, a location-only model is likely to understate,
332 rather than overstate, the upper-tail rainfall and hence the compression under negative-IOD
333 conditions. The reported compression is in this sense conservative.

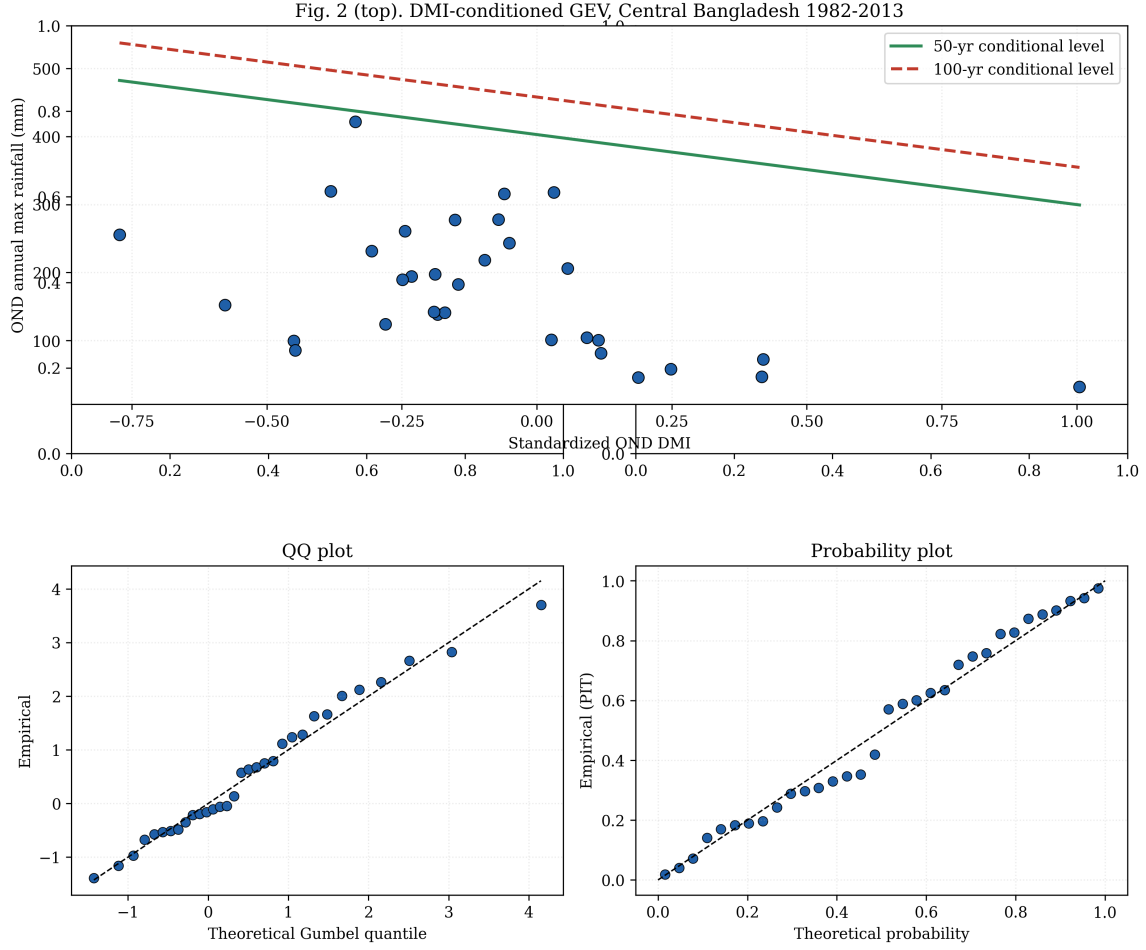


Figure 2: Data diagnostics for the DMI-conditioned GEV, Central Bangladesh. Top: observed OND annual maximum rainfall versus standardized DMI, with the 50-year and 100-year conditional return levels; both decline with DMI. Bottom: nonstationary quantile–quantile plot (left) and probability plot (right) of the probability-integral-transformed maxima against the standard Gumbel distribution.

4.4 Regional heterogeneity

Table 3 and Fig. 3(b) report single-covariate fits for the four regions with complete 1950–2013 coverage. The climate signal is spatially organized rather than uniform. Central and Northeastern Bangladesh show significant sensitivity to both indices; the Coastal region is strongly ENSO-sensitive ($\beta = -42.1 \text{ mm } \sigma^{-1}$, $p < 0.01$) but not significantly DMI-sensitive over the full record; and the Northwestern region is essentially decoupled from both indices. ENSO provides the better single-covariate model in every region over this 64-year window, which is consistent with its full-record stability noted above; the DMI contribution is concentrated in the post-1982 period and in the Central and Northeastern regions. This spatial pattern carries direct implications for risk management. Climate-state adjustments are strongly supported for Central Bangladesh, supported for the Coastal region through robust ENSO sensitivity, supported for Northeastern Bangladesh, and not supported for the Northwestern region.

Table 3: Regional single-covariate GEV results, OND annual maxima, 1950–2013 ($n = 64$ per region). The Southwestern region is reported separately (Section 2.1).

Region	Stations	Mean (mm)	β_{DMI}	p (DMI)	β_{ENSO}	p (ENSO)
Central	10	168.8	−22.0	< 0.001	−25.1	< 0.001
Northeastern	7	207.8	−20.8	0.008	−22.3	0.007
Coastal	8	274.1	−18.6	0.127	−42.1	0.002
Northwestern	5	142.5	−6.9	0.116	−5.7	0.283

5 Hazard and risk implications of climate-state variability

This section translates the audited statistical models into the three quantities that govern hazard assessment and hydraulic design practice: design rainfall depths, effective recurrence of the design event, and lifetime reliability. All results refer to Central Bangladesh, 1982–2013, the region and period for which both covariates are significant and the record

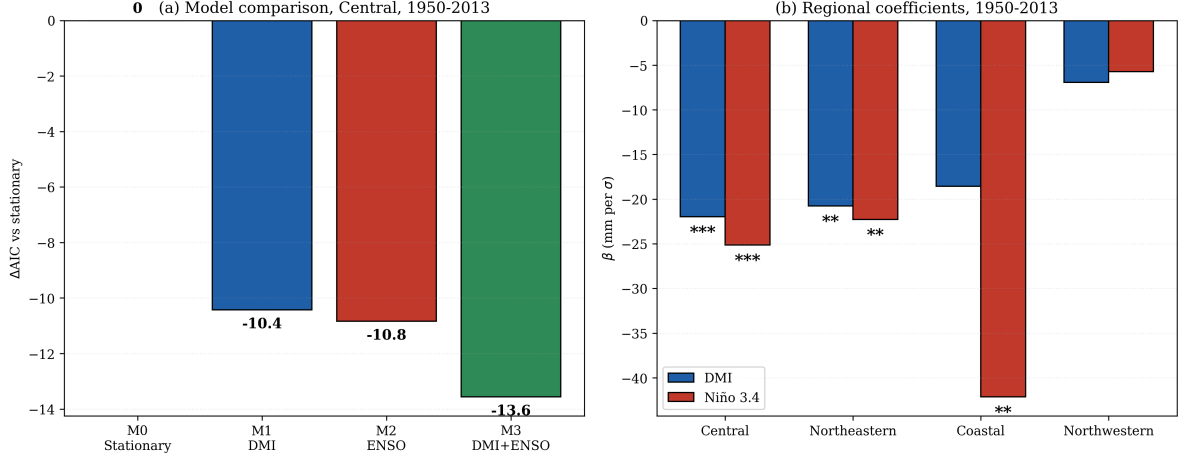


Figure 3: Statistical evidence for climate conditioning of OND extreme rainfall, 1950–2013. (a) AIC improvement of climate-conditioned GEV models over the stationary model for Central Bangladesh. (b) Regional covariate coefficients for the DMI and Niño 3.4 indices; asterisks denote likelihood-ratio significance against the stationary model.

is homogeneous. The stationary GEV fit for this window yields stationary design depths of 410 mm (50-year) and 452 mm (100-year) for the OND maximum monthly rainfall; the latter serves as the reference design event throughout. Consistent with Section 2.1, these depths quantify the regional seasonal flood-loading index, and the protection-level statements below should be read at that level rather than as direct sizing inputs for individual structures.

5.1 Climate-state-dependent design rainfall

The hazard analysis conditions design rainfall on the IOD (DMI) as the primary index, for three reasons that are physical rather than statistical. First, the IOD peaks during the OND season itself, so it is the in-season mode of variability most directly contemporaneous with the rainfall extremes being designed for, whereas the ENSO signal over Bangladesh acts partly through its influence on the Indian Ocean (Section 5.8). Second, the DMI effect is strongest and most clearly significant in the post-1982 window, where it is of comparable magnitude to the ENSO effect. Third, conditioning on a single in-season index yields a transparent, observable design covariate. Because the two indices are correlated and ENSO is marginally the stronger covariate over the full record, every quantity is additionally reported under the

ENSO-conditioned and dual models (Section 5.4), so that no conclusion rests on the choice of DMI alone.

Table 4 and Fig. 4 report 50- and 100-year return levels conditional on the IOD state, computed from the DMI-conditioned model (M_1). Moving from a strongly positive to a strongly negative IOD state ($+2\sigma$ to -2σ of OND DMI, approximately $\pm 0.4^\circ\text{C}$) raises the 50-year design depth from 345 mm to 479 mm and the 100-year depth from 400 mm to 534 mm, an approximately 33% (134 mm) modulation of design rainfall attributable to a single observable ocean index. The neutral-state values (412 mm and 467 mm) closely reproduce the stationary estimates, as they should, confirming internal consistency of the conditional model. Values are reported as point estimates: both bootstrap and profile-likelihood interval construction proved unstable for upper-tail quantiles at this sample size (Section 3.3), and interval estimates that failed the audit are deliberately not reported. Uncertainty is instead characterized by the leave-one-out stability of the underlying coefficients (Table 2) and by the cross-model sensitivity analysis of Section 5.4.

Table 4: Return levels of OND maximum monthly rainfall conditional on IOD state (DMI-conditioned GEV, Central Bangladesh, 1982–2013). Point estimates; see text for uncertainty treatment.

IOD state (OND DMI)	Conditional μ (mm)	50-year (mm)	100-year (mm)
Strongly negative (-2σ)	202	479	534
Weakly negative (-1σ)	169	445	501
Neutral (0)	135	412	467
Weakly positive ($+1\sigma$)	102	379	434
Strongly positive ($+2\sigma$)	69	345	400

5.2 Recurrence compression of the nominal design event

A more decision-relevant statement of the same physics asks how often the stationary 100-year design depth (452 mm) is actually exceeded under each climate state. Table 5 and Fig. 5 report the equivalent return period $T_e(s)$ across the IOD spectrum. The relationship is strictly monotonic, with no reversals at any of the nine states examined: the equivalent return

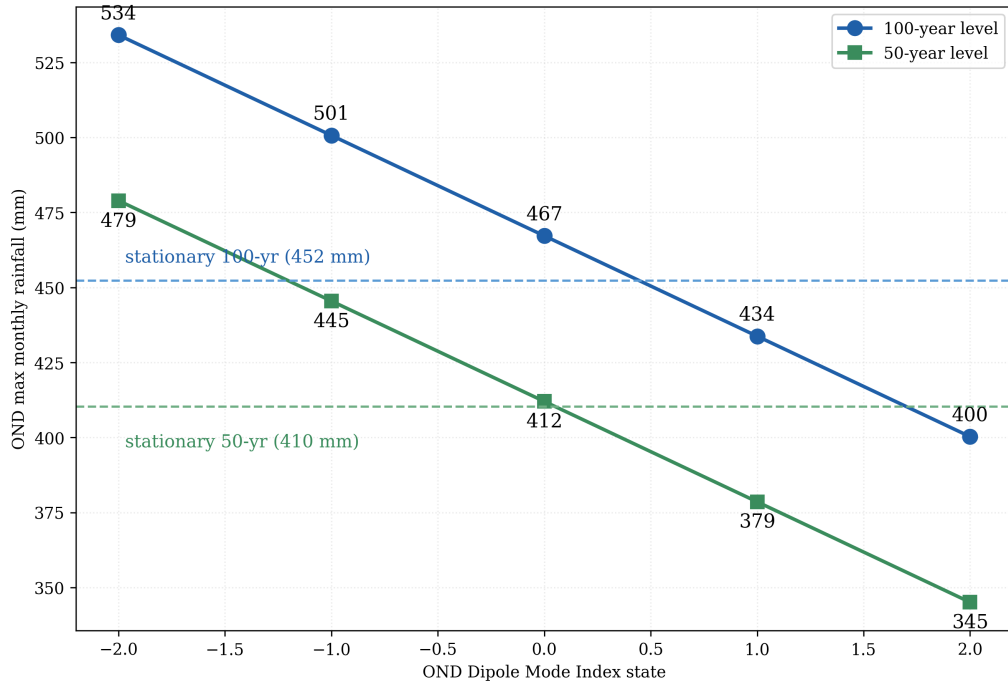


Figure 4: Design rainfall as a function of IOD state: 50- and 100-year OND maximum monthly rainfall from the DMI-conditioned GEV model (Central Bangladesh, 1982–2013), with stationary design depths shown as dashed lines. The state-conditioned levels span the stationary values, modulating design rainfall by approximately 33% across the observed IOD range.

period rises smoothly from 36 years at -2σ to 189 years at $+2\sigma$, a 5.3-fold modulation. Under strongly negative IOD conditions, the nominal 100-year event behaves as an approximately 36-year event, a compression factor of 2.8; under strongly positive conditions, the same depth becomes rarer than its nominal frequency. The smoothness and monotonicity of this relationship, together with its accelerating increments toward positive states, are exactly the behavior expected of a genuine location shift in the parent distribution and argue against statistical artifact.

Table 5: Equivalent return period of the stationary 100-year design depth (452 mm) as a function of IOD state. Differences between successive rows are strictly positive (monotonicity verified numerically).

OND DMI state	Equivalent return period (years)	Interpretation
-2.0σ	36	Strong compression (factor 2.8)
-1.5σ	44	Compression
-1.0σ	55	Compression
-0.5σ	67	Compression
0	83	Mild compression
$+0.5\sigma$	102	Approximately nominal
$+1.0\sigma$	126	Dilation
$+1.5\sigma$	154	Dilation
$+2.0\sigma$	189	Strong dilation (factor 1.9)

Two qualifications make this result explicit. First, a lower-bound sensitivity: if the smaller full-record DMI coefficient ($-22.0 \text{ mm } \sigma^{-1}$, Section 4.2) is substituted for the post-1982 value with all other parameters held fixed, the compression at -2σ weakens but remains well below the nominal 100 years; the qualitative conclusion—roughly two- to three-fold compression of the design event under strongly negative states—therefore survives even under the most conservative admissible coefficient, and only its magnitude depends on the analysis window. Second, an honest decomposition of the curve: the mild compression at the neutral state (83 rather than 100 years) is not a climate effect but a baseline offset between the four-parameter conditional fit and the three-parameter stationary fit to 32 observations, two parameterizations that distribute upper-tail probability slightly differently. The climate signal proper is the monotonic spread of the curve about its own neutral value; the baseline

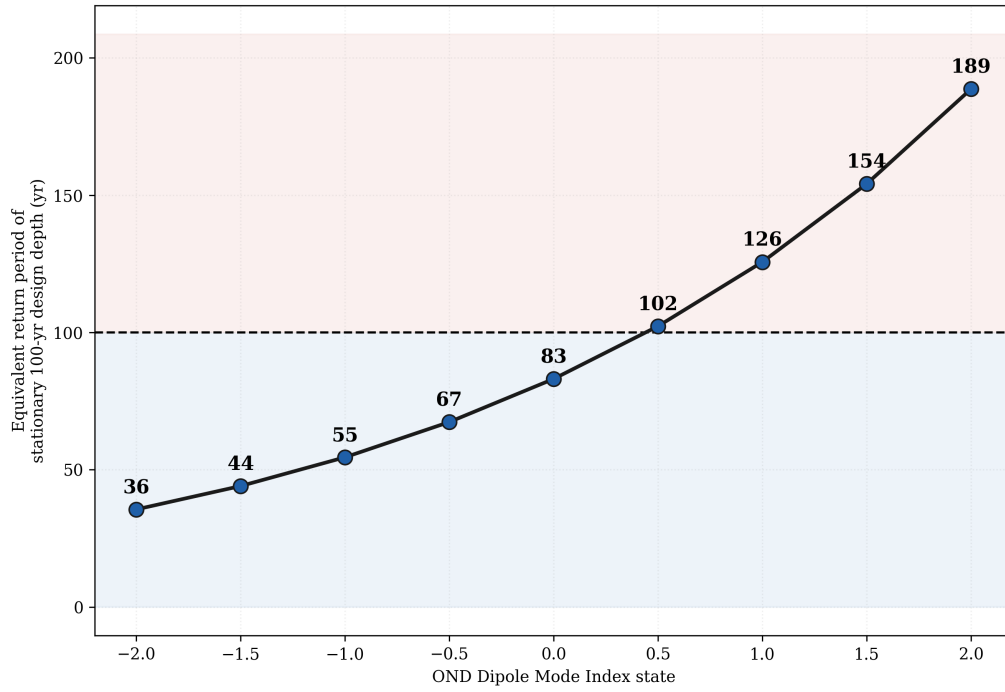


Figure 5: Recurrence compression of the nominal design event. Equivalent return period of the stationary 100-year design depth (452 mm) as a function of the OND DMI state. The relationship is strictly monotonic across all nine states examined: under strongly negative IOD conditions the design event behaves as an approximately 36-year event (compression factor 2.8), while under strongly positive conditions it becomes rarer than nominal.

offset should be attributed to model form, not to the ocean.

5.3 Lifetime reliability of stationary designs

Table 6 and Fig. 6 report the probability that a structure designed to the stationary 100-year standard experiences at least one design exceedance during a 50-year service life. Under stationarity this probability is 39.5% by construction. Under the climatological weighting, in which states occur with their observed frequencies, the lifetime probability is 29–49% across the three model formulations (49% DMI, 29% ENSO, 43% dual), a range that brackets the stationary value. This is the central honest finding of the reliability analysis: averaged over the climatological distribution of states, stationary design is approximately unbiased, and the analysis does not manufacture a spurious across-the-board risk inflation.

The significance lies instead in the conditional structure that the average conceals. If the service life is dominated by strongly negative IOD/ENSO conditions, the lifetime exceedance probability rises to 63–76% depending on the covariate model; under persistently positive conditions it falls to 7–23%; and the equal-time stress cycling scenario yields 36–54%. Because observed IOD and ENSO states decorrelate on interannual timescales, typically persisting for one to two years rather than across a multi-decadal service life (Torrence and Compo 1998; Luo et al. 2007), the persistent-phase figures should be read as stress-test bounds rather than as expected service-life exposure, with the climatologically weighted value the more representative long-horizon estimate. The stationary calculation is therefore not uniformly conservative or unconservative; its realized bias depends on the climate states actually encountered, which is precisely the information stationary analysis discards.

The practically important consequence is the temporal clustering of risk: during negative-phase periods the annual exceedance probability of the design event roughly triples. This clustering is what makes the result a multi-hazard rather than a single-driver finding. The negative-phase seasons in which extreme OND rainfall becomes roughly three times more likely are the same seasons in which antecedent river stages are elevated and Bay of Bengal

cyclogenesis is favoured (Islam and Peterson 2009; Zscheischler et al. 2018), so the three principal loading mechanisms on delta infrastructure—rainfall, river stage, and storm surge—are positively coupled through the same ocean state rather than arriving independently. The probabilities reported here are conditioned on rainfall alone and therefore represent the marginal component of a joint exposure. Because compound analyses consistently find that single-driver treatments understate risk when drivers are positively dependent (Ikeuchi et al. 2017; Zscheischler et al. 2018), the lifetime exceedance figures in Table 6 should be read as lower bounds on true compound hazard, and the negative-phase columns in particular understate the concentration of risk by an amount this analysis cannot quantify.

Table 6: Probability of at least one exceedance of the stationary 100-year design depth during a 50-year service life, by covariate model and climate-state assumption. Stationary benchmark: 39.5%.

Climate-state assumption	DMI model	ENSO model	Dual model
Persistent strongly negative state	76%	63%	69%
Persistent neutral state	45%	24%	40%
Persistent strongly positive state	23%	7%	20%
Climatological weighting ($s \sim N(0, 1)$)	49%	29%	43%
Equal-time stress cycling ($-2\sigma/0/+2\sigma$)	54%	36%	47%

5.4 Sensitivity to model formulation

Because no single covariate model can be declared definitively superior (Section 4), every quantity above was recomputed under all three formulations. Table 7 summarizes the comparison at the neutral state. The three models place the 100-year design depth within a 44 mm band (423 mm to 467 mm, approximately $\pm 5\%$ of the stationary value), and all three reproduce the qualitative findings: monotonic recurrence compression toward negative states and elevated lifetime risk under negative-phase persistence. The ENSO-only model is the most conservative in reliability terms and the DMI-only model the least; the dual model, which has the strongest statistical support over the full record, lies between them. The conclusions of Sections 5.2–5.3—compression of the design event under negative ocean states

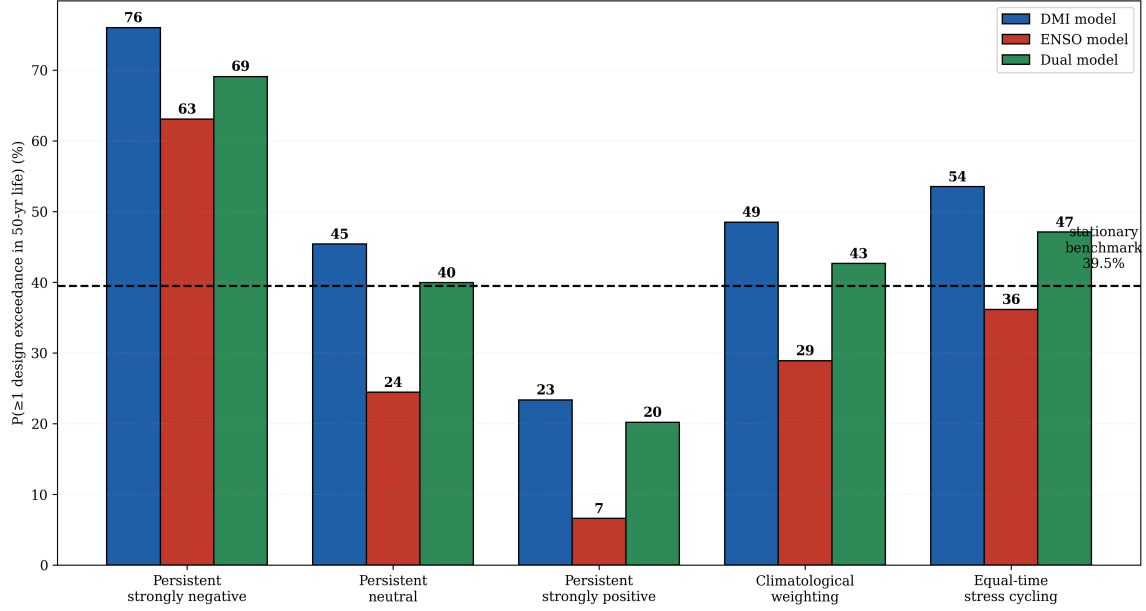


Figure 6: Lifetime reliability of the stationary design under climate-state variability: probability of at least one exceedance of the stationary 100-year design depth during a 50-year service life, by covariate model and climate-state assumption. The dashed line marks the stationary benchmark of 39.5%.

by roughly a factor of two to three and a 36–54% lifetime exceedance probability under cycling—are therefore robust to the choice of climate covariate, even though the attribution of variance between the two correlated indices is not fully resolvable from 32–64 years of data.

Table 7: Cross-model sensitivity of hazard and reliability metrics (Central Bangladesh, 1982–2013).

Metric	DMI only	ENSO only	DMI+ENSO
100-yr design depth, neutral state (mm)	467	423	453
Lifetime exceedance, climatological weighting (%)	49	29	43
Lifetime exceedance, equal-time stress cycling (%)	54	36	47

5.5 Temporal stability across calibration periods

Because the record ends in 2013, it is reasonable to ask whether the recurrence-compression result is an artifact of the 1982–2013 calibration period. To test this without extending the dataset or altering the model, the DMI-conditioned GEV was refitted over eight overlapping

30-year windows advancing in 5-year steps, and the equivalent recurrence period of the stationary 100-year design depth under strong negative IOD (-2σ) was recomputed in each window using the identical formulas of Section 3.4. The compression implication is present in every window without exception (Fig. 8): the equivalent recurrence period under -2σ remains below the nominal 100 years throughout. The strength of the compression intensifies toward the present, with the single-covariate DMI coefficient rising in magnitude across the windows.

To confirm that the apparent intensification is not an artifact of the evolving station network, the rolling-window audit was repeated on a fixed panel of the six stations reporting continuously since 1948–1953 (Dhaka, Faridpur, Barisal, Khulna, Jessore, Satkhira), which removes all compositional drift (Fig. 7). On this fixed panel the DMI coefficient still strengthens toward the present (early-half mean ≈ -20 , late-half mean $\approx -28 \text{ mm } \sigma^{-1}$), and the equivalent recurrence period under -2σ still trends downward. The strengthening is therefore predominantly a genuine intensification of the IOD–rainfall coupling rather than a consequence of adding stations to the regional average—a finding consistent with the documented tightening of Indo-Pacific coupling and with projected increases in extreme IOD variability under greenhouse warming (Cai et al. 2014; Abram et al. 2020). The operative conclusion is that the recurrence-compression implication holds across every calibration period tested over six decades, with its most pronounced and most decision-relevant expression in the recent decades.

5.6 Distribution-free validation and specification checks

Because the likelihood-ratio tests of Section 4 rely on asymptotic χ^2 theory that is only approximate at $n = 32$, the significance of the DMI–rainfall relationship was reassessed with four resampling and placebo procedures that make no distributional assumption, together with two specification checks. All were applied to the DMI-conditioned model for Central Bangladesh, 1982–2013, and are summarized in Table 8.

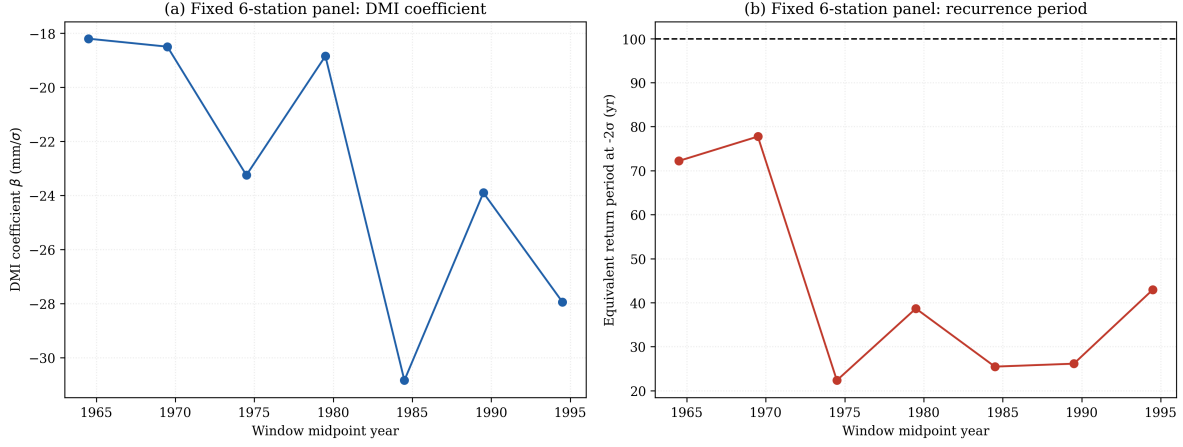


Figure 7: Fixed-panel confirmation of the temporal trend. The rolling-window audit repeated using only the six Central stations reporting continuously since 1948–1953, eliminating compositional drift. (a) The DMI coefficient strengthens toward the present. (b) The equivalent recurrence period under -2σ IOD remains below 100 years in every window, confirming the intensification is not an artifact of the expanding station network.

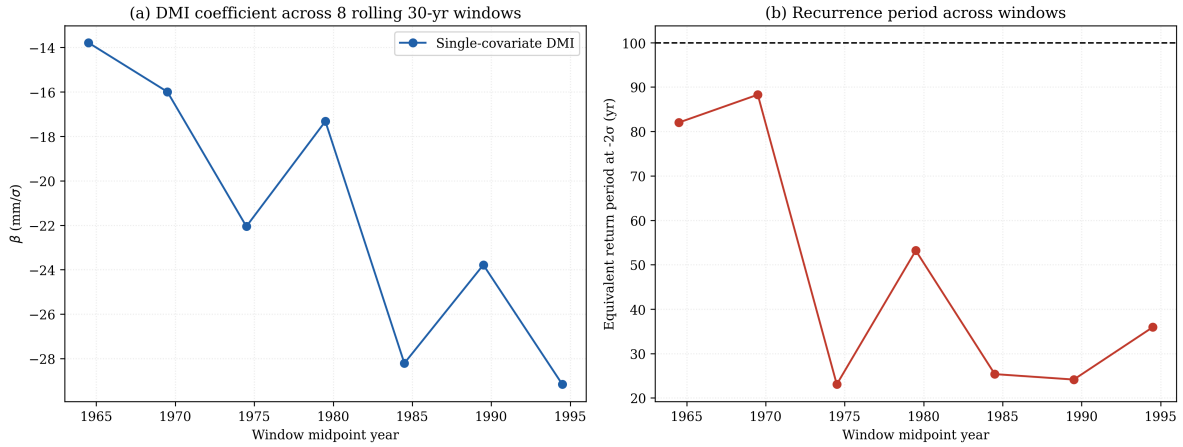


Figure 8: Temporal stability audit using eight overlapping 30-year calibration windows (5-year steps). (a) DMI location-parameter coefficient across windows. (b) Equivalent recurrence period of the stationary 100-year design depth under -2σ IOD: compression ($T < 100$ yr) is present in every window and intensifies toward the present.

First, a *permutation test* shuffled the pairing between rainfall maxima and DMI values 2,000 times; the observed likelihood-ratio statistic (10.44) was exceeded by only 0.3% of permutations. Second, a *phase-randomized surrogate test* generated 2,000 covariate series that preserve the DMI power spectrum and autocorrelation but destroy its phase alignment to rainfall—a stricter null that controls for the covariate’s temporal structure—yielding $p = 0.004$. Third, a *circular-shift null*, which rigidly lags the DMI series by every possible offset and thus preserves its autocorrelation exactly, placed the observed statistic above all 31 shifted alternatives ($p = 0.031$). Fourth, a *placebo test* refitted the identical model using five physically-unrelated covariates (three AR(1) surrogates matched to the DMI autocorrelation, a linear time index, and an 11-year sinusoid); none reached significance and every placebo statistic fell far below the DMI value, confirming that the modeling procedure does not manufacture significance from covariates with comparable statistical texture but no physical link to Bangladesh rainfall.

Two specification checks complete the assessment. A nonlinearity check added a quadratic DMI term to the location parameter; the term was not significant (LRT $p = 0.47$) and inflated the AIC, so the linear-in-DMI location structure is adequate over the observed index range. Finally, residual diagnostics on the probability-integral-transformed maxima showed no departure from uniformity (Kolmogorov–Smirnov $p = 0.73$), approximate normality of the transformed residuals (Anderson–Darling 0.26, below the 5% critical value 0.73), and no significant lag-1 serial correlation ($r_1 = -0.24$); a weak positive association between residual magnitude and fitted value ($r = 0.19$) recovers, as an independent diagnostic, the mild scale-dependence on climate state already noted in Section 4.3, which renders the location-only compression estimate conservative. The DMI effect is thus significant under four independent distribution-free tests, is not produced by placebo covariates, and arises from a correctly specified conditional model.

Table 8: Distribution-free validation and specification checks for the DMI-conditioned GEV, Central Bangladesh 1982–2013. LRT p -value shown for reference; all resampling tests confirm significance without asymptotic assumptions.

Test	Result	Interpretation
Likelihood-ratio (asymptotic)	$p = 0.0012$	reference
Permutation (2,000)	$p = 0.0030$	significant, distribution-free
Phase-randomized surrogate (2,000)	$p = 0.0040$	robust to covariate autocorrelation
Circular-shift null (31 offsets)	$p = 0.031$	no accidental alignment
Placebo covariates (5)	0/5 significant	procedure does not over-fit
Nonlinearity (linear vs. quadratic)	quad. n.s. ($p = 0.47$)	linear location adequate
Residual PIT (KS)	$p = 0.73$	GEV fit not rejected
Residual serial correlation (lag 1)	$r_1 = -0.24$ (n.s.)	no autocorrelation structure

5.7 Seasonal covariate window (lead–lag analysis)

The covariates are averaged over the OND rainfall season itself (Section 2.2). To test whether a leading seasonal window would serve as well or better—which would bear directly on the seasonal-forecast application of Section 6.2—the single-covariate models were refitted using each of six seasonal windows from boreal spring (MAM) through the synchronous OND window, for both indices. The DMI relationship strengthens monotonically as the window approaches OND, consistent with the boreal-autumn peak of the IOD, and is strongest synchronously; however, the autumn windows (ASO, SON, OND) are mutually correlated at 0.91–0.97 and share calendar months, so this progression reflects one signal measured through overlapping windows rather than independent confirmation and does not establish OND as uniquely optimal.

The robust and decision-relevant contrast is between the well-separated windows: the ENSO relationship is already at essentially full strength by the monsoon season (JJAS, a one-to-four-month lead; $\beta \approx -33 \text{ mm } \sigma^{-1}$, $p = 0.011$) and does not sharpen further toward OND, whereas the DMI relationship is only marginal at that lead ($p = 0.052$) and consolidates through the autumn. Neither index shows any relationship in the well-separated spring window (MAM, $p \approx 0.49$). The practical implication is that ENSO carries a longer effective lead time for the pre-season operational triggers of Section 6.2, while the IOD

provides its strongest signal contemporaneously with the season it modulates.

5.8 Physical interpretation of the climate–extremes linkage

The sign, seasonality, and spatial pattern of the fitted relationships are consistent with established Indo-Pacific dynamics, and no novel mechanism needs to be invoked. During boreal autumn, when the IOD peaks, a negative IOD event places anomalously warm water and enhanced convection in the eastern equatorial Indian Ocean (Saji et al. 1999; Schott et al. 2009). The associated anomalous circulation strengthens low-level convergence and moisture transport from the Bay of Bengal toward its northern rim, while warmer eastern-basin and Bay of Bengal surface waters raise boundary-layer moist static energy for the deep convective systems—post-monsoon depressions and tropical cyclones—that produce the largest OND monthly totals in Bangladesh (Islam and Peterson 2009). Positive IOD events reverse this configuration, and the negative DMI coefficient on extreme rainfall is the direct statistical expression of this asymmetry. The ENSO pathway is complementary: cool (La Niña) states strengthen the ascending branch of the Walker circulation over the Maritime Continent and Bay of Bengal sector, favoring enhanced convection and post-monsoon cyclogenesis, while warm (El Niño) states suppress it (Rasmusson and Carpenter 1983; Webster et al. 1998). Because positive IOD events co-occur preferentially with El Niño (Ashok et al. 2001; Krishnamurthy and Kirtman 2003), the two indices are correlated, and the dual model’s partial coefficients are accordingly smaller than the single-covariate estimates.

The regional gradient of sensitivity follows the same moisture-routing logic. The Central, Northeastern, and Coastal regions receive their OND extremes predominantly from marine systems advected inland from the Bay, so their extremes inherit the Bay’s ocean-state modulation directly; the Coastal region’s especially strong ENSO coefficient is consistent with first-landfall exposure to cyclonic systems whose basin-scale activity responds to ENSO. The Northwestern region lies furthest from the coast, outside the principal marine moisture corridors, and derives a larger share of its cool-season rainfall from western disturbances

and locally triggered convection; its statistical decoupling from both indices is therefore the expected outcome of geography rather than an anomaly requiring explanation.

5.9 Scope of the claims the record supports

The analysis deliberately stops short of claims the data cannot support. The record does not establish IOD dominance over ENSO: over 64 years ENSO is marginally the more consistent covariate, the apparent post-1982 intensification of the DMI effect is directionally clear but not statistically confirmable, and the two indices co-vary too strongly for 32–64 annual maxima to apportion variance definitively.

What the data do establish, robustly and across every audit applied, is the decision-relevant statement: observable ocean states modulate the effective frequency of the design rainfall event by a factor of roughly two to five, monotonically across the index range (Fig. 5), consistently across three model formulations (Table 7), insensitively to the removal of individual extreme years (Table 2), and across all rolling 30-year calibration windows. This framing aligns with a broader shift in the nonstationary-hazard literature away from open-ended time-trend extrapolation and toward physically interpretable, observable covariates (Luke et al. 2017; Yan et al. 2023; Vinnarasi and Dhanya 2022). The contribution of this study is therefore not a new teleconnection claim but a quantified, audited demonstration that the stationarity assumption embedded in hazard estimation and design practice conceals a large, structured, and partially predictable component of flood risk.

6 A climate-informed risk-management framework

The audited results of Section 5 support a four-component framework through which existing Bangladeshi hazard assessment and operational practice can incorporate climate-state information without abandoning its statutory basis in the BWDB design manuals (Bangladesh Water Development Board 2013b), the MPO/NWMP return-period framework (Master Plan

577 Organization 1986; Water Resources Planning Organization 2004), and the BNBC (Housing
 578 and Building Research Institute 2020) (Fig. 9). The framework is intentionally conserva-
 579 tive in construction: every quantity it uses is a point estimate that survived the audits of
 580 Section 3.3, every component is a verification or prioritization layer added on top of, not in
 581 place of, conventional stationary analysis, and each component degrades gracefully to current
 582 practice if climate information is unavailable or distrusted.

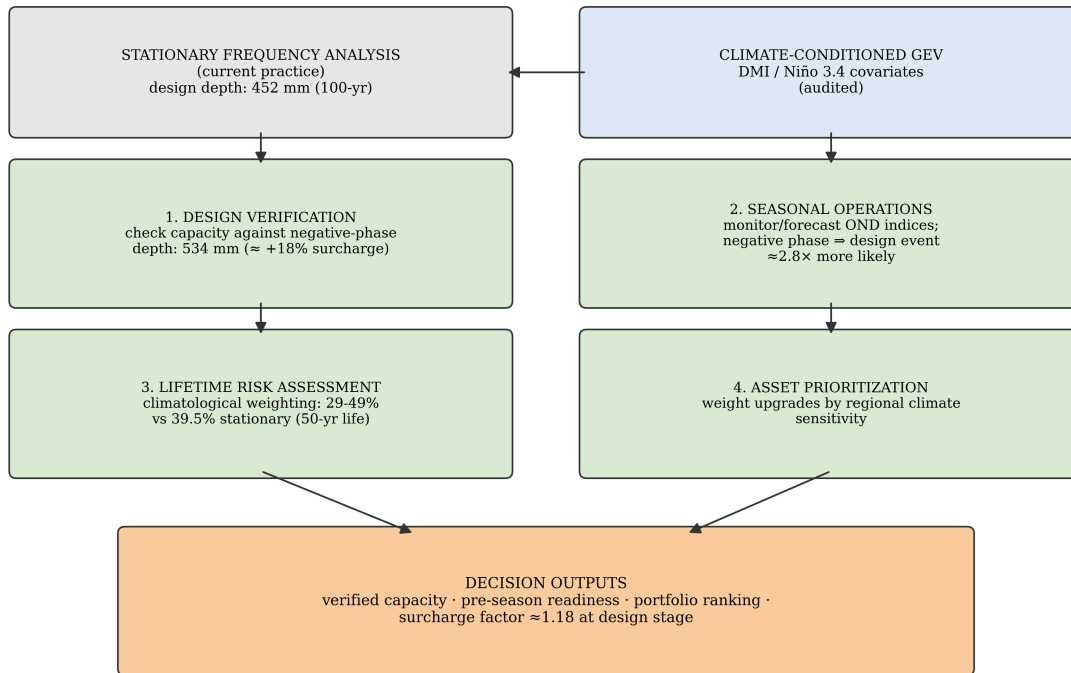


Figure 9: Climate-informed risk-management framework derived from the audited results. Climate-conditioned models (right) supplement, and are benchmarked against, conventional stationary frequency analysis (left); the four numbered components feed design verification, seasonal operations, lifetime risk assessment, and portfolio prioritization.

583 6.1 Design verification depth and the climate surcharge factor

584 The first and most immediately implementable component is a verification check at the
 585 design stage. For Central Bangladesh, the negative-phase (-2σ) design depths of Table 4

exceed the stationary depths by an almost constant ratio: $479/410 = 1.17$ at the 50-year level and $534/452 = 1.18$ at the 100-year level. This ratio functions as a *climate surcharge factor* of approximately 1.18, a single dimensionless number by which the stationary design depth is multiplied to obtain the depth that conventional reliability targets would require if the structure had to deliver its nominal performance during negative-phase conditions. The near-constancy of the factor across return periods is a consequence of the location-only conditioning and makes the check trivial to apply within existing design workflows: no refitting, no software change, simply a second capacity check at 1.18 times the code depth. This approach is a physically-grounded analogue of the safety-factor methods now being proposed for designing urban infrastructure under nonstationary conditions (Kim et al. 2021; Yan et al. 2023).

A worked example illustrates the decision content. Consider a drainage regulator in the Dhaka region sized for the stationary 100-year OND rainfall of 452 mm. Section 5.2 shows that during strongly negative IOD seasons this depth is exceeded with annual probability $1/36 \approx 2.8\%$, not the nominal 1%. Over a single decade dominated by negative-phase conditions, the exceedance probability is $1 - (1 - 1/36)^{10} = 25\%$, against 9.6% implied by the design documents, equivalent to approximately a 2.5-fold understatement of short-horizon risk, precisely when antecedent river stages and cyclone exposure are also elevated. If the same structure is instead verified against the surcharge depth of 534 mm, its nominal reliability is preserved across the full range of observed climate states. Because conveyance capacity exhibits strong economies of scale at the design stage, while post-construction retrofitting is disproportionately expensive, the surcharge check is a low-regret intervention: its cost is incurred where capacity is cheapest and its benefit is concentrated in the climate states in which failure is most likely and most consequential.

Two boundaries on the factor must be respected. It is derived from, and applies to, regional OND monthly maxima in Central Bangladesh; Section 4.4 supports analogous (separately calibrated) factors for the Northeastern and Coastal regions but explicitly does not

support any climate surcharge in the Northwest, where applying one would waste capital on a linkage the data do not exhibit. And it is a verification depth for climate-state robustness, not a revised statutory standard: adopting it as a mandatory design basis would require the cost-benefit and policy analysis that standard-setting demands, which this study informs but does not perform.

6.2 Seasonal operational risk management

The second component exploits the observability of the covariates. Unlike a time trend, the OND climate state is monitored in near-real time and is forecast with useful skill at one-to-two-season leads by operational coupled models (Luo et al. 2007, 2008; Barnston et al. 2012; Shi et al. 2012). The compression curve of Fig. 5 converts such a forecast directly into decision-relevant language: a forecast strongly negative IOD season implies that every structure in the climate-sensitive regions is operating, for that season, at an effective protection level of roughly its nominal level divided by 2.8. Concrete operational responses follow at near-zero capital cost: pre-season drawdown of regulators and retention storage where rule curves permit; verification of polder pump readiness and embankment inspection before, rather than during, the season; pre-positioning of emergency drainage assets in the Central and Northeastern regions; and escalation triggers tied to published index thresholds rather than to ad hoc judgment.

6.3 Lifetime reliability and asset-portfolio prioritization

The third and fourth components operate at the planning horizon. Table 6 establishes that the realized reliability of a stationary design depends materially on the sequence of climate states over the service life. For asset management this converts directly into a prioritization rule: among structures of equal nominal standard and equal consequence-of-failure, those in climate-sensitive regions whose remaining service life is expected to overlap negative-phase-rich periods carry the higher realized risk and should rank higher for inspection, re-

habilitation, and upgrade budgets. The state-occupation weights in the lifetime formula of Section 3.4 are deliberately exposed as inputs: agencies holding scenario information about future IOD and ENSO statistics, including projected increases in extreme IOD frequency under greenhouse warming (Cai et al. 2014; Abram et al. 2020), can substitute their own weights without any change to the framework.

6.4 Scope and intended use

To preclude misapplication, the framework’s scope is stated explicitly. (i) It applies to regional OND monthly maxima; sub-daily urban drainage design responds to different storm physics and requires separate analysis. (ii) It applies to the Central, Northeastern, and Coastal regions; the Northwest showed no significant climate linkage and the Southwestern stations were reported separately for data reasons. (iii) Its quantities are audited point estimates whose uncertainty is expressed through cross-model ranges (Table 7) and coefficient stability (Table 2), not through formal intervals, and decisions should weigh the full cross-model range rather than any single column. (iv) It is additive to, and benchmarked against, stationary practice: every component reduces to current practice when the climate state is neutral or unknown, which is the appropriate behavior for a verification layer.

6.5 Relation to nonstationary design theory

The framework instantiates, for Bangladesh, the design-life and equivalent-reliability concepts developed for nonstationary conditions (Rootzén and Katz 2013; Salas and Obeysekera 2014; Read and Vogel 2015). Those formulations require a model of how exceedance probability evolves over the service life; the present study supplies that ingredient in covariate form, with a decisive practical advantage over time-trend formulations: the covariate is bounded, recurrent, and observable, so the fitted model is interpolative rather than extrapolative and cannot generate the open-ended projections that make trend-based nonstationary design contentious (Luke et al. 2017; Serinaldi and Kilsby 2015). The cautions of Serinaldi and Kilsby

(2015) regarding uncertainty in nonstationary models apply with full force at $n = 32$ and motivated two structural decisions: the refusal to report interval estimates that failed audit, and the presentation of every quantity across three competing model formulations so that the model-choice component of uncertainty is visible in the decision quantities themselves.

7 Limitations

Several limitations bound the conclusions. (i) *Sample size*: the homogeneous analysis window contains 32 annual maxima; upper-tail interval estimation is unstable at this size, and uncertainty is accordingly expressed through sensitivity ranges rather than confidence intervals. (ii) *Attribution*: DMI and Niño 3.4 are correlated, and the partition of influence between them cannot be settled with this record; all conclusions are therefore reported across competing formulations. (iii) *Covariate structure*: only the GEV location parameter was conditioned on climate state; scale or shape responses, if present, would modify tail behavior in ways this model cannot capture, but could not be estimated stably here. (iv) *Spatial aggregation*: regional station-mean maxima smooth localized convective extremes; station-scale applications would require local recalibration. (v) *Block choice*: monthly OND maxima target multi-day, basin-scale loading; sub-daily urban drainage design responds to different storm physics and may exhibit different climate sensitivity. Furthermore, the lifetime-reliability metrics are conditioned on rainfall alone; because the post-monsoon season exposes delta infrastructure to compound surge, river-stage, and rainfall loading whose joint occurrence single-driver analyses tend to understate (Ikeuchi et al. 2017; Zscheischler et al. 2018), the reported exceedance probabilities should be read as lower bounds on true multi-hazard risk. (vi) *Stationarity within states*: the framework assumes the conditional distributions are themselves stable; secular climate change may alter both the index distributions and the conditional response, and projected increases in extreme IOD frequency (Cai et al. 2014) would shift the state-occupation weights used in lifetime calculations. (vii) The

climate surcharge factor is region- and variable-specific, derives from the DMI-conditioned model at the protective end of the cross-model range, and is proposed as a verification depth, not as a revised statutory standard. (viii) *Multiplicity*: several models, regions, and periods were examined; although the headline relationships are strongly significant and survive leave-one-out testing, no formal multiplicity correction was applied, and marginal results should be read accordingly. (ix) *Dependence*: annual maxima are treated as conditionally independent given the covariate; residual serial dependence inherited from the autocorrelated indices was not modeled and would, if present, mildly widen effective uncertainty. (x) *Block size and extrapolation*: each annual maximum is the largest of only three monthly totals, so the GEV is adopted as an empirically validated family rather than an asymptotic necessity, and the 100-year quantile is an extrapolation to roughly three times the record length with a weakly constrained shape parameter; these are standard, but real, caveats on all tail statements.

8 Conclusions

Nonstationary extreme-value analysis of 64 years of post-monsoon rainfall maxima across Bangladesh, subjected to leave-one-out, optimization-stability, interaction, and formula audits, supports the following conclusions.

1. Post-monsoon rainfall extremes in Central, Northeastern, and Coastal Bangladesh are significantly modulated by observable ocean climate states. ENSO is a persistent covariate across the full 1950–2013 record; the IOD is a comparably strong covariate in the post-1982 period (−33.5 mm per standard deviation of OND DMI in Central Bangladesh). The Northwestern region shows no significant linkage to either index.
2. The dominant consequence for hazard estimation is recurrence compression. The rainfall depth corresponding to the stationary 100-year design event in Central Bangladesh (452 mm) has an effective return period that varies monotonically from approximately 36 years under strongly negative IOD states to approximately 189 years under strongly

positive states, a five-fold modulation reproduced by ENSO-based and dual-covariate models. A rolling-window audit over eight overlapping 30-year calibration periods confirms that this compression is present in every period and intensifies toward the present, a strengthening confirmed on a fixed six-station panel and therefore consistent with an intensification of the IOD response rather than with correlated covariates or evolving station coverage.

3. Stationary reliability statements are state-dependent. The lifetime probability that a 50-year-service structure designed to the stationary 100-year standard experiences a design exceedance is 39.5% under stationarity and 29–49% under climatological state weighting depending on model formulation, confirming approximate unbiasedness on average, but rises to 63–76% if the service life is dominated by negative-phase conditions. The significance of the climate linkage is the temporal clustering of risk, not a uniform bias of stationary analysis—and because the negative phase also elevates river stage and cyclone exposure, the rainfall-only figures are lower bounds on compound hazard.

4. These results translate into an implementable framework: a climate surcharge factor of approximately 1.18 on stationary design depths (the protective, DMI-conditioned end of the cross-model range) for verification in the climate-sensitive regions; seasonal operational triggers tied to monitored and forecastable index thresholds, under which the design event becomes roughly 2.8 times more likely than nominal; and lifetime reliability and asset-prioritization calculations with explicit, user-replaceable climate-state weights. Each component is additive to existing practice and reduces to it when climate information is absent.

Collectively, the results demonstrate that climate-state variability materially alters the reliability of stationary hazard and design assumptions in Bangladesh, and they provide audited, model-robust quantities through which design verification, seasonal operations, and

asset management can incorporate that variability without recourse to speculative trend extrapolation.

Statements and Declarations

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Competing interests

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author contributions

Sadman Arshad: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Visualization, Writing — original draft, Writing — review and editing. As the sole author, Sadman Arshad is responsible for all aspects of the work.

Data availability

The post-monsoon rainfall records were obtained from the Bangladesh Meteorological Department (BMD) under institutional arrangement and are not publicly redistributable; they may be requested directly from BMD (<http://www.bmd.gov.bd>). The climate indices used as covariates are publicly available: the Dipole Mode Index was computed from the HadISST dataset (Rayner et al. 2003) provided by the UK Met Office Hadley Centre, and the Niño 3.4 index from NOAA ERSSTv5 (Huang et al. 2017) provided by the NOAA Physical Sciences Laboratory.

Code availability

The analysis code and processed (non-restricted) datasets supporting the findings of this study are available from the author on reasonable request.

Ethics approval

Not applicable.

Declaration of generative AI and AI-assisted technologies

During the preparation of this work the author used a large language model-based AI assistant in order to improve the language, structure, and clarity of the manuscript and to assist with reference checking, code auditing, and formatting. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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