

El Niño-Southern Oscillation, Indian Ocean Dipole, and Local Sea-Surface Temperature Forcing of Humid-Heat Extremes in the Arabian Peninsula

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El Niño-Southern Oscillation, Indian Ocean Dipole, and Local Sea-Surface Temperature Forcing of Humid-Heat Extremes in the Arabian Peninsula

Abstract

Climate model simulations often underestimate humid-heat extremes (HHEs) in arid coastal environments because they depend critically and at high resolution on atmospheric humidity, which is difficult to represent accurately. While local sea-surface temperatures (SSTs) are known to strongly constrain HHEs in the Arabian Peninsula (AP) and remote SST variability modulates regional temperature and moisture distributions, how these relationships combine to shape the tail-end behavior of HHEs remains poorly understood. Given the substantial health and economic risks associated with HHEs, directly quantifying these relationships provides a complementary approach for understanding how HHEs may evolve. Here, we leverage the historical relationship between HHEs and SSTs through a Bayesian peaks-over-threshold (POT) framework. We model peak daily wet-bulb temperature (T_w) using temporally lagged remote SST predictors, including the El Niño-Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD), and local SST warming perturbations for a selection of populous cities in the AP. We quantify how ENSO and IOD alter humid-heat exceedance probabilities and modify surrounding basin SSTs. Finally, we model how local and remote SST variability combines to modulate HHEs, including for "super" ENSO events. We find that ENSO strongly modulates T_w in the central Arabian Desert and Persian Gulf coast, where La Niña (El Niño) events enhance (suppress) T_w extremes through enhanced near-surface atmospheric moisture. The IOD exerts substantially weaker influences, with only modest suppression during positive IOD events. In eastern Saudi Arabia, a La Niña (-1°C) event increases the absolute probability of T_w exceeding 95th-percentile (p_{95}) by 3.8 percentage points, nearly doubling the likelihood, and a hypothetical "super" La Niña (-2.5°C anomaly) by 14.5 percentage points, quadrupling the likelihood. Under 2°C local SST anomalies, T_w 99th-percentile (p_{99}) in Doha increases by $\sim 0.5^\circ\text{C}$, to a dangerous value of 31.4°C ; combined with a "super" La Niña, Doha's p_{99} increases by $\sim 2.5^\circ\text{C}$ (33.3°C). Together, these results demonstrate that future HHEs in the AP depend on both large-scale and local climate variability, with combined ENSO episodes and SST variability producing nonlinear increases in extreme T_w .

1 Introduction

The coastal Arabian Peninsula (AP) lies at the intersection of some of the highest dry-bulb air temperatures (T_a) and sea-surface temperatures (SSTs) on Earth, producing the most severe humid-heat extremes (HHEs) globally (Alawad et al. 2023; Patlakas et al. 2019; Raymond et al. 2020). Wet-bulb temperature (T_w), a humidity-sensitive humid-heat metric (Baldwin et al. 2023), has already reached dangerous levels in cities such as Doha and Dubai and is projected to increase further under climate change (Raymond et al. 2020; Vinodhkumar et al. 2025). These conditions have contributed to mass mortality (Matthews, Ramsay, et al. 2025; Pradhan et al. 2019), economic losses, and reduced labor productivity (Parsons et al. 2021), with impacts expected to intensify as both atmospheric temperature and moisture increase (Pal and Eltahir 2016; Zittis et al. 2021).

Despite this growing risk, future HHEs in the region remain difficult to represent accurately. The sixth phase of the Coupled Model Intercomparison Project (CMIP6) models have known limitations in simulating humidity extremes, particularly in arid coastal environments, and may therefore underestimate future HHEs in the AP (Simpson et al. 2024). At the same time, the physical controls on HHEs provide a basis for more targeted analysis. Local SSTs strongly influence coastal moisture availability and humid heat, while large-scale modes of atmosphere-ocean variability, including El Niño-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD), can alter regional temperature, moisture transport, and circulation (Raymond et al. 2021; Zheng and Hoteit 2025; Abid et al. 2018; Almazroui et al. 2019). However, these local and remote oceanic influences have not been evaluated together in the context of HHEs in the AP. Here, we investigate how projected warming of nearby marine basins may combine with remote SST variability to shape future HHEs across the AP. Because the societal impacts of humid heat are driven disproportionately by the most extreme events rather than average summer conditions, our analysis focuses explicitly on the upper tail of the humid-heat distribution (Matthews, Ramsay, et al. 2025; Matthews, Raymond, et al. 2025). Here, we employ a Bayesian peaks-over-threshold (POT) framework that explicitly models the tails of HHE distributions, quantifies uncertainty, and leverages historical relationships between SSTs and HHEs to estimate future changes in HHE exceedance probability and magnitude under SST perturbations.

Local SSTs of the surrounding basins (Gulf of Aden, Gulf of Oman, Red Sea, and Persian Gulf) influence humid-heat conditions in the AP through spatially and temporally distinct processes that are well understood (Raymond et al. 2021, 2024; Fonseca et al. 2022; Duan et al. 2024; Zolina et al. 2017). The Persian (Arabian) Gulf and Red Sea are semi-enclosed seas with high SSTs and salinity. Evaporation from these seas dominates the regional moisture supply, which is advected inland by mesoscale winds and local climate dynamics such as sea breezes into populous urban environments (Figure 1) (Zolina et al. 2017; Raymond et al. 2021, 2024). Convection is often capped in this region due to dry-air entrainment, which keeps the near-surface moisture elevated without the relief of atmospheric ventilation or cloud cover (Duan et al. 2024). As basin SSTs increase due to

anthropogenic climate change (Shaltout and Eladawy 2024), enhanced moisture may be transported into coastal and inland desert environments under rising T_a via stronger sea breezes (Zittis et al. 2021). In contrast, moisture in the southern AP is controlled by South Asian monsoon dynamics, particularly the Somali Jet.

Much less is known about the relationship between remote SSTs and HHEs in the AP. Atmospheric and oceanic processes dictate transport of moisture and are, in turn, modulated by remote, large-scale modes of ocean-atmosphere variability, namely the El Niño-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) (Zheng and Hoteit 2025; Abid et al. 2018; Alawad et al. 2023; Lachkar et al. 2025). The ENSO cycle is the oscillation between anomalous warming/cooling (El Niño/La Niña) of the central Pacific, while the IOD is a dipole mode of variability between the eastern and western Indian Ocean (Alexander et al. 2002; Saji et al. 1999; Webster et al. 1999). Both ENSO and IOD influence regional atmospheric circulation, temperature, and moisture variability. La Niña events increase extreme precipitation in the southern AP, strengthen monsoonal inflow, and intensify near-surface T_a in the northern AP, while negative IOD (nIOD) events influence temperature and precipitation patterns through nonlinear advection and cloud-radiation feedback mechanisms (Alizadeh and Mousavizadeh 2025; Abid et al. 2018; Almazroui et al. 2019). Importantly, ENSO and IOD do not function independently as they are interconnected with the two teleconnections acting either synergistically or antagonistically (Cai et al. 2019; Izumo et al. 2010; Hochman and Gildor 2025). Despite these established influences on regional temperature, moisture, and atmospheric circulation, how ENSO and IOD, independently and jointly, modulate the probability and magnitude of HHEs in the AP, especially in conjunction with local SST variability, remains poorly understood.

To address these knowledge gaps, we pursue five complementary objectives. First, we quantify how HHEs respond to ENSO and IOD phases at lagged monthly intervals across the AP using a composite analysis. Second, we estimate the joint influence of ENSO and IOD on the probability of exceeding extreme humid-heat thresholds in major AP cities using a Bayesian Bernoulli-process POT framework. Third, we determine how ENSO and IOD modulate SSTs in the marine basins surrounding the AP. Fourth, we quantify how future warming of adjacent seas alters the magnitude of coastal HHEs using a Bayesian generalized Pareto distribution (GPD) POT framework. Finally, we assess the joint interaction between remote SST variability and local basin SST variability using a Bayesian GPD POT framework. Together, these analyses provide a process-based framework linking large-scale ocean variability and local SST forcing to present and future HHEs in the AP.

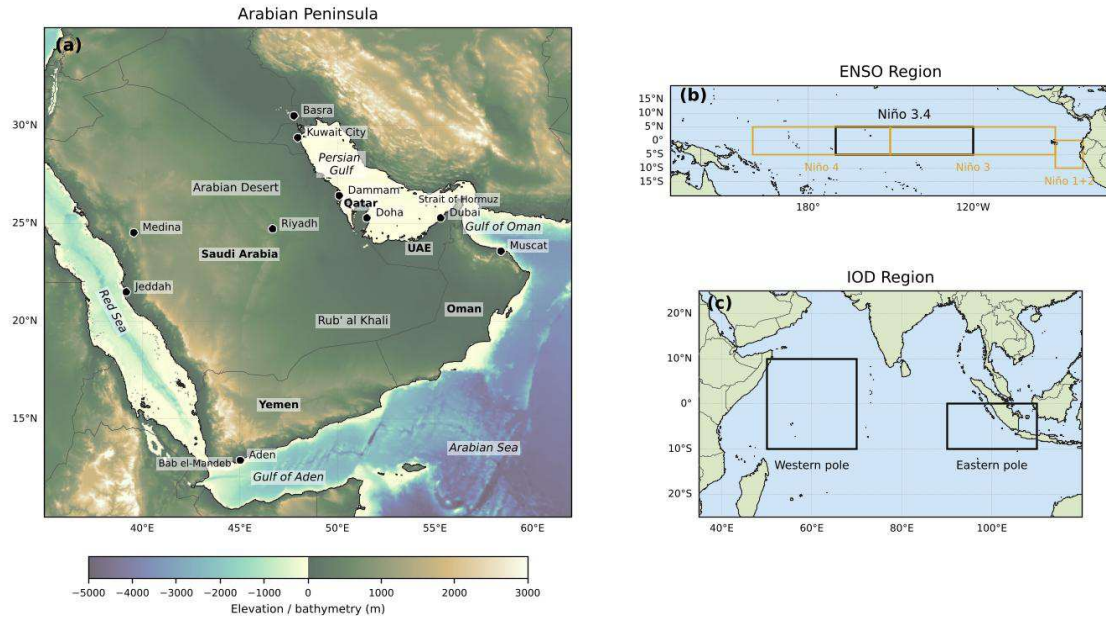


Figure 1: Reference Map of (a) the AP with elevation and bathymetry, (b) ENSO region with the highlighted Niño 3.4 region, and (c) the IOD region with the western (50°–70°E, 10°S–10°N) and eastern (90°–110°E, 10°S–0°) poles

2 Results

2.1 ENSO and IOD phase-dependent spatial patterns of humid heat across the AP

We find that HHEs across the AP are strongly amplified during specific ENSO or IOD phases in boreal summer (JJAS) (Figure 2). This is especially true of ENSO events, which form spatially coherent anomalies that peak over the central Arabian Desert and stretch from the western coastal regions to Qatar and the northern Persian Gulf (Figure 2a,b). Across all phases, specific-humidity (q) anomalies closely track the sign and spatial pattern of T_w anomalies (Figure 2i–l). ENSO drives the majority of this variability through regionally coherent moisture increases, whereas the IOD contributes a weaker and less organized signal. Composite differences between each ENSO or IOD phase and neutral conditions (Figure 2) show consistent shifts in 95th-percentile (p_{95}) T_w alongside the corresponding T_a and q at peak humid heat.

Examining ENSO in isolation, strong amplification (suppression) of HHEs occurs across the central and northern AP during La Niña (El Niño) events (Figure 2a,b). A significant and distinctive V-shaped spatial pattern emerges in extreme T_w . This pattern is present during both phases, with a reversal in sign between El Niño (negative) and La Niña (positive). The southern extent of the AP, from the outflow of the Red Sea to the eastern tip of Oman, shows no coherent humid-heat response.

In contrast to ENSO, the IOD events exhibit unique patterns in intensity, organization, and symmetry. The positive (pIOD) and negative (nIOD) composites of extreme T_w show no strong intensification or suppression of HHEs (Figure 2c,d). Much of Saudi Arabia and the northern border of Yemen exhibits the relatively strongest warming during nIOD events (Figure 2d), but these anomalies are not significant and are substantially weaker than La Niña-associated warming. The entirety of the coasts in the AP in the pIOD or nIOD composites lacks a spatially coherent extreme humid-heat signal. The suppression of HHEs during pIOD events is stronger than the marginal response during nIOD events (Figure 2c,d). The response is asymmetric, with negative extreme- T_w anomalies during pIOD events occurring without comparable positive anomalies during nIOD events. There are small pockets of warming during pIOD events, notably much of the interior United Arab Emirates (UAE).

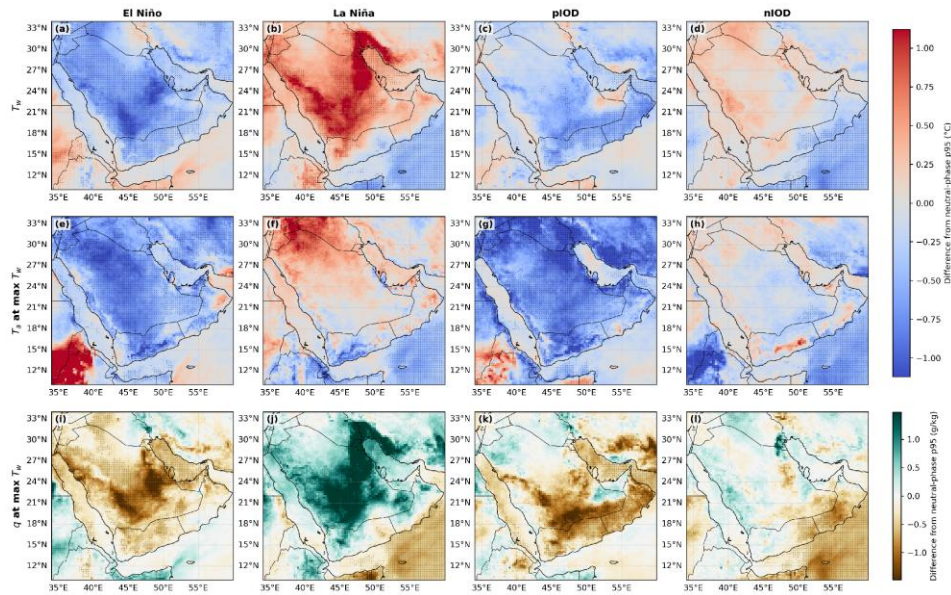


Figure 2: Phase-specific p95 T_w (a–d), T_a (e–h), and q (i–l) anomalies relative to neutral conditions during boreal summer (JJAS). Columns correspond to El Niño, La Niña, positive IOD (pIOD), and negative IOD (nIOD), respectively. ENSO phases are lagged by two months and IOD phases by one month. T_a and q represent conditions concurrent with daily peak T_w . Stippled areas indicate pixels where the 95% bootstrap confidence interval of the phase-minus-neutral anomaly does not include zero.

To understand the reason for the observed changes in T_w , we explore the constituents of T_w , namely T_a and q . Moisture anomalies closely track the patterns in the T_w composites, as Figure 2 panels (a–d) closely mirror (i–l). This reflects the strong sensitivity of T_w to humidity (Kong et al. 2025). During La Niña events, there is a strong amplification of q which agrees spatially with positive T_w anomalies (Figure 2j). The opposite is true of El Niño events (Figure 2i), where humidity is suppressed across the Arabian Desert and the Persian Gulf. nIOD exerts little influence on moisture during HHEs, except for suppression of q over Oman and the Arabian Sea (Figure 2l). Conversely, the effect of pIOD on moisture is substantially stronger and more spatially coherent. There is significant widespread drying

of the southern AP including much of Yemen, Oman, and the majority of southern Saudi Arabia (Figure 2k). Marine near-surface atmospheric moisture is suppressed over the Persian Gulf and the Gulf of Oman, and to a lesser extent the Red Sea.

In contrast to moisture-driven variability, the thermodynamic response to ENSO and IOD, as reflected in T_a at maximum daily T_w , is more spatially homogeneous (Figure 2e–h). During El Niño and pIOD, T_a exhibits nearly spatially uniform cooling during maximum T_w (Figure 2e,g). During La Niña events, the thermodynamic signature is weaker than during El Niño events, although there is widespread but moderate warming, with localized cooling during HHEs over Qatar and Yemen (Figure 2f). The strongest warming occurs primarily over Jordan and Iraq, extending into northern Saudi Arabia. During nIOD, there are no significant changes in T_a , and the response lacks spatial coherence across the AP (Figure 2h).

2.2 ENSO–IOD influence on Exceedance Probability

Distinct phases of ENSO and IOD independently alter tail-end humid-heat conditions; however, exceedance probabilities under more extreme ENSO–IOD cases are more difficult to assess. Here, we use a Bayesian framework to probabilistically assess changes in extreme-event frequency using a Bernoulli process (Section 4.7). Changes in the magnitude of extreme events were also assessed using a GPD framework; these results are provided in the Supplementary Information (SI Figure S1) and are broadly consistent with the frequency-based findings presented here.

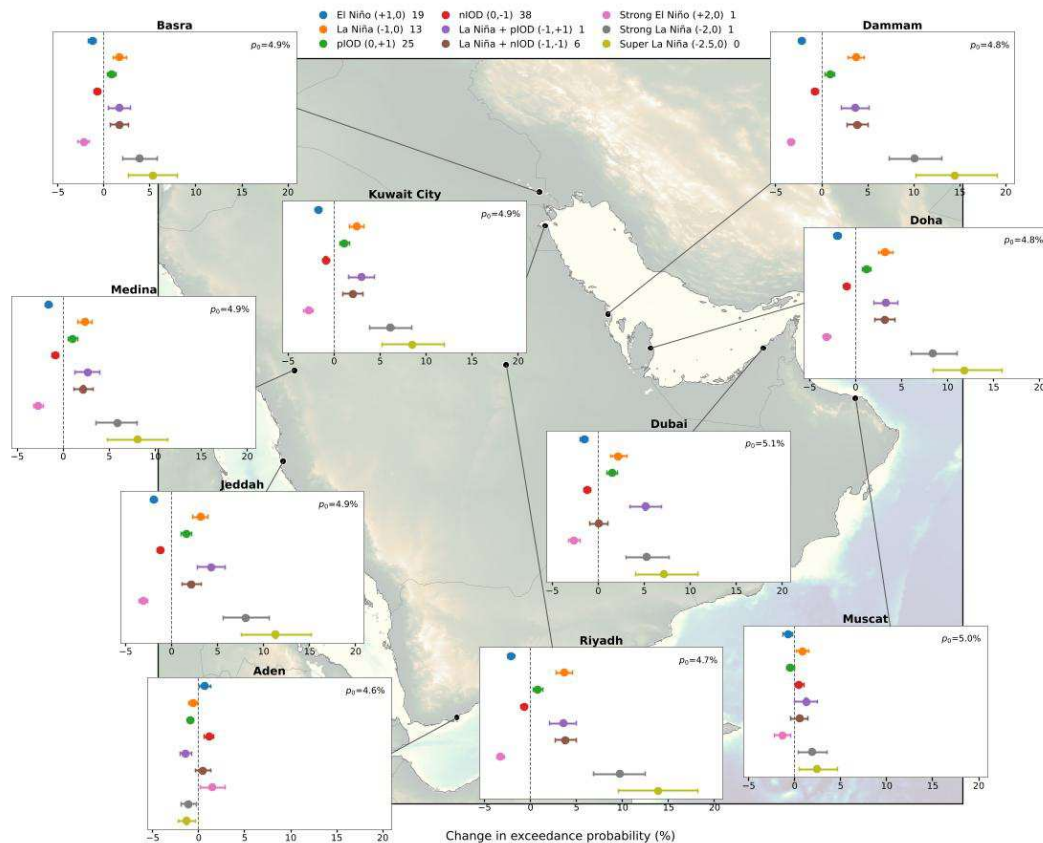


Figure 3: City-specific changes in $p_{95} T_w$ exceedance probability under ENSO and IOD scenarios for Basra, Dammam, Medina, Kuwait City, Doha, Jeddah, Dubai, Aden, Riyadh, and Muscat, estimated using a Bayesian Bernoulli-process exceedance model based on ERA5 data. The baseline probability (p_0) represents the probability of exceeding $p_{95} T_w$ under neutral ENSO and IOD conditions. Points represent posterior estimates of the absolute change in exceedance probability, and horizontal intervals represent 94% highest density intervals (HDIs). The pair (A,B) given in the legend represents the ENSO anomaly (A) and IOD anomaly (B) prescribed for each scenario. Numbers following each scenario indicate the number of JJAS months during 1950–2024 in which those conditions occurred in the historical record.

Across all cities, La Niña conditions are associated with substantial increases in exceedance probability of extreme T_w , while El Niño conditions suppress extremes (Figure 3), consistent with the previous section. In Dammam, the baseline exceedance probability of extreme T_w is $\sim 4.8\%$ of summer days under neutral ENSO–IOD conditions. Under La Niña conditions, this probability increases by 3.8 percentage points (to 8.6%), corresponding to nearly a doubling of extreme-event frequency. Under more intense La Niña cases, exceedance probabilities increase nonlinearly, increasing by 14.5 percentage points for a “super” La Niña. This implies that nearly 20% of JJAS days under these conditions would exceed the historical p_{95} threshold of 29.0°C . The responses are similar in Doha and Dubai, albeit with smaller increases in exceedance probability. Jeddah

exhibits a similar response in the probability of HHEs, but without a comparable change in magnitude (SI Figure S1). This suggests that Jeddah may experience more days exceeding the historical p95 threshold without a corresponding increase in the magnitude of those exceedances. The northern Persian Gulf cities of Kuwait City and Basra show a similar response to the aforementioned southern Persian Gulf cities, but with smaller probability shifts.

In contrast to the Persian Gulf, Aden and Muscat exhibit a much weaker response to ENSO and IOD conditions. This is a consistent result for Muscat and the Gulf of Oman; HHEs in the city and SST variability in the Gulf of Oman exhibit weak coupling and limited sensitivity to large-scale SST forcing.

The inland desert cities of Riyadh and Medina were included in this analysis as they lie within the band of enhanced moisture during La Niña identified in Section 2.1. This moisture anomaly is consistent with the elevated exceedance probabilities. The response to La Niña conditions for both cities is strong, with Riyadh exhibiting a response comparable to Doha and Dammam. These cities experience extreme air temperatures, with T_a reaching 50°C during summer months (Zittis et al. 2021). Moisture is anomalously high during La Niña events, which can substantially elevate humid-heat conditions through the combination of high T_a and increased humidity.

2.3 ENSO–IOD influence on Local SSTs in the AP

During La Niña events, strong positive moisture anomalies occur across the central AP during summer and are further amplified during p95 T_w days. Normally, the AP's surface moisture availability is dominated by local evaporation from nearby seas rather than long-range moisture transport (Zolina et al. 2017). In this section, we investigate whether ENSO and IOD modulate local SSTs, providing a potential source of enhanced evaporation and atmospheric moisture during HHEs.



Figure 4: Local SST responses to distinct oceanic modes. The primary value in each cell represents the posterior mean change in SST ($\Delta\mu$), and the interval represents the corresponding 94% HDI. The pair (A,B) given for each scenario represents the ENSO anomaly (A) and IOD anomaly (B) used for each counterfactual case. All SST changes are given in °C.

The Red Sea, Gulf of Aden, and Gulf of Oman exhibit only moderate warming during La Niña events (Figure 4). However, intense warming occurs in the Persian Gulf during La Niña events. This result is consistent with previous research showing that much of the variability in the Persian Gulf is attributable to ENSO and the North Atlantic Oscillation (NAO) (Lachkar et al. 2025; Alawad et al. 2023). The IOD acts as a background enhancer or suppressor of SSTs in the Persian Gulf, where pIOD can act in concert with La Niña to further enhance Persian Gulf SSTs. The strongest mean warming in the Persian Gulf occurs during a hypothetical "super" La Niña, defined as anomalous cooling of 2.5°C in the Niño 3.4 region. Given that climate-model and statistical analyses project increased ENSO variability, such an extreme La Niña provides a plausible high-end scenario for assessing future HHE sensitivity (Cai et al. 2022). In the Persian Gulf, a "super" La Niña event produces a $\Delta\mu$ shift of +0.88°C, approximately three standard deviations of historical Persian Gulf SST variability.

In Figure 2b,j, we do not see intense T_w warming during La Niña events over the Red Sea, nor do we see a signature of increased moisture along the coast at maximum T_w . Yet,

inland of the Sarawat Mountains (Figure 1), anomalous moisture is present across the western AP during La Niña events at peak T_w . From Figure 4, mean Red Sea SSTs do not respond to ENSO or IOD forcing to the extent observed in the Persian Gulf. Thus, increased Red Sea SST alone is unlikely to explain the anomalous moisture observed across the western AP. Other processes, including changes in wind-driven evaporation or larger-scale moisture transport, may contribute to this response. The source of this excess moisture during La Niña events warrants further investigation.

2.4 City Level Responses to SST Variability in Local Basins

Multi-model mean SST warming in the Persian Gulf, Gulf of Oman, and Gulf of Aden is projected to exceed 1.5°C by century's end under SSP3–7.0 (SI Figure S2). A few of the GCM/ESM projections exceed 2.0°C by the end of the century. More relevant to the near-term perturbations considered here, each basin is projected to warm by 0.5°C–1.0°C by 2050. This increase in SST occurs alongside increasing global temperatures; however, here we isolate the influence of local SST warming on coastal T_w by modeling its historical relationship with local SST variability. In this section, we model tail behavior above the p95 threshold and examine changes in the overall daily p97.5 and p99 under local SST warming perturbations. Each city is modeled against SSTs in its most proximate basin.

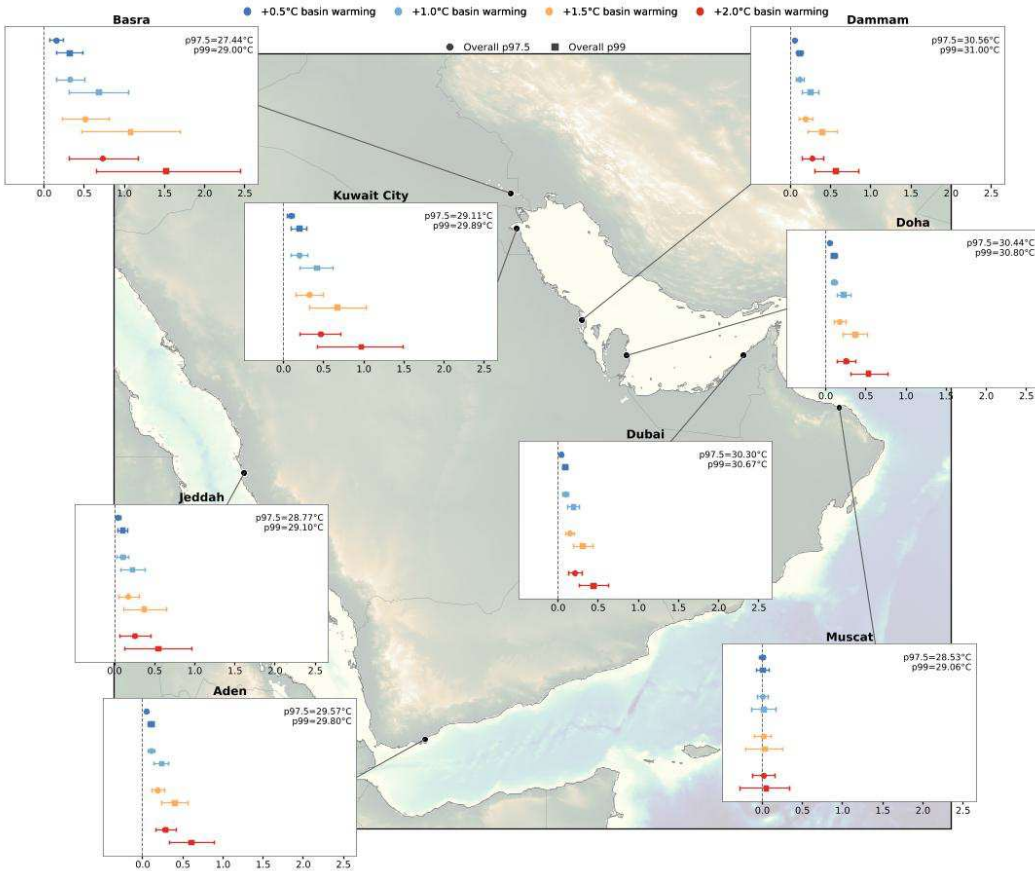


Figure 5: Posterior response of the overall (unconditional) daily p97.5 and p99 T_w to local basin SST warming across AP coastal cities during JJAS. Points indicate posterior-mean changes relative to the neutral local-SST anomaly baseline, with horizontal bars representing 94% HDIs. Circles and squares represent the overall p97.5 and p99, respectively. The baseline p97.5 and p99 values shown in each panel are the modeled T_w values when local basin warming equals zero.

Along the Persian Gulf, Dammam, Doha, and Dubai exhibit clear sensitivity of upper-tail T_w to local SST warming (Figure 5). Under 2.0°C of imposed Persian Gulf warming, Doha's overall daily p97.5 increases by 0.3°C (94% HDI:0.2-0.4°C), while its p99 increases by 0.5°C (94% HDI:0.3-0.8°C). Dammam exhibits a similarly strong response, increasing by 0.3°C at p97.5 and 0.6°C at p99. The response is weaker in Dubai, where the corresponding percentiles increase by 0.2°C and 0.5°C, respectively.

Kuwait City and Basra exhibit comparatively strong sensitivity to local Persian Gulf SSTs (Figure 5), particularly a p99. Under +2.0°C of warming, Kuwait City's overall daily p97.5 and p99 increase by 0.5°C and 1.0°C, respectively. Basra's p97.5 and p99 increase by 0.7°C and 1.5°C, respectively. Basra is the most sensitive to Persian Gulf SST variability, even though it is the only modeled city not located directly on the coast. Moreover, Basra exhibits the largest posterior uncertainty among the selected cities, with a p99 94% HDI of 0.7-2.5°C under +2.0°C warming.

On the western and southern margins of the AP, Jeddah and Aden (Figure 5) also respond positively to adjacent-basin warming, although their responses are weaker than those found in the southern Persian Gulf cities. Under 2.0°C of Red Sea warming, Jeddah’s overall daily p97.5 and p99 increase by 0.2°C and 0.6°C, respectively. Aden responds slightly more strongly to Gulf of Aden warming, increasing by 0.3°C at p97.5 and 0.6°C at p99. Muscat exhibits little detectable sensitivity of upper-tail T_w to the simulated Gulf of Oman SST perturbations. This does not imply that extreme T_w will not increase in Muscat, but rather that the fitted historical relationship provides little evidence that such increases are directly associated with Gulf of Oman SST variability.

2.5 The Future of HHEs in the AP based on SST Forcing

Given that both ENSO–IOD teleconnections and local basin SSTs influence HHE severity, it is important to consider these forcing mechanisms jointly as local SSTs warm and ENSO variability increases in future climates (Cai et al. 2022; Alawad et al. 2023).

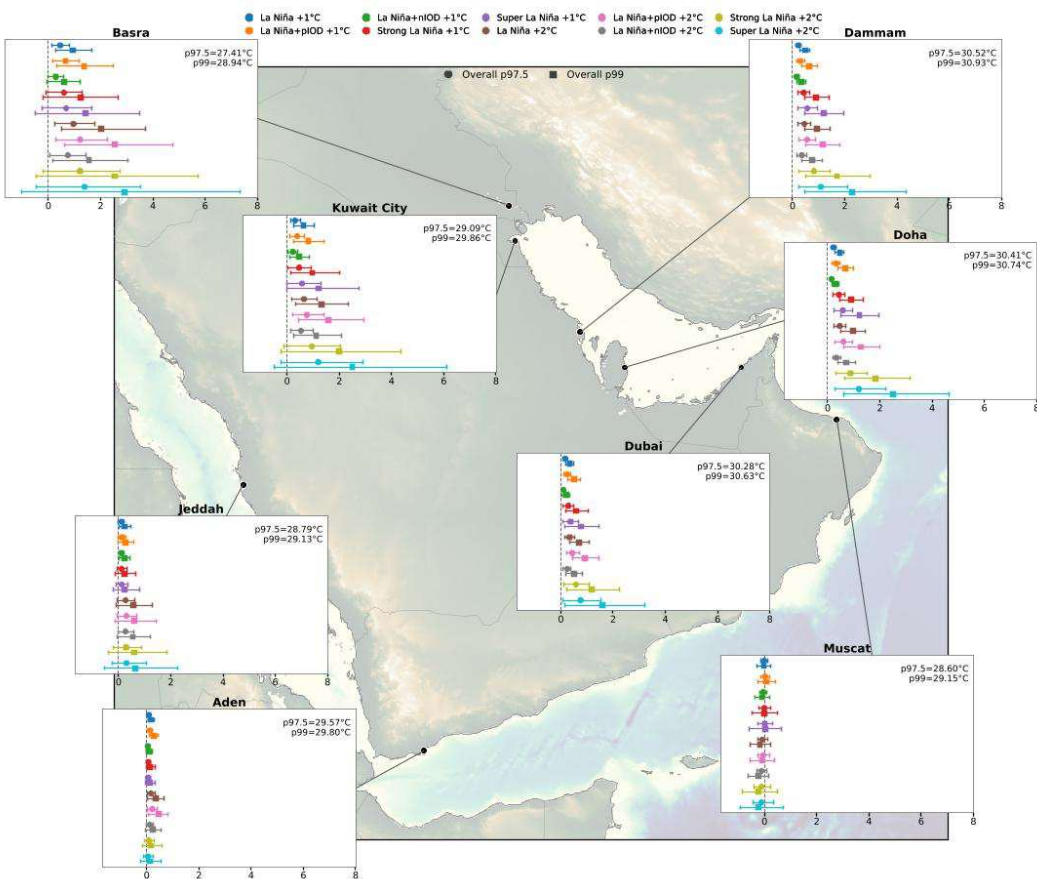


Figure 6: Modeled changes in overall daily p97.5 and p99 T_w under compound La Niña, IOD, and adjacent-basin warming experiments. Points show posterior-mean changes relative to the neutral ENSO, neutral IOD, and zero imposed basin-warming baseline, with horizontal bars denoting 94% HDIs. Neutral baseline overall daily p97.5 and p99 values are shown in the upper-right corner of each panel. Basin-warming experiments impose +1°C or

+2°C on the modeled SST anomaly of each city's adjacent basin. ENSO and IOD anomalies are represented by the pair (A,B), where A is the ENSO anomaly and B is the IOD anomaly used in combination with the imposed basin warming for each counterfactual experiment.

The joint experiments reveal strong geographic differences in how ENSO, IOD, and local-basin warming combine to influence future HHEs (Figure 6). The largest responses occur in cities bordering the Persian Gulf, where increasingly strong La Niña conditions combine with local SST warming to produce the largest increases, particularly at p99. Under a "super" La Niña and +2°C of adjacent-basin warming, the modeled p99 increases by 2.9°C in Basra, 2.5°C in Doha, 2.5°C in Kuwait City, and 2.3°C in Dammam. Dubai also exhibits substantial amplification, although its response is smaller than those of the other Persian Gulf cities.

IOD phase further modulates this compound response. Across the Persian Gulf cities, pIOD conditions consistently strengthen the increase associated with La Niña and basin warming, whereas nIOD conditions reduce it. For example, with La Niña and +2°C of basin warming, Doha's p99 increases by 1.3°C under pIOD, compared with 1.0°C under neutral IOD and 0.7°C under nIOD. A similar ordering is evident in Dammam, Dubai, Kuwait City, and Basra.

This amplification is not uniform across the AP. Jeddah responds primarily to Red Sea warming, with only limited additional sensitivity to La Niña strength: its modeled p99 increase ranges from 0.6°C under ordinary La Niña and +2°C warming to 0.7°C under the corresponding super La Niña experiment. Aden exhibits only modest changes, with the modeled response weakening as La Niña intensifies. Muscat remains effectively insensitive across the compound experiments, with posterior-mean changes near zero or slightly negative.

The compound interaction introduces substantial uncertainty in projections of future HHEs. This increase in uncertainty is expected because the strongest compound cases combine levels of ENSO variability and regional SST warming that have little historical observational analog. Consequently, posterior uncertainty grows with increasing La Niña intensity and imposed basin warming, particularly in the upper tail of the distribution. The joint framework demonstrates that future humid heat is not simply the sum of local basin warming and interannual variability. Rather, remote climate variability and local SST warming can combine to produce substantial amplification in the upper tail of the humid-heat distribution. This framework isolates the component of HHE variability associated with SST forcing but does not explicitly account for processes independent of SST variability, including changes in atmospheric circulation, air temperature, or soil moisture. Therefore, these results represent a partial estimate of potential HHE changes under increased SST variability and warming in future climates.

3 Conclusion

Taken together, the spatial patterns and Bayesian attribution framework demonstrate that HHEs in the AP arise in part through the nonlinear interaction of local basin SSTs and remote ENSO–IOD variability. This is consistent with established research showing that natural climate variability and regional warming can interact to substantially amplify climate extremes (Estrada et al. 2025; Singh et al. 2022). Local SSTs provide a strong thermodynamic constraint on coastal humid heat, while remote SST teleconnections modulate the spatial distribution and severity of favorable humid-heat environments. By separating local SST forcing from large-scale teleconnection effects and explicitly modeling tail behavior, this framework reveals that coastal HHEs are not only linked to local SSTs but are also modulated by remote SST variability, and that these two influences can compound to produce disproportionately large changes in the upper tail of the distribution (Figure 6).

The spatial correspondence between La Niña-associated HHEs, atmospheric moisture, and local SST variability provides insight into how these remote and local influences may interact. ENSO may influence regional moisture availability in part through its modulation of SSTs in the surrounding basins, particularly the Persian Gulf. La Niña produces substantial warming of the Persian Gulf, providing a plausible local contribution to the enhanced atmospheric moisture observed across the Gulf region during HHEs. However, this relationship does not explain the full spatial pattern of anomalous moisture across the AP. In particular, enhanced moisture occurs across portions of the western AP during La Niña events despite a comparatively weak SST response in the Red Sea. This contrast is notable because moisture advected from the Red Sea constitutes a major component of the moisture budget along the western AP (Zolina et al. 2017). Evaporation in the Red Sea may be enhanced by other physical processes, or large-scale moisture transport may be enhanced from sources such as the Somali Jet or African monsoon (Cai et al. 2025; Wang et al. 2025). Our analysis does not distinguish among these potential pathways. Explicit moisture-source attribution using integrated vapor transport diagnostics and event-based moisture tracking would therefore be valuable for determining the origin and transport pathways of the anomalous moisture associated with La Niña HHEs across the western and interior AP.

The implications of humid heat increases in the AP during La Niña events warrant consideration in a global context. El Niño events are commonly associated with increased risks from both global air-temperature extremes and HHEs (Arblaster and Alexander 2012; Rogers et al. 2021; Zhang et al. 2024). Here we show that, in one of the hottest regions on Earth, La Niña events substantially amplify HHEs. As a humidity-sensitive metric, T_w captures the contribution of enhanced atmospheric moisture that temperature-focused metrics may underestimate, particularly where it coincides with already extreme T_a . These La Niña-associated, moisture-enhanced risks are spatially heterogeneous and merit similar investigation in other hot, humid regions.

Beyond these regional findings, this study also demonstrates the utility of Bayesian extreme-value methods for connecting natural climate variability with long-term changes in humid-heat risk. While Bayesian POT frameworks have been applied previously in climate science for a wide range of applications including forecasts (García et al. 2023), projections (Tebaldi and Sansó 2009), and attribution (Katzfuss et al. 2017), to our knowledge they have not been used to jointly quantify the influence of remote ocean variability and future basin warming on HHEs. This application is particularly useful in the AP because humidity contributes disproportionately to extreme T_w (Kong et al. 2025), while atmospheric moisture is strongly constrained by nearby SSTs (Raymond et al. 2021, 2024). Consequently, the combination of teleconnected ocean variability and long-term basin warming provides a physically interpretable basis for probabilistic estimates of HHEs. Although we focus on the AP, the statistical framework developed here is readily transferable to other humid coastal regions where SSTs strongly regulate atmospheric moisture, including Southeast Asia (Gushchina et al. 2020), India (Zore and Landu 2025), or northwestern Mexico (Ivanovich et al. 2026).

The Bayesian POT framework employed here is well suited for humid-heat applications in general because the most dangerous conditions often arise from short-lived humidity maxima occurring on sub-daily timescales that are not always well represented in climate model projections (Simpson et al. 2024). Rather than relying solely on the raw occurrence of these rare events in future simulations, our approach leverages observed historical relationships to statistically characterize the upper tail while explicitly quantifying uncertainty. Because the framework is agnostic to the specific climate hazard considered, it may also be applicable to a broad range of climate extremes beyond humid heat.

Together, these physical and statistical results provide a more complete picture of how natural variability and long-term ocean warming can jointly shape future HHEs. Our results suggest that future humid-heat risk cannot be understood from regional conditions or climate variability in isolation; rather, their interaction governs the most dangerous events. Local mechanisms, particularly basin SST variability, produce strong effects on HHEs, while natural climate variability can compound these effects to produce disproportionately large changes in the upper tail. These relationships may also provide useful predictors for HHE early-warning systems by incorporating both remote climate variability and local SST conditions. Moreover, mitigating emissions and thereby limiting local basin warming may constrain the background conditions upon which extreme ENSO variability acts, reducing the potential for nonlinear amplification of HHEs in the AP's most vulnerable coastal regions.

4 Methods

4.1 Study Area

The AP contains coastal cities subjected to some of the world's most severe humid-heat conditions while bordering diverse marine environments (Raymond et al. 2020; Fonseca et

al. 2022). We therefore focus on major coastal population centers including Dammam, Saudi Arabia; Doha, Qatar; Dubai, United Arab Emirates (UAE), Kuwait City, Kuwait; Basra, Iraq; Jeddah, Saudi Arabia; Aden, Yemen; and Muscat, Oman (Figure 1). Riyadh and Medina are chosen to be modeled in section 2.2 based on their proximity to increases in HHEs found in Section 2.1.

4.2 Data

For this study, we use the ERA5 global reanalysis dataset from the European Center for Medium-Range Weather Forecasts (ECMWF) (Hersbach et al. 2020). The input data are hourly, from which the daily maximum T_w and the concurrent T_a and q are extracted for each day from 1950 to 2024. ERA5 provides the variables required for analysis, including SST, 2-m temperature (T_a), pressure (P) and 2-m dew point temperature (T_d).

We use CMIP6 with a historical baseline of 1995-2014, and projections from 2020–99 using the moderately high emission pathway + shared socioeconomic pathway (SSP) of SSP3–7.0 to assess local SST warming (Eyring et al. 2016; World Climate Research Programme 2019). We select nine general circulation models/earth system models that possessed data for both SSP3–7.0 and each basin around the AP (SI Table S1). SSP3–7.0 is used as a possible, yet intense forcing scenario. This data is not used in any modeling or statistical capacity, only to assess how adjacent basins are projected to warm into the future to make reasonable modeling choices in Section 2.4 and 2.5.

Terrain and bathymetric context for Figure 1a were provided using the Earth topology (ETOPO) 2022, a global 60-arc-second relief model developed by the National Oceanic and Atmospheric Administration (NOAA) that integrates multiple terrestrial elevation and ocean bathymetry bedrock datasets into a global digital elevation model (MacFerrin et al. 2025).

4.3 Metric Creation

Specific humidity (q), T_a , and P are used to calculate T_w with a moist-adiabatic formulation following (Warren 2025), which accounts for thermodynamic equilibrium between humidity, air temperature, and pressure. The latter two are directly provided by ERA5. Specific humidity was generated from ERA5 using T_w and P .

For creating the indices for monitoring the ENSO and IOD phase, we use the Relative Oceanic Niño Index (RONI) and the Dipole Mode Index (DMI), respectively. RONI is an improved method of representing anomalies in the equatorial Pacific Ocean, which is a novel adjustment to the canonical Oceanic Niño Index (ONI) (Sabeerali et al. 2026; Trenberth 1997). It is defined as the SST anomaly in the Niño 3.4 region (Figure 1b) relative to the tropical mean SST. This formulation removes the influence of long-term warming trends and isolates internal variability relevant for teleconnection analysis. The DMI, defined as the difference in SST anomalies between the western (50°–70°E, 10°S–10°N) and southeastern (90°–110°E, 10°S–0°) equatorial Indian Ocean (Figure 1c), characterizes

the difference in average SST between the western and eastern Indian Ocean (Saji et al. 1999). A negative dipole is denoted nIOD and the positive phase is denoted pIOD.

4.4 Wet-bulb Temperature Threshold Selection and Teleconnection Lag Optimization

For each city, extreme humid-heat events were defined using the historical 95th percentile (p95) of daily maximum T_w , fixed throughout the analysis. The p95 threshold was selected as a compromise between isolating physically meaningful extremes and retaining sufficient exceedances for robust statistical inference. Lower thresholds incorporate a larger fraction of non-extreme events and may violate POT statistical assumptions, whereas higher thresholds substantially reduce sample size and increase uncertainty (Bommier 2014; Pickands 1975). City-specific thresholds were held fixed throughout all analyses to provide a consistent definition of HHEs across time and teleconnection states.

Atmospheric composites and GPD analyses were conditioned on p95 T_w exceedances as defined below, while the Bernoulli analysis modeled the occurrence and non-occurrence of city-specific exceedances across all JJAS days.

Teleconnection lags were selected empirically to maximize the response of HHEs to ENSO and IOD forcing. We evaluated monthly lag structures between the RONI, DMI, and city-level p95 exceedance probabilities. The strongest and most spatially coherent responses occurred using a two-month lag for ENSO and a one-month lag for the IOD. These lagged indices were therefore adopted throughout the analysis, yielding

$$N_t = \text{RONI}_{t-2}, D_t = \text{DMI}_{t-1}$$

This approach allows the analysis to capture the delayed atmospheric and oceanic adjustments through which large-scale SST anomalies influence extreme T_w across the AP.

4.5 Composite Spatial Analysis of ENSO and IOD modulations of HHEs

To establish the spatial modulation of ENSO and IOD on humid heat across the AP, we first perform a composite analysis (Section 2.1). Daily p95 T_w exceedances are conditioned on the phase of the lagged ENSO (RONI) and IOD (DMI) indices to identify spatial patterns associated with each climate mode. A regional p95 T_w exceedance is defined as a day on which the mean daily maximum p95 T_w across all coastal cities (Section 4.1) exceeds the average of the historical city-specific daily maximum p95 T_w thresholds. Each JJAS day is assigned the corresponding lagged monthly RONI (2-month lag) and DMI (1-month lag) values. Days for which the associated lagged index exceeds $\pm 0.5^\circ\text{C}$ are grouped according to climate-mode phase, and composites are constructed from the daily maximum T_w , together with the concurrent T_a and q at the time of maximum T_w . Composite anomalies are then calculated as the cold- or warm-phase minus the neutral phase.

Because the RONI is lagged by two months, the resulting JJAS composites primarily reflect the atmospheric response during the decay phase of ENSO events (Alexander et al. 2002). In contrast, the one-month DMI lag associates JJAS HHEs with contemporaneous or near-peak IOD conditions (Saji et al. 1999). Consequently, the composite samples are not expected to contain equal numbers of days from each month of JJAS, but instead reflect the temporal evolution of each climate mode and the imposed lag structure.

Composite analysis provides spatially continuous information across the AP and serves as an exploratory framework for identifying regions influenced by ENSO and IOD. Bayesian POT models are subsequently applied at selected city locations to quantify exceedance probabilities, extreme-event severity, and associated uncertainties in Section 2.2.

4.6 Staged Bayesian Attribution Framework for HHEs

We adopt this staged Bayesian extreme-value framework: first, we ask whether ENSO and IOD alter the probability that an extreme humid-heat event occurs (i.e. a daily maximum $T_w \geq p95 T_w$) (ENSO–IOD joint variability $\rightarrow$ AP cities $p95 T_w$ probability exceedance shifts); second, we ask whether ENSO and IOD alter the local SSTs which directly influence coastal humid-heat conditions (ENSO–IOD joint variability $\rightarrow$ local basin-scale SST mean shifts); third, we ask how projected local SST warming changes the intensity of future HHEs (direct local SST warming $\rightarrow$ $p95 T_w$ magnitude shifts). The analysis culminates in the question: what does this combined forcing mean for HHEs in the future of the AP (joint effect of local SST warming plus ENSO–IOD variability on city-specific HHEs)? These questions are addressed separately because the processes controlling how often an event occurs may differ from those controlling how severe that event becomes (Raymond et al. 2021). All analyses are conducted within a unified Bayesian framework to enable coherent uncertainty propagation across stages (Berliner et al. 1998).

All models were implemented in PyMC using Markov chain Monte Carlo (MCMC) sampling. Analyses are restricted to JJAS. Cities are modeled independently, except for partial pooling among Dammam, Doha, and Dubai because of their geographic and climatological similarity (Raymond et al. 2021; Fonseca et al. 2022; Veenman et al. 2024).

Full model specifications, prior distributions, hierarchical structures, posterior sampling procedures, and model diagnostics (Tables S2–S5) are provided in the Supplementary Information.

4.7 ENSO–IOD influence on HHE occurrence

To quantify the influence of large-scale climate variability on HHE occurrence, we modeled daily city-level exceedances of the fixed historical $p95 T_w$ threshold using a Bayesian Bernoulli process. Exceedance probability was modeled as a function of standardized, temporally lagged RONI and DMI indices and their interaction. Posterior samples were evaluated under prescribed ENSO–IOD states, including strong and extreme ENSO conditions, to estimate changes in HHE exceedance probability.

4.8 ENSO–IOD influence on local SSTs

To quantify how large-scale climate variability modifies ocean conditions adjacent to the AP, we modeled SST anomalies across the Persian Gulf, Red Sea, Gulf of Oman, and Gulf of Aden using a spatial hierarchical Bayesian Student-*t* regression. Standardized, lagged RONI and DMI were used as predictors, with ENSO represented asymmetrically to allow SST responses to differ between El Niño and La Niña conditions. Posterior distributions were evaluated under prescribed ENSO–IOD states and spatially aggregated to estimate the corresponding basin-scale SST response.

4.9 Local SST Influence on HHE Magnitude

To isolate the influence of local ocean warming on HHE intensity, exceedance magnitudes above the historical city-specific p95 T_w threshold were modeled using a Generalized Pareto Distribution (GPD), with the scale parameter varying as a function of monthly SST anomalies in the adjacent basin. The fitted relationships were evaluated under controlled basin-warming perturbations of +0.5°C, +1.0°C, +1.5°C, and +2.0°C to estimate changes in the p97.5 and p99 of daily maximum T_w . These experiments isolate the local SST influence while holding large-scale circulation and other non-SST covariates fixed.

4.10 Joint ENSO–IOD and Local SST Forcing

Finally, we combined the modeled ENSO–IOD influence on basin SSTs with the dependence of HHE magnitude on local SSTs, allowing uncertainty in the remote-to-local SST response to propagate into city-level HHE estimates. For a prescribed ENSO–IOD state (N,D) and basin-warming perturbation ΔT_b , the SST forcing entering the HHE model was represented as

$$\Delta SST_{\text{joint}(b)} = \mu_{\text{SST}(b)}(N,D) + \Delta T_b$$

Posterior samples were evaluated under prescribed combinations of ENSO, IOD, and +1.0°C or +2.0°C basin warming to estimate conditional changes in the p97.5 and p99 of daily maximum relative to neutral ENSO–IOD conditions and zero imposed warming.

4.11 Inference and Model Evaluation

All models were estimated using MCMC No-U-Turn Sampler (NUTS) (Berliner et al. 1998; Hoffman and Gelman 2014). Convergence was assessed using standard diagnostics, and posterior predictive checks were performed for exceedance rates, exceedance magnitudes, and return-level behavior (Bommier 2014). Counterfactual humid-heat risk under specific ENSO–IOD states and SST perturbation scenarios was quantified using posterior draws of exceedance frequency and GPD parameters, enabling coherent estimation of changes in both the likelihood and severity of extreme HHEs. This framework assumes stationarity in the relationship between SST, humidity, and extreme T_w , which may evolve under future climate conditions. Uncertainty reflects posterior variability and increases under larger perturbations due to extrapolation beyond observed conditions.

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Declarations

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- Consent to Participate
Not applicable.

- 776 ● Consent for Publication
777 Not applicable.
- 778 ● Data Availability
779 All data used in this study are publicly available including ERA5, CMIP6, and ETOPO.
780 ERA5 is available at C3S Climate Data Store (<https://cds.climate.copernicus.eu>),
781 CMIP6 at <https://esgf.llnl.gov/projects/cmip6/>, ETOPO 2022 is available at
782 <https://www.ncei.noaa.gov/products/etopo-global-relief-model>.
- 783 ● Materials availability
784 The code used for metric generation, analysis, and figure creation is available on
785 GitHub: https://github.com/db1015/bayesian_extremes/.
- 786 ● Author contribution
787 Author Contributions: Daniel Bose: Conceptualization, Methodology, Software,
788 Validation, Formal analysis, Investigation, Data curation, Visualization, Writing –
789 original draft, Writing – review & editing. Colin Raymond: Funding acquisition,
790 Writing – review & editing. Robbie Parks: Writing – review & editing. Cascade
791 Tuholske: Conceptualization, Supervision, Funding acquisition, Writing – review &
792 editing.
- 793

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