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El Niño amplifies subseasonal humid-heat risk across the tropics

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10 Abstract

11 Humid-heat extremes are becoming more frequent across the tropics and subtropics,
12 threatening human health. Yet how tropical variability interacts across timescales to
13 amplify humid heat remains poorly understood. Using reanalysis and logistic regression,
14 we show that humid heat responds more strongly and more spatially coherently to El
15 Niño than dry heat, with humid-heat risk increasing up to eightfold across the tropics. At
16 subseasonal timescales, Kelvin waves emerge as a leading driver of humid heat across
17 the equatorial tropics. Critically, El Niño amplifies Kelvin-wave and MJO-associated risk
18 from less than twofold under neutral conditions to sevenfold, primarily through greater
19 proximity to thresholds rather than stronger subseasonal anomalies. Tropical variability
20 drives wet-bulb temperature extremes through temperature and humidity changes, with
21 temperature pathways surprisingly widespread for this humidity-sensitive metric.
22 Together, these findings reveal a multiscale framework in which interannual variability
23 preconditions subseasonal risk, providing a physical basis for improved prediction and
24 early warning.

Heat extremes are becoming increasingly frequent and dangerous across the tropics and subtropics^{1–4}. Dry heat, defined using temperature alone, and humid heat, which depends on temperature and humidity, can adversely affect human health, increase mortality, and disrupt economic activity. Both are projected to become more frequent and severe across many regions during the twenty-first century^{5–7}. Humid-heat extremes combining the effects of temperature and atmospheric moisture are of particular concern because they limit the body’s ability to cool through sweating^{8–10}. Recent events, including the 2023 Southeast Asian heatwave, highlight the substantial risks that extreme heat and humidity pose to human health. Recent assessments suggest that extreme heat events have contributed to more than 260,000 deaths worldwide since 2000¹¹.

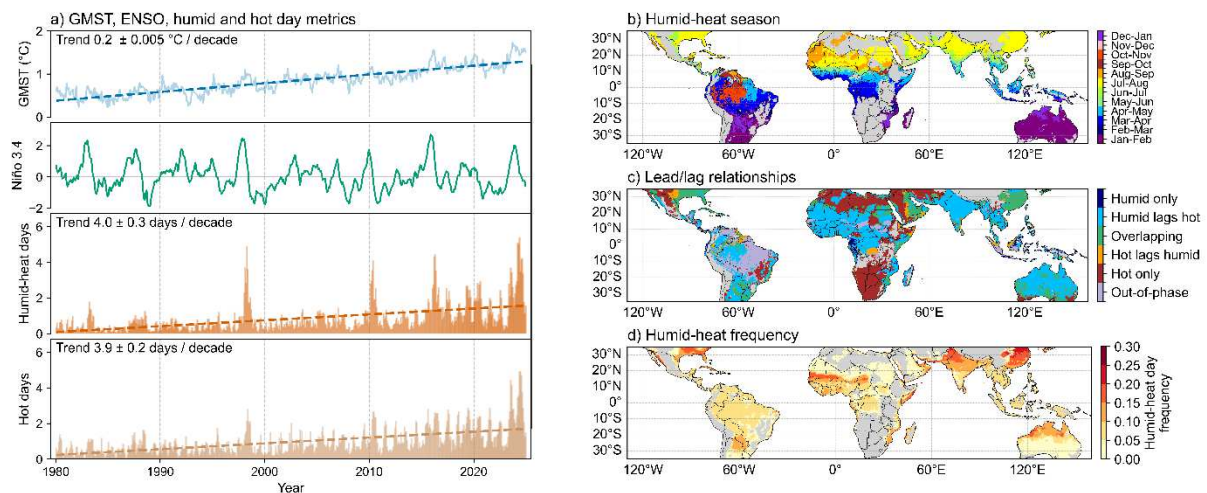
Unlike mid-latitude dry-heat extremes, which are associated with persistent blocking, subsidence and soil-moisture depletion^{12,13}, tropical humid heat is strongly regulated by processes that promote high boundary-layer humidity, including antecedent rainfall^{14,15}, suppression of moist convection, and strong surface moisture fluxes^{16,17}. The relative importance of these processes for tropical humid heat varies geographically, reflecting differences between energy-limited regimes in the moist tropics and moisture-limited regimes in drier tropical and subtropical regions¹⁸. Tropical modes of climate variability modulate humid heat through organised changes in circulation, convection, temperature and moisture^{19–21}. The El Niño–Southern Oscillation (ENSO) is the dominant driver of interannual climate variability²² and has been linked to increased humid-heat occurrence across tropical and subtropical regions^{3,20,23}. Humid heat has also been associated with Indian and Atlantic Ocean sea-surface temperature variability^{24,25}. On intraseasonal timescales, the Madden–Julian Oscillation (MJO) modulates humid heat through coupled temperature and moisture anomalies^{21,26}. Further, equatorial waves modulate tropical convection and rainfall^{27,28} and interactions between tropical modes may amplify regional humid-heat extremes^{29,30}. Together, these studies indicate that interacting tropical modes organise humid-heat variability across timescales.

There is no systematic tropics-wide assessment of how multiple sources of tropical variability jointly modulate humid-heat risk across regions and timescales. Existing studies typically focus on individual modes or specific regions, leaving the relative importance of interannual and intraseasonal variability poorly quantified at the tropical scale. Moreover, because humid and dry heat often occur in different seasons and meteorological regimes³, particularly in monsoon regions, it remains unclear whether tropical modes influence humid heat in the same manner as temperature-based heat extremes. It also remains unclear whether different modes influence humid heat through common or distinct thermodynamic pathways, or whether their impacts combine linearly or nonlinearly through interactions. These uncertainties limit both physical understanding and forecast capability.

Here we quantify how tropical variability modulates humid-heat occurrence across the global tropics and subtropics using ERA5 reanalysis and logistic regression. We compare humid-heat extremes, defined using wet-bulb temperature (Twb), and dry-heat extremes, defined using dry-bulb temperatures, to assess whether tropical modes exert similar influences on extremes with distinct seasonality and underlying physical drivers. We show that El Niño is the dominant large-scale driver of interannual humid-heat variability, while the Indian and Atlantic Oceans exert important regional influences. We demonstrate that the MJO and equatorial Kelvin waves produce coherent regional modulation of humid-heat risk at subseasonal timescales. El Niño strongly amplifies this subseasonal humid-heat risk, primarily by shifting regional climates towards humid-heat thresholds rather than by strengthening the underlying meteorological anomalies. Finally, we show that humid-heat responses arise through distinct regional thermodynamic pathways linked to temperature and humidity.

Global warming and climate variability shape tropical humid heat

Humid and dry heat days over land were identified from ERA5 reanalysis using percentile-based local thresholds combined with fixed absolute temperature thresholds (Methods). Humid and dry heat days increased substantially across the tropics during 1980–2024, by approximately 4 days decade⁻¹, while exhibiting pronounced monthly and interannual variability (Fig. 1a). Variability around the long-term trend indicates that humid-heat occurrence is strongly modulated by climate variability. Interannual variability in humid-heat days is associated with both variability in monthly global mean surface temperature (GMST) and ENSO. Peaks in humid heat coincided with peaks in GMST, with the strongest correlation when GMST led humid heat by 1–2 months ($r=+0.65$ at a 2-month lead). ENSO explains much, but not all, humid-heat variability. Major El Niño events generally precede humid-heat peaks by 3–5 months ($r=+0.47$ at a 4-month lead), although humid-heat frequency varies considerably between El Niño events, suggesting a substantial role for other sources of tropical variability. Although monthly occurrences of humid heat are closely correlated with dry heat ($r=+0.82$ at zero lag), humid heat exhibits proportionally larger peaks during major El Niño years, particularly in 1998 and 2024, suggesting greater



93

94 **Fig.1|Trends, seasonality and occurrence of humid heat. a**, Trends and variability in
 95 monthly global mean surface temperature (GMST), Niño 3.4, and the occurrence of
 96 humid and dry heat days per year per ERA5 land grid cell, 1980–2024, 35°S - 35°N. Humid
 97 and dry heat days are derived from ERA5 reanalysis and defined as days exceeding both
 98 a local 95th percentile threshold and an absolute global temperature threshold
 99 (Methods). **b**, Humid-heat season as represented by the 2-month period with peak
 100 occurrences of humid-heat days. **c**, The lead/lag relationship between the peak
 101 occurrences of humid and dry heat. Overlapping: peak humid and dry heat seasons
 102 overlap by at least 1 month. Humid lags dry and dry lags humid: peak seasons are
 103 separated by 2-3 months. Out-of-phase: peak seasons are separated by more than 3
 104 months. **d**, The frequency of occurrence of humid-heat days during local humid-heat
 105 seasons. In **b – d**, grey shading indicates regions where there were no heat days.

106 Humid heat exhibits regionally distinct seasonal behaviour (Fig. 1b). In much of the
 107 equatorial tropics, humid heat occurs preferentially during March–May (sometimes
 108 September–November), whereas subtropical regions exhibit peak humid heat during
 109 local summer seasons. Across most tropical regions, humid heat occurred 2–3 months
 110 later in the seasonal cycle than dry heat (Fig. 1c and Supplementary Fig. 1a), suggesting
 111 that humidity availability, arriving with the monsoon³¹, plays an important role in the
 112 timing of humid-heat occurrence. Humid-heat frequencies (Fig. 1d), like dry heat
 113 (Supplementary Fig. 1b), were highest in regions with pronounced seasonality. Together,
 114 these results show that humid and dry heat frequently differ in their seasonal timing,
 115 motivating an assessment of how tropical climate variability influences humid and dry
 116 heat across regions and timescales.

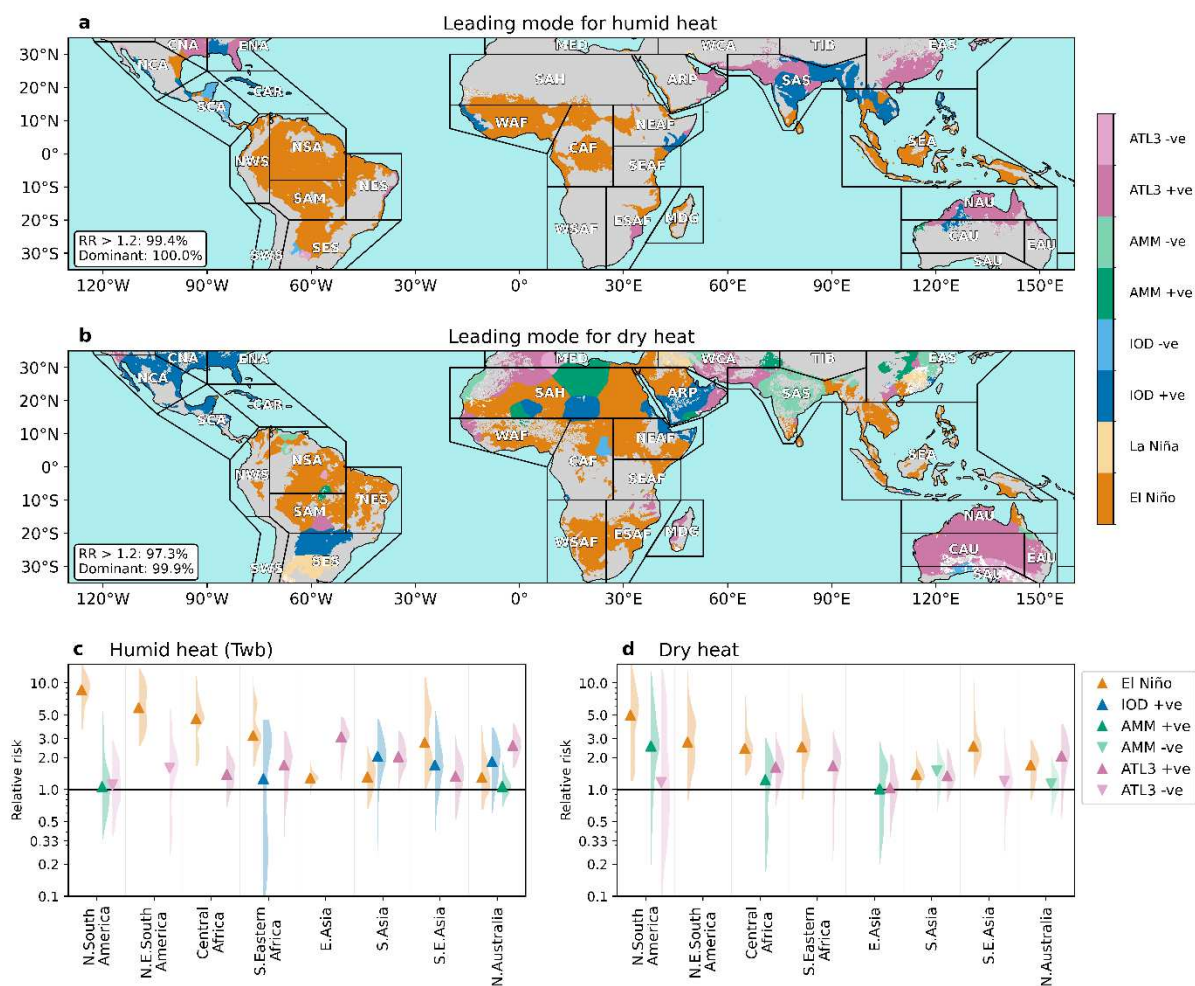
Interannual tropical variability drives extreme heat occurrence

Relative risk (RR) quantifies how much more or less likely heat extremes are during a given climate mode relative to neutral conditions (e.g., a RR of 2 indicates that heat extremes are twice as likely). RRs were estimated using logistic regression while controlling for long-term trends and ENSO variability. ENSO is the dominant interannual influence on humid heat across much of the equatorial tropics (approximately 10°S–10°N) (Fig. 2a), where El Niño increased humid-heat occurrence by four-eightfold, apart from parts of East Africa, which is unusually arid for its latitude.

Other ocean basins also exert important regional controls. The Indian Ocean dipole (IOD), characterised by an east–west tropical Indian Ocean sea surface temperature (SST) gradient, was the leading mode in several regions around the Indian Ocean basin. ATL3, an index of equatorial Atlantic SST variability often associated with the Atlantic Niño, dominated several subtropical regions, particularly in Australia and East Asia (Fig. 2a,c; Supplementary Fig. 2 for all regions), likely through perturbations to the Walker circulation and convection extending beyond the Atlantic basin^{32,33}. In contrast, the Atlantic Meridional Mode (AMM), characterised by a cross-equatorial Atlantic SST gradient, exerted comparatively limited influence, consistent with its weaker and more regionally confined impacts on tropical climate^{34–36}. Several regions, including South Asia, showed no clear leading mode, indicating that interannual heat variability can reflect comparable contributions from multiple tropical ocean basins rather than a dominant driver.

Humid heat responds differently to tropical variability than dry heat (Fig. 2b,d). Humid heat exhibited more spatially coherent responses to ENSO, with El Niño the leading mode across a larger fraction of tropical land (Fig. 2a,b). RR responses were also generally larger for humid heat than for dry heat, particularly in tropical South America (Fig. 2c,d), indicating greater sensitivity of humid heat to interannual tropical variability.

These results show that humid heat is particularly sensitive to large-scale tropical variability and reflects coupled influences from multiple ocean basins rather than ENSO alone, consistent with the large-scale organisation of temperature and humidity



147

148 **Fig.2|Relative risk of humid and dry heat for interannual modes. a,** The leading mode
149 of interannual variability in humid heat according to RR. **b,** The leading mode of
150 interannual variability in dry heat. In **a** and **b**, grey shading indicates where heat
151 occurrence was absent or too infrequent for robust analysis; white shading indicates
152 regions with RR < 1.2; and, the inset text box shows the percentage of grid cells exceeding
153 this threshold. Hatched regions indicate areas with no clear leading mode, where in more
154 than 60% of neighbouring grid cells the relative risk associated with the leading mode is
155 within 10% of that associated with the second-ranked mode. To reduce grid-scale noise,
156 leading-mode classifications and weak-dominance regions (hatching) were spatially
157 aggregated using a 31 × 31 grid cell majority filter. **c,** The median (triangles) and 95th
158 percentile distribution (shading) where the width of the shaded distribution shows the
159 relative frequency of grid cells with a given RR for each of the interannual modes in a
160 subset of the regions (see Supplementary Fig. 2 for other regions). **d,** As **c** but for dry heat.

161 El Niño amplifies intraseasonal humid-heat risk

162 Equatorial Kelvin waves and the MJO emerge as the dominant sources of intraseasonal
163 humid-heat variability, although with distinct spatial structures (Fig. 3a). Equatorial Kelvin

waves, which are eastward-propagating disturbances in equatorial winds and convection³⁹, were the leading mode across 28% of (sub)tropical land experiencing humid heat, particularly over Central Africa, but only 9% of land experiencing dry heat (Fig. 3b). In contrast, the MJO was the most spatially extensive intraseasonal mode for both humid and dry heat, accounting for 43% and 52% of (sub)tropical land areas, respectively, with influences extending into the subtropics. Equatorial Rossby-1 waves contributed more strongly to dry heat than humid heat with impacts concentrated in subtropical regions outside South America, whereas westward mixed Rossby-gravity (WMRG) waves exhibited comparatively weak and regionally confined influences.

Kelvin-wave influences are strongly phase dependent (Fig. 3c,e; Supplementary Fig. 3 for all regions). RR for humid and dry heat peaked during phase 5, following phases characterised by low-level divergence and the development of anomalous low-level easterlies. Conversely, humid-heat occurrence was suppressed during convectively active phases associated with enhanced cloudiness and low-level convergence. This phase dependence is consistent with the short timescale of Kelvin waves, whose phases typically persist for only 1–2 days¹⁹, potentially limiting the duration of heat extremes. Under ENSO-neutral conditions, Kelvin-wave RR magnitudes were similar for humid and dry heat, with peak RRs of 1.4 and 1.3, respectively. However, under El Niño conditions, Kelvin-wave modulation was greatly amplified, with peak RRs increasing to 7.4 for humid heat and 3.8 for dry heat. Elevated humid-heat risk persisted even during Kelvin-wave phases that suppress heat occurrence under ENSO-neutral conditions, reflecting the warmer and more humid El Niño background state.

The MJO also has a pronounced amplifying effect on humid and dry heat (Fig. 3d,f), although the phase of peak RR varied among regions (not shown). As for Kelvin waves, El Niño strongly amplified MJO-related heat risk, particularly for humid heat, increasing peak RR to 6.9 compared with 5.6 for dry heat.

The strong amplification of intraseasonal RR during El Niño raises the question of whether El Niño modifies Kelvin-wave and MJO meteorological responses or simply amplifies their impacts through a different mechanism. To address this, we fitted logistic-regression models containing explicit El Niño × Kelvin-wave and El Niño × MJO interaction terms (Methods) and quantified their contribution to humid-heat RR (Fig. 4). Positive interaction effects indicate that the combined influence of El Niño and Kelvin waves (or the MJO) exceeds the sum of their individual effects on humid-heat occurrence, whereas negative interactions indicate a weaker-than-additive response.

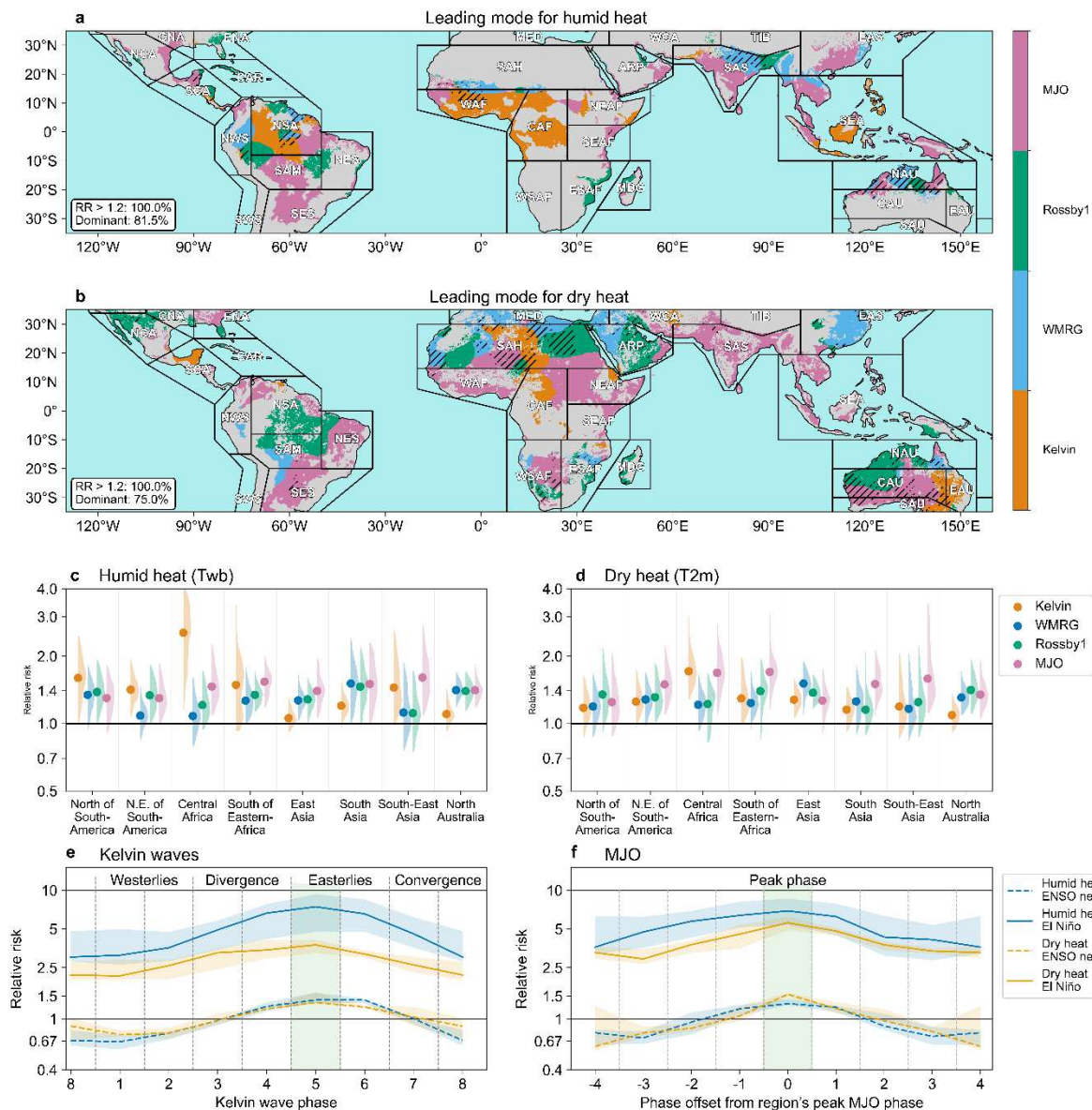


Fig.3|Relative risk of humid and dry heat for intraseasonal modes. **a**, The leading mode of intraseasonal variability in humid heat according to RR. **b**, The leading mode of intraseasonal variability in dry heat. In **a** and **b**, grey shading indicates where heat occurrence was absent or too infrequent for robust analysis. Hatched regions indicate areas with no clear leading mode, where in more than 60% of neighbouring grid cells the relative risk associated with the leading mode is within 10% of that associated with the second-ranked mode. To reduce grid-scale noise, leading-mode classifications and weak-dominance regions (hatching) were spatially aggregated using a 31×31 grid cell majority filter. **c**, The median (circles) and 95th percentile distribution (shading) where the width of the shaded distribution shows the relative frequency of grid cells with a given RR for each of the 4 intraseasonal modes in a subset of the regions. **d**, As **c** but for dry heat. **e**, RR of humid heat by Kelvin wave phase (blue) and dry heat (orange). Dashed lines show RR of humid and dry heat for Kelvin waves under a neutral-ENSO background and solid lines show RR of humid and dry heat for Kelvin waves under an El Niño background. The shaded regions show inter-quartile ranges. **f**, As **e** but for the MJO. MJO

phases are shifted so that the MJO phase with maximum RR in each region is presented as phase 0 with the other phases presented as offsets (-4 to +4) relative to this peak. RRs are derived from logistic regression models controlling for long-term trends and ENSO variability.

Strong positive interaction effects occur across tropical South America, central Africa and the Maritime Continent, with 95th-percentile of local non-additive contributions to relative-risk of +7.0 and +10.6 for Kelvin waves and the MJO, respectively (Fig. 4a,c). Despite the magnitude of these interaction terms, accompanying analyses reveal little evidence that El Niño fundamentally alters the meteorological responses associated with Kelvin waves or the MJO (Supplementary Fig. 5), indicating that the amplification does not arise from stronger meteorological anomalies.

Instead, the amplification is explained by a threshold-proximity effect. El Niño shifts regional temperature and humidity distributions closer to local humid-heat thresholds, increasing the sensitivity of threshold exceedance to subsequent intraseasonal perturbations. Consistent with this mechanism, the proportion of humid-heat-prone land lying within 0.5 °C of its local threshold increased from almost zero under neutral conditions to approximately 1% during El Niño alone (Fig. 4b,d). Kelvin waves and the MJO acting independently have a negligible effect on this proportion. However, when superimposed on an El Niño background state, the proportion increased to ~9% for El Niño–Kelvin-wave events and ~10% for El Niño–MJO events (Fig. 4b,d), substantially exceeding the sum of the individual contributions. El Niño therefore preconditions regional climates by narrowing the margin to humid-heat thresholds and allowing otherwise modest intraseasonal perturbations to trigger widespread humid-heat exceedances. An analogous threshold-proximity mechanism also explains the interactions for dry heat (Supplementary Fig. 4), although the more gradual threshold distribution indicates that exceedances are triggered less abruptly than for humid heat.

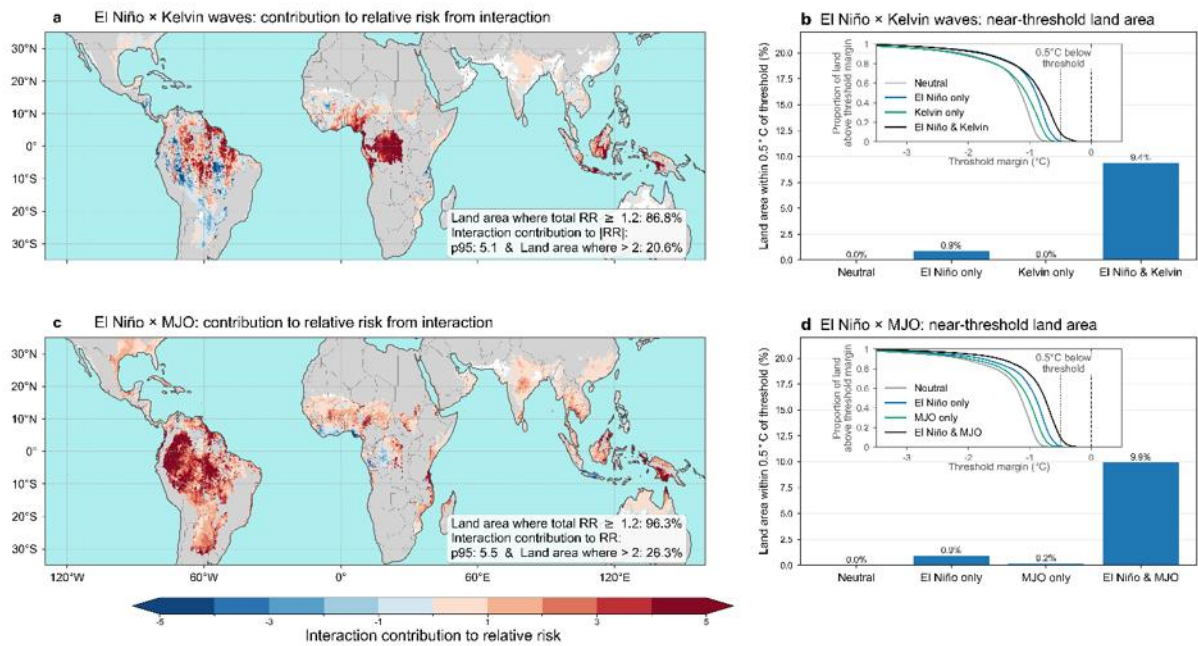


Fig.4| Contributions to relative risk from interactions between Kelvin waves and the MJO with El Niño. **a**, Contribution to RR of humid heat from interactions between El Niño and Kelvin wave phase 5. Grid cells with total RR less than 1.2 are shaded white. **b**, Threshold proximity, the proportion of humid-heat prone land within 0.5 °C of the local humid-heat threshold for neutral conditions (neutral ENSO and Kelvin waves not in phase 5), El Niño conditions, Kelvin-wave phase 5 under ENSO-neutral conditions, and concurrent El Niño and Kelvin-wave phase 5 conditions. The inset shows the proportion of humid-heat prone land within a given threshold margin (x-axis). **c**, Contribution to RR of humid heat from interactions of El Niño and the MJO phase with peak local RR. **d**, As c except for the MJO. In **a** and **c**, grey shading indicates regions where heat occurrence was absent or too infrequent for robust analysis.

Distinct thermodynamic pathways govern humid-heat responses

The dominant thermodynamic pathways linking tropical variability to humid heat differ substantially among regions and modes (Fig. 5). Humid-heat risk was partitioned into temperature-mediated (T-mediated) and humidity-mediated (q-mediated) components using the relative contributions of near-surface temperature and humidity anomalies to humid-heat occurrence (Methods). Although Twb was used to define humid-heat days and is highly sensitive to atmospheric moisture^{8,40}, 22% of tropical regions exhibited joint temperature–humidity (T–q) sensitivity, while a further 1% were primarily temperature-sensitive during humid-heat seasons (Fig. 5a). Joint T–q-sensitive regions were concentrated in the moist tropics, where humidity remains persistently high and modest warming substantially increases humid-heat occurrence. In contrast, q-sensitive regions dominated overall and were concentrated in regions with marked atmospheric moisture variability, including many monsoonal regions.

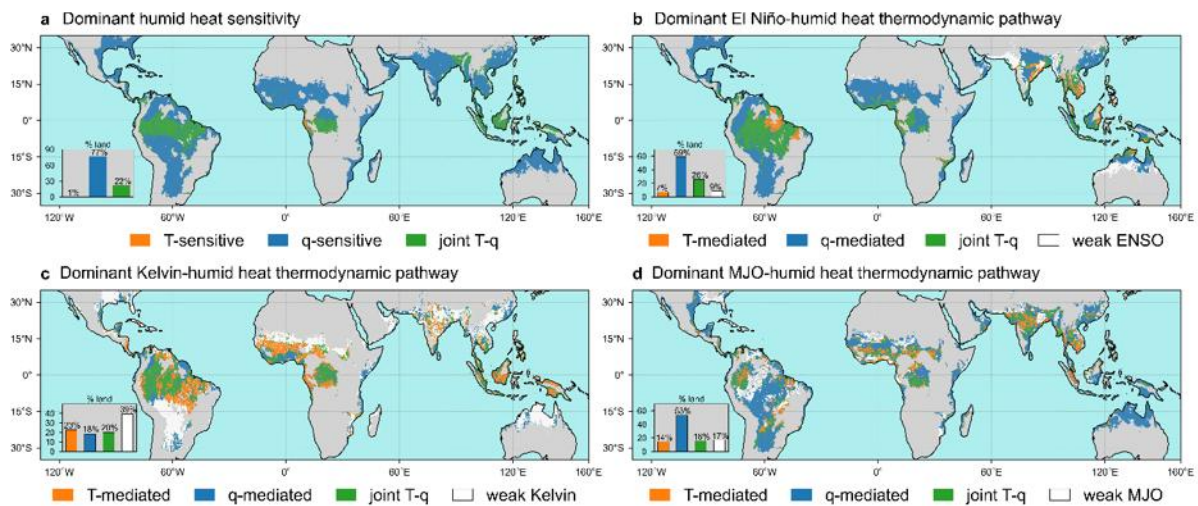


Fig.5| Temperature and humidity pathways for El Niño, Kelvin waves, and the MJO. a, The dominant sensitivity of humid heat to standardised changes in near surface temperature and humidity. Sensitivity of temperature or humidity is categorised as dominant when its variability alone accounts for more than 60% of the variability in humid-heat days. **b,** The dominant thermodynamic pathway for El Niño on humid-heat days. T- or q-dominated pathways are categorised as dominant when they account for more than 60% of the variability in humid-heat days. Where the RR from El Niño is less than 1.2 that region is categorised as “Weak ENSO” and shown in white. **c,** As **b** but for Kelvin waves. **d,** As **b** but for the MJO. In **a – d**, grey shading indicates regions where heat occurrence was absent or too infrequent for robust analysis.

The dominant El Niño humid-heat pathways (Fig. 5b) broadly mirror the underlying sensitivity structure (Fig. 5a). q-mediated pathways dominated across much of the tropics, whereas T-mediated and joint T–q pathways occurred preferentially in regions already sensitive to temperature variability. This similarity shows that El Niño enhances both temperature and humidity, with the realised humid-heat response determined primarily by local thermodynamic sensitivity.

Kelvin-wave pathways are more strongly T-mediated than those associated with El Niño (Fig. 5c). T-mediated responses dominated across parts of tropical South America, West and Central Africa, and the Maritime Continent, consistent with near-surface warming from Kelvin-wave modulation of cloudiness and surface shortwave radiation. These regions coincide with areas exhibiting strong Kelvin-wave influence on humid heat and support a shortwave radiation pathway linking Kelvin-wave phase evolution to humid-heat occurrence (Supplementary Fig. 5).

In contrast, MJO pathways are more regionally heterogeneous (Fig. 5d). Parts of tropical South America shifted towards q-mediated responses, whereas parts of West Africa became more T-mediated. These contrasts likely reflect regional differences in the MJO phase associated with peak humid-heat risk, with some regions responding primarily to

moisture convergence and advection and others to suppressed-convection phases that favour enhanced surface heating.

Implications of interacting tropical variability for humid-heat extremes

Variability in extreme humid heat emerges from interactions between tropical variability, threshold proximity and regionally varying thermodynamic sensitivity, rather than from a single dominant climate mode. Although El Niño exerts the strongest large-scale influence on humid-heat variability, substantial modulation arises from intraseasonal disturbances, particularly the MJO and equatorial Kelvin waves. A key result is that intraseasonal variability can produce disproportionately large increases in humid-heat occurrence during El Niño, not because meteorological perturbations are substantially stronger, but because El Niño shifts regional seasonal mean climates closer to critical humid-heat thresholds. This mechanism is consistent with the broader nonlinear sensitivity of threshold exceedances to changes in the background climate state⁴¹. The coherent influence of equatorial Kelvin waves across the tropics^{19,28} further demonstrates that tropical variability can modulate humid heat through distinct physical pathways, including changes in cloud cover and surface shortwave radiation. This is supported by recent evidence from equatorial Southeast Asia showing that Kelvin-wave dry phases enhance humid-heat risk through subsidence and increased shortwave radiation³⁰. The widespread importance of temperature-mediated and joint temperature-humidity pathways indicates that variability in humid heat is not controlled by variability in atmospheric moisture alone, even when quantified using Twb. Further, comparison with dry heat shows that tropical variability exerts a stronger and more spatially coherent influence on humid heat than on temperature-defined heat extremes. Although many of the tropical modes affect both forms of heat, the additional sensitivity of humid heat to atmospheric moisture allows tropical variability to produce larger and more coherent changes in humid-heat risk, particularly during El Niño.

Previous studies have shown that humid heat is governed by strong regional contrasts in thermodynamic control, including transitions between energy- and moisture-limited regimes and differing sensitivities of wet-bulb temperature to temperature and moisture variability^{42,14}. At regional scales, subseasonal humid heat during the South Asian monsoon is closely linked to atmospheric moisture variability²⁶. At finer scales, local soil-moisture anomalies can further amplify wet-bulb temperature extremes through their influence on boundary-layer structure and moisture accumulation⁴³. Unlike dry heat, whose responses to tropical variability are generally weaker and less spatially coherent, humid heat is governed by the combined evolution of temperature and atmospheric moisture, making it particularly sensitive to tropical variability across both interannual and subseasonal timescales. Our results show that thermodynamic sensitivities provide a unifying framework for understanding how multiple sources of tropical variability influence humid heat across the global tropics and subtropics. ENSO broadly reflects the

underlying thermodynamic sensitivities of a region, whereas Kelvin waves are associated with changes in cloudiness and surface shortwave radiation and the MJO with changes in atmospheric moisture perturbations (see Supplementary Fig. 5). More generally, interannual and intraseasonal tropical variability provides the forcing, while regional thermodynamic sensitivity governs the resulting humid-heat response.

These results highlight opportunities to improve humid-heat prediction by exploiting seasonal and intraseasonal tropical variability alongside its more traditional role in tropical convection and rainfall. ENSO is already central to seasonal prediction^{44,45}, but our results show that humid-heat forecasts should also account for lagged regional responses that modify temperature, humidity and threshold proximity. On subseasonal timescales^{46,47}, the MJO and equatorial Kelvin waves provide additional sources of predictability. Together, these results suggest that early-warning systems could benefit from combining seasonal predictions of the interannual background state with subseasonal forecasts of tropical variability and their regionally specific thermodynamic impacts. This predictability is not yet explicitly exploited in operational heat-health warning systems, which remain largely based on short-range weather forecasts and temperature thresholds⁴⁸. Realising this potential will require improved representation of convectively coupled equatorial waves in forecast systems⁴⁹. In comparison with dry heat, these advances may yield particularly large improvements for humid-heat prediction because humid heat is more strongly and more coherently modulated by tropical variability.

Several limitations should be acknowledged. The study relies on the ERA5 reanalysis, which may contain regional biases in temperature and humidity, particularly in data-sparse tropical regions. However, ERA5 is a state-of-the-art global reanalysis for this type of study, and the consistency of our results across multiple analyses suggests that the principal conclusions are robust to such uncertainties. In addition, we focus on a subset of major tropical modes and do not separately isolate the influence of potentially relevant sources of variability, including extratropical influences on subtropical heat extremes, land–atmosphere feedbacks, and mesoscale convective processes.

While this study focuses on atmospheric drivers of dry and humid-heat extremes, future work should examine how interacting tropical variability influences environmental heat-stress metrics, such as the Heat Index and Wet-Bulb Globe Temperature. Such work should also evaluate predictability by forecast systems and representation in climate models, building on emerging evidence that convective-scale processes substantially influence projections of future heatwave characteristics⁵⁰.

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511

512 Figure legends

513 **Fig.1|Trends, seasonality and occurrence of humid heat. a,** Trends and variability in
514 monthly global mean surface temperature (GMST), Niño 3.4, and the occurrence of
515 humid and dry heat days per year per ERA5 land grid cell, 1980–2024, 35°S - 35°N. Humid
516 and dry heat days are derived from ERA5 reanalysis and defined as days exceeding both
517 a local 95th percentile threshold and an absolute global temperature threshold
518 (Methods). **b,** Humid-heat season as represented by the 2-month period with peak
519 occurrences of humid-heat days. **c,** The lead/lag relationship between the peak
520 occurrences of humid and dry heat. Overlapping: peak humid and dry heat seasons
521 overlap by at least 1 month. Humid lags dry and dry lags humid: peak seasons are
522 separated by 2-3 months. Out-of-phase: peak seasons are separated by more than 3
523 months. **d,** The frequency of occurrence of humid-heat days during local humid-heat
524 seasons. In **b – d**, grey shading indicates regions where there were no heat days.

525 **Fig.2|Relative risk of humid and dry heat for interannual modes. a,** The leading mode
526 of interannual variability in humid heat according to RR. **b,** The leading mode of
527 interannual variability in dry heat. In **a** and **b**, grey shading indicates where heat
528 occurrence was absent or too infrequent for robust analysis; white shading indicates
529 regions with $RR < 1.2$; and, the inset text box shows the percentage of grid cells exceeding
530 this threshold. Hatched regions indicate areas with no clear leading mode, where in more
531 than 60% of neighbouring grid cells the relative risk associated with the leading mode is
532 within 10% of that associated with the second-ranked mode. To reduce grid-scale noise,
533 leading-mode classifications and weak-dominance regions (hatching) were spatially
534 aggregated using a 31×31 grid cell majority filter. **c,** The median (triangles) and 95th
535 percentile distribution (shading) where the width of the shaded distribution shows the
536 relative frequency of grid cells with a given RR for each of the interannual modes in a
537 subset of the regions (see Supplementary Fig. 2 for other regions). **d,** As **c** but for dry heat.

538 **Fig.3|Relative risk of humidity and dry heat for intraseasonal modes. a,** The leading
539 mode of intraseasonal variability in humid heat according to RR. **b,** The leading mode of
540 intraseasonal variability in dry heat. In **a** and **b**, grey shading indicates where heat
541 occurrence was absent or too infrequent for robust analysis. Hatched regions indicate
542 areas with no clear leading mode, where in more than 60% of neighbouring grid cells the
543 relative risk associated with the leading mode is within 10% of that associated with the
544 second-ranked mode. To reduce grid-scale noise, leading-mode classifications and
545 weak-dominance regions (hatching) were spatially aggregated using a 31×31 grid cell
546 majority filter. **c,** The median (circles) and 95th percentile distribution (shading) where the
547 width of the shaded distribution shows the relative frequency of grid cells with a given RR
548 for each of the 4 intraseasonal modes in a subset of the regions. **d,** As **c** but for dry heat.
549 **e,** RR of humid heat by Kelvin wave phase (blue) and dry heat (orange). Dashed lines show
550 RR of humid and dry heat for Kelvin waves under a neutral-ENSO background and solid

lines show RR of humid and dry heat for Kelvin waves under an El Niño background. The shaded regions show inter-quartile ranges. **f**, As **e** but for the MJO. MJO phases are shifted so that the MJO phase with maximum RR in each region is presented as phase 0 with the other phases presented as offsets (-4 to +4) relative to this peak. RRs are derived from logistic regression models controlling for long-term trends and ENSO variability.

Fig.4| Contributions to relative risk from interactions between Kelvin waves and the MJO with El Niño. a, Contribution to RR of humid heat from interactions between El Niño and Kelvin wave phase 5. Grid cells with total RR less than 1.2 are shaded white. **b**, Threshold proximity, the proportion of humid-heat prone land within 0.5 °C of the local humid-heat threshold for neutral conditions (neutral ENSO and Kelvin waves not in phase 5), El Niño conditions, Kelvin-wave phase 5 under ENSO-neutral conditions, and concurrent El Niño and Kelvin-wave phase 5 conditions. The inset shows the proportion of humid-heat prone land within a given threshold margin (x-axis). **c**, Contribution to RR of humid heat from interactions of El Niño and the MJO phase with peak local RR. **d**, As **c** except for the MJO. In **a** and **c**, grey shading indicates regions where heat occurrence was absent or too infrequent for robust analysis.

Fig.5| Temperature and humidity pathways for El Niño, Kelvin waves, and the MJO. a, The dominant sensitivity of humid heat to standardised changes in near surface temperature and humidity. Sensitivity of temperature or humidity is categorised as dominant when its variability alone accounts for more than 60% of the variability in humid-heat days. **b**, The dominant thermodynamic pathway for El Niño on humid-heat days. T- or q-dominated pathways are categorised as dominant when they account for more than 60% of the variability in humid-heat days. Where the RR from El Niño is less than 1.2 that region is categorised as “Weak ENSO” and shown in white. **c**, As **b** but for Kelvin waves. **d**, As **b** but for the MJO. In **a – d**, grey shading indicates regions where heat occurrence was absent or too infrequent for robust analysis.

577 Methods

578 Data

579 ERA5 reanalysis

580 ERA5 reanalysis data from the European Centre for Medium-Range Weather Forecasts
581 (ECMWF) were used on the native $0.25^\circ \times 0.25^\circ$ grid. All analyses are based on daily
582 means computed from hourly data using 00–24 UTC days. To ensure a consistent
583 calendar, 29 February is excluded from leap years, yielding 365 days per year. The
584 analysis covers the period 1980–2024, and climatologies for heat days and related
585 variables are defined over a 30-year period following World Meteorological Organization
586 practice (1993–2022).

587 Global mean surface temperature (GMST)

588 GMST data were obtained from the “Indicators of Global Climate Change 2024” dataset
589 of⁵¹, which provides updated climate indicators through the end of 2024 (version
590 v2025.06.02).

591 Definition of heat extremes

592 Wet-bulb temperature (Twb)

593 Daily mean Twb was calculated at each grid cell using daily mean dry-bulb temperature,
594 dew-point temperature, and surface pressure from ERA5. Calculations follow Davies-
595 Jones⁵² using the Python implementation provided by Raymond⁵³. Further details of the
596 calculation of Twb from ERA5 and its evaluation against station observations are provided
597 in Jackson et al.¹⁸

598 Identification of humid- and dry-heat days

599 Humid-heat days were identified over land areas between 35°S and 35°N for 1980–2024.
600 They were defined independently for each grid cell as days when daily mean Twb
601 exceeded both the local 95th percentile and an absolute threshold of 24°C . Percentile
602 thresholds were computed separately for each grid cell using daily data from 1993–2022,
603 thereby accounting for local seasonality and regional variations in Twb. The local humid-
604 heat season was defined as the set of calendar days on which at least one humid-heat
605 day occurred during 1980–2024.

Dry-heat days were identified using an analogous method based on daily mean 2m air temperature from ERA5 reanalysis. Dry-heat days were defined as days exceeding both the local 95th percentile and an absolute threshold of 28.5°C.

Tropical mode indices

El Niño–Southern Oscillation

ENSO variability was characterised using the Niño 3.4 index obtained from the NOAA Climate Prediction Center (CPC), National Centers for Environmental Prediction (NCEP). Niño 3.4 anomalies adjusted using centred 30-year base periods were used to account for long-term ocean warming. ENSO states were defined monthly as El Niño (Niño 3.4 ≥ 1), La Niña (≤ -1), and neutral otherwise.

Indian Ocean Dipole

The Indian Ocean Dipole was characterised using the Dipole Mode Index (DMI)⁵⁴ obtained from the NOAA Physical Sciences Laboratory (PSL) climate indices repository. To isolate IOD variability, the DMI was decorrelated from ENSO over 1993–2022, and the decorrelated index was used in all regression analyses. Positive and negative IOD states were defined using thresholds of ± 0.4 , consistent with operational monitoring practice and approximately corresponding to one standard deviation of the index distribution.

Atlantic Meridional Mode

The Atlantic Meridional Mode (AMM) index³⁶ was obtained from the NOAA Physical Sciences Laboratory (PSL). Positive and negative AMM states were defined using ± 1 standard deviation thresholds, with neutral conditions otherwise.

Atlantic Niño

Equatorial Atlantic SST variability was characterised using the ATL3 index⁵⁵ for all calendar months, obtained from the NOAA Climate Prediction Center (CPC), National Centers for Environmental Prediction (NCEP). Positive and negative ATL3 states were defined using ± 1 standard deviation thresholds. Because the ATL3 index was used throughout the annual cycle rather than being restricted to the canonical Atlantic Niño season, it should be interpreted as a measure of equatorial Atlantic SST variability rather than a pure measure of Atlantic Niño variability.

Equatorial waves

Equatorial wave activity was derived from the ERA5-based dataset of Yang et al.⁵⁶, which classifies Kelvin ($n = -1$), westward-moving mixed Rossby–gravity (WMRG; $n = 0$), and

equatorial Rossby-1 (ER; $n = 1$) waves. Six-hourly 850 hPa zonal and meridional winds were used to reconstruct wave dynamics. Wave amplitude and phase were computed following Crook et al.³⁹ using the diagnostic variables W1 and W2 at latitudes representative of each wave mode. Amplitudes were standardised by their period-of-record standard deviation and considered active when ≥ 1 . The data were converted to daily means and regridded to the ERA5 spatial resolution.

Madden–Julian Oscillation

The phase and amplitude of the MJO index for 1980–2024 were sourced from the Australian Bureau of Meteorology (<http://www.bom.gov.au/climate/mjo/#tabs=Monitoring>) on 13/2/26. An amplitude threshold of 1.0 was used to discriminate between active and inactive conditions.

Logistic regression and relative risk (RR)

The probability of a hot humid day occurring during a given phase of a tropical mode was estimated using logistic regression applied independently at each grid cell. The model includes a linear time trend, ENSO state and when appropriate, a second tropical mode. This approach isolates the influence of individual tropical modes while accounting for long-term trends and ENSO variability where appropriate. Model performance was assessed using McFadden’s pseudo- R^2 ⁵⁷ and the Brier skill score⁵⁸ (Supplementary Figs. 6 and 7).

To account for delayed climate responses, interannual modes are commonly represented using lagged predictors⁴⁵. Previous studies have represented lagged ENSO influences using a reference-month approach, whereby lagged effects are referenced to a fixed calendar month (e.g., the preceding December). Sensitivity tests showed that RR estimates at daily and regional scales could vary appreciably with the choice of reference month (e.g., see Supplementary Fig. 8 for November versus December), indicating that this approach may not adequately capture spatially heterogeneous lag structures. We therefore represented interannual modes using distributed lags spanning 1–11 months within a distributed lag modelling framework⁵⁹.

Although the lagged predictors are inherently correlated, inference was based on probabilities and RRs derived from their combined effect rather than on individual lag coefficients, thereby quantifying the integrated influence of each mode across its lag structure. The analysis therefore estimates the net influence of each mode across its full lag structure without attributing physical significance to specific lags. Sensitivity tests using ridge regression yielded very similar predictions and RRs, demonstrating that the results were robust to multicollinearity among lagged predictors (see Supplementary Fig. 9).

674 The formula for the regression of ENSO is:

675
$$\text{logit}(\text{Pr}(\text{HHD})) = \beta_0 + \beta_1 \times Y + \sum_{\text{lag } i}^{11} \beta_{2i} \times S_{\text{ElNino}} + \sum_{\text{lag } i}^{11} \beta_{3i} \times S_{\text{LaNina}} \quad (\text{Eq.1})$$

676 where HHD is humid-heat day, Y is calendar year in 1980–2024, monthly lags from 1-11
677 are represented by i, S_{ElNino} is a binary El Niño state (1 El Niño, 0 otherwise) and S_{LaNina} is
678 the La Niña state (1 La Niña, 0 otherwise). The regression coefficients are represented by
679 the β terms. The data used to fit the regression models are daily, including all days in the
680 local (grid cell) hot humid seasons over the years 1980–2024.

681 RR was defined as the probability of a hot humid day during an active (positive or
682 negative) mode state divided by the corresponding probability during neutral conditions.
683 For example, for El Niño:

684
$$\text{Relative risk} = \frac{\text{Pr}(\text{HHD}|\text{ENSO}_{\text{ElNino}}, \text{Year})}{\text{Pr}(\text{HHD}|\text{ENSO}_{\text{Neutral}}, \text{Year})} \quad (\text{Eq.2})$$

685 Probabilities were evaluated using model predictions for the year 2010 with ENSO fixed
686 in its neutral state and the tropical mode set to each of its states. Year 2010 was chosen
687 because it lies within the analysis period and slightly after the midpoint of the record. The
688 models are not used for prediction or comparison against observations, therefore the
689 choice of year does not affect inference regarding the role of tropical modes.

690 ENSO influence metric (E^*)

691 To facilitate analyses of tropical mode interactions and thermodynamic pathways, an
692 ENSO influence metric (E^*) was constructed to summarise the distributed lagged ENSO
693 response using a single predictor. E^* was calculated for years 1980–2024 and used in
694 logistic regression models fitted for the interaction analysis and thermodynamic
695 decomposition, and in the anomaly composite analysis. For each grid cell, E^* was
696 calculated as the sum of the fitted coefficients for lagged El Niño and La Niña states
697 multiplied by the corresponding lagged ENSO-state indicators, yielding a daily time
698 series representing the net local influence of ENSO.

699
$$E^*(\text{lat}, \text{lon}, \text{day}) = \sum_{\text{lag } i=1}^{11} \beta_i^g \times S_i^d \quad (\text{Eq.3})$$

700 where β_i^g are the regression coefficients from the explicit lagged regression model for grid
701 cell g with lag i months (Eq.1), and S_i^d is the ENSO state on day d with lag i months.

702 This approach preserves the combined effect of the full lag structure while avoiding the
703 large increase in regression terms that would result from including all lagged predictors
704 in interaction and decomposition models. Validation tests showed that logistic

regression models using E^* (Eq.3) produced predictions that were nearly identical to those obtained from models containing the full set of explicit lagged ENSO terms (Eq.1), indicating that E^* provides an accurate low-dimensional representation of ENSO influence (Supplementary Fig. 10). For analyses requiring discrete ENSO states, E^* values exceeding ± 0.5 standard deviations from the mean were classified as El Niño-like or La Niña-like conditions, with intermediate values classified as neutral.

Interaction analyses

Interactions between El Niño and intraseasonal variability were evaluated separately for Kelvin waves and the MJO using logistic regression. The interaction models were fitted using data from 1980–2024. For Kelvin waves, the regression formula is:

$$\text{logit}(\text{Pr}(HHD)) = \beta_0 + \beta_1 Y + \beta_2 E^* + \beta_3 K + \beta_4 E^* K \quad (\text{Eq.4})$$

where Y is calendar year in 1980–2024, E^* is the ENSO influence metric, and K is a binary indicator of Kelvin wave phase (1 for phase 5, 0 otherwise). The regression coefficients are represented by the β terms. RRs were calculated for El Niño and Kelvin waves phase 5 individually and for their concurrent occurrence. Positive interaction effects indicate that the combined influence of El Niño and Kelvin waves exceeds the sum of their individual effects on humid-heat occurrence, whereas negative interactions indicate a weaker-than-additive response. An equivalent analysis was followed for the MJO using a regression formula with a binary indicator of MJO phase (1 for the local phase with the greatest RR, 0 otherwise) in the regression formula.

Anomaly composites

Anomaly composites were constructed by averaging daily mean fields during the local humid-heat season for selected states of ENSO, Kelvin waves, and the MJO. Composites were calculated using days on which the mode of interest was active, defined as El Niño conditions, Kelvin wave phase 5, or the MJO phase associated with the highest local humid-heat RR during years 1980–2024. For each mode, composites were calculated both for the mode acting alone (with all other modes in their neutral states) and for interaction states comprising concurrent El Niño and Kelvin wave phase 5 conditions, and concurrent El Niño and the local peak-risk MJO phase. Anomalies were calculated

relative to a local baseline defined by days during the humid-heat season when all modes were in their neutral states.

The interaction anomaly was defined as the residual difference between the concurrent-state anomaly and the sum of the individual mode anomalies relative to the baseline, thereby quantifying departures from a purely additive response. The formula for the interaction anomaly between El Niño and Kelvin waves phase 5 is:

$$A_{int} = A_{both} - A_{ENSO} - A_{Kelvin} + A_{base} \quad (\text{Eq.5})$$

where A_{int} is the interaction anomaly, A_{both} is the anomaly when both El Niño and Kelvin waves phase 5 prevail, $A_{El\ Niño}$ is the anomaly for El Niño alone, A_{Kelvin} is the anomaly for Kelvin waves phase 5 alone, and A_{base} is the anomaly for the baseline (i.e., not El Niño and not Kelvin phase 5). An analogous formula was used to calculate the interaction anomalies for the MJO and El Niño.

Thermodynamic decomposition

Thermodynamic decomposition was used to quantify the extent to which El Niño influences humid-heat occurrence through temperature and humidity pathways. The thermodynamic decomposition was performed for years 1980–2024. Logistic regression models were fitted relating humid-heat occurrence to year, the ENSO influence metric (E^*), near-surface air temperature (T), and specific humidity (q).

$$\text{logit}(PR(HHD)) = \beta_0 + \beta_1 Y + \beta_2 E^* + \beta_3 T' + \beta_4 q' \quad (\text{Eq.6})$$

where T' and q' are anomalies from seasonal means and the remaining terms are as defined for Eq.1. Additional linear regression models relating T' and q' to year and E^* were used to estimate the ENSO-induced components of temperature and humidity variability.

$$T' = \alpha_0 + \alpha_1 Y + \alpha_2 E^* \quad (\text{Eq.7})$$

$$q' = \gamma_0 + \gamma_1 Y + \gamma_2 E^* \quad (\text{Eq.8})$$

The sensitivity of humid-heat occurrence was calculated using:

$$S_T = |\beta_3| \times \sigma_T \quad (\text{Eq.9})$$

for temperature sensitivity where σ_T is the local standard deviation of T' and β_3 is from Eq.6. An analogous formula was used for humidity-sensitivity (S_q). In Fig. 5a, regions were classified as temperature-sensitive where $S_T > 1.5 \times S_q$, humidity-sensitive where $S_q > 1.5 \times S_T$, and joint-sensitive otherwise.

These models were combined to partition the total ENSO effect on humid-heat probability into temperature-mediated, humidity-mediated, and joint-mediated components, thereby quantifying the dominant thermodynamic pathways linking El Niño variability to humid-heat risk.

The temperature mediated change in $\text{logit}(PR(HHD))$ was calculated using:

$$T_{mediation} = |\beta_3| \times T' \quad (\text{Eq.10})$$

where β_3 is from Eq.6 and T' is from Eq.7. An analogous calculation was used for $q_{mediation}$. In Fig.5b, regions were classified as temperature-mediated where $T_{mediation} > 1.5 \times q_{mediation}$, humidity-mediated where $q_{mediation} > 1.5 \times T_{mediation}$, and joint-mediated otherwise. Analogous calculations were used for Kelvin waves and the MJO.

Leading-mode classifications and weak-dominance regions

To emphasise robust regional-scale patterns in maps of leading-mode classifications and weak-dominance regions (Figs. 2 and 3), categorical fields were spatially aggregated using a 31×31 grid-cell majority (modal) filter prior to plotting. For each grid cell, the displayed classification was assigned as the most frequently occurring category within the surrounding 31×31 grid-cell neighbourhood. Grid cells where humid-heat extremes were absent were excluded from the filtering procedure and subsequently restored, preventing classifications from being propagated into regions without humid-heat occurrence. The filtering was applied solely for visualisation.

Data availability

ERA5 reanalysis data are produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) and are available from the Copernicus Climate Data Store (<https://cds.climate.copernicus.eu>).

The Niño 3.4 and ATL3 indices were obtained from the NOAA Climate Prediction Center (CPC), National Centers for Environmental Prediction (NCEP) (<https://www.cpc.ncep.noaa.gov>). The Dipole Mode Index (DMI) and Atlantic Meridional Mode (AMM) index were obtained from the NOAA Physical Sciences Laboratory (PSL) climate indices repository (<https://psl.noaa.gov>).

Equatorial wave data derived from ERA5 are available from the dataset of Yang *et al.* (<https://zenodo.org/records/7490606>). GMST data were obtained from the Indicators of Global Climate Change 2024 dataset (Smith *et al.*, 2025), available via Zenodo (<https://zenodo.org/records/15327155>).

Code availability

Python 3 is used for data processing, analysis, and plotting. All custom codes use published implementations of standard methods and statistical techniques. The final analysis code will be made available in a repository on acceptance.

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Author contributions

C.E.B., J.H.M. and L.S.J. designed the study. L.S.J. performed the analysis and wrote the first draft of the manuscript. C.E.B., G.C., J.H.M. and C.M.T. contributed to the interpretation of results and to writing of the final version of the manuscript.

812 **Competing interests**

813 The authors declare no competing interests.

Supplementary Files

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