
Climate-mode-conditioned exposure of a sporting mega-event: an event-based assessment of Rugby World Cup 2027 in Australia

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Climate-mode-conditioned exposure of a sporting mega-event: an event-based assessment of Rugby World Cup 2027 in Australia

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ABSTRACT

The environmental risk of sporting mega-events is usually assessed from host-city climatologies or, more recently, from tournament design (venue, date, kick-off time). Both overlook a distinct axis: the interannual state of the large-scale climate modes into which a given edition falls. We ask to what extent the phase of the El Niño–Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) shapes the mix of playing-condition regimes a mega-event is exposed to, using the Rugby World Cup 2027 (Australia; the first 24-team edition, 52 matches, 8 stadiums, 7 cities, October–November) as a case study. Hourly ERA5-Land and ERA5 reanalysis is sampled around each scheduled match (± 2 days, kick-off window) over October–November 1996–2025; each realisation is assigned to one of five mutually exclusive weather types (Fair, Hot, Wet, Windy, Compound) built from three hazard families (thermal, wet, wind). The type distribution is estimated conditionally on climate-mode phase. Moisture-driven matches (Wet+Compound) roughly double under La Niña and under negative IOD relative to their opposite phases (year-level bootstrap contrasts $+10.9$ percentage points, 95% CI $[+4.1, +17.4]$ for ENSO; $+12.0$ pp $[+1.2, +21.7]$ for IOD), whereas Windy matches are slightly more frequent in the dry phases and heat is negligible at this latitude and season. The phase sensitivity is spatially structured: north-eastern venues are ENSO-led, south-eastern coastal venues IOD-led, and the west and tropical north are weakly sensitive. Because mode phase is partially forecastable months ahead, the phase-conditioned hazard profile becomes a planning variable with seasonal lead time rather than an unforecastable background.

Keywords: ENSO, Indian Ocean Dipole, Australia, multi-hazard exposure, match-weather typology, mega-events, Rugby World Cup 2027, ERA5-Land

Introduction

The El Niño–Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD; Saji et al., 1999) are two major modes of interannual climate variability affecting Australia. Their phases reorganise seasonal rainfall, temperature and wind across much of the continent, with a particularly strong imprint during the austral spring. Positive IOD events and El Niño are associated with below-average spring rainfall, drought and elevated fire risk over southern and south-eastern Australia, whereas their opposite phases favour wetter conditions (Cai et al. 2009, Risbey et al. 2009,Ummenhofer et al. 2009). Because ENSO is among the most predictable components of the climate system at seasonal lead times, with skilful forecasts of warm and cold events routinely issued several months ahead (Barnston et al., 2012), large-scale climate modes are operationally used to anticipate sector impacts in agriculture and food security (Anderson et al., 2019), public health (Anttila-Hughes et al., 2021), water management and disaster risk reduction.

Climate change and climate variability are increasingly recognised as material risks for organised sport (Orr and Inoue, 2019; Orr et al., 2022), yet this seasonal-forecasting capability has received little explicit attention in assessments of sporting mega-events. Existing sport-climate assessments generally rest on host-city climatologies, event-window extremes, or tournament design choices such as venue selection, calendar structure and kick-off times. Rugby union, the focus of this study, has a hazard profile that differs from the football tournaments that dominate much of the sport-heat literature. As a collision sport played largely on natural turf, it is plausibly sensitive to weather-mediated surface conditions, including traction, surface wetness and ground hardness, as well as to wind, which can influence kicking, territorial play and restarts. Extreme heat, the headline hazard of many summer football and Olympic competitions in warmer settings (Craig and Karabas, 2024; Mullan et al., 2025), is by contrast expected to be secondary for a tournament played in late austral spring (October–November).

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Assessments of the climate risk of mega-events have so far followed two main axes. The first characterises conditions at the host cities, typically focusing on heat load for athletes, spectators or tourists (Craig and Karabas, 2024; Mullan et al., 2025). The second shows that tournament design—the choice of venues, dates and kick-off times—translates climatic variability into structured and uneven exposure across teams, groups or venues (Defrance et al., 2026). Both approaches are necessary, but they tend to treat interannual climate variability as a static background rather than as a phase-dependent component of event exposure.

We place at the centre of this study a structural mismatch in the planning of sporting mega-events. Host cities are selected, stadiums built or upgraded, and the competition window fixed years to decades before the event. The calendar and broadcast windows are also locked in well before the tournament. By contrast, the ENSO and IOD state of the specific edition becomes predictable only a few seasons before kick-off: too late to relocate venues and usually too late to reschedule, but early enough to inform operational preparedness. Climate-mode phase therefore forms an intermediate layer between the long-term climatology used in strategic planning and the day-ahead weather forecast used in operations. This layer has been widely used in climate-sensitive sectors, but has rarely been translated into the exposure space of a fixed sporting mega-event.

We therefore ask: to what extent does the phase of large-scale climate modes structure the distribution of playing-condition regimes to which a mega-event schedule is exposed, and what does this dependence imply for preparedness under forecast uncertainty? We address this question using the Rugby World Cup 2027 in Australia as a case study. The tournament will be the first 24-team edition of the competition, with 52 matches across 8 stadiums in 7 cities, held during October–November. Australia is a suitable test case because spring rainfall and related hazards are strongly modulated by ENSO and the IOD, while rugby provides a useful counterpoint to sport-climate studies centred primarily on heat.

We do not attempt to forecast the weather of the 2027 tournament itself. Rather, we quantify how the fixed 2027 schedule would have sampled match-weather regimes under the range of ENSO and IOD states observed in recent historical analogues. The analysis uses hourly reanalysis data to construct an event-based typology of match-weather conditions and estimates how the distribution of Fair, Hot, Wet, Windy and Compound regimes changes across climate-mode phases. We stress three points. First, the study concerns environmental exposure, not realised impacts on play, injuries or match outcomes. Second, the rugby consequences of wet, windy or compound conditions are interpreted using existing literature rather than measured directly. Third, generalisation to other mega-events is treated as a methodological implication rather than as a claim that the Rugby World Cup 2027 case is representative of all sport-climate risks.

Data and methods

Tournament schedule and meteorological data

The analysis uses the official Rugby World Cup 2027 schedule, comprising 52 matches across 8 stadiums in 7 Australian cities, with venue, date and local kick-off time specified for each match. The tournament is held in October–November and is therefore analysed as a late-spring event.

Hourly meteorological fields were extracted at the grid point nearest each stadium for the period 1996–2025. ERA5-Land was used for near-surface and land variables at 0.1° spatial resolution: 2-m air temperature (T), 2-m dew-point temperature (T_d), surface solar radiation downwards (R_s), total precipitation (P), and 10-m wind components (u_{10}, v_{10}). ERA5 was used for 10-m wind gusts at 0.25° resolution. All timestamps were converted to local stadium time before event sampling. Air and dew-point temperatures were converted from K to °C, precipitation from m to mm, and hourly accumulated solar radiation from J m^{-2} to W m^{-2} by dividing by 3600. The 10-m wind speed was computed as

$$U_{10} = \sqrt{u_{10}^2 + v_{10}^2}. \tag{1}$$

Derived hourly heat-stress variables

Relative humidity was estimated from air temperature and dew-point temperature using saturation vapour pressure:

$$e_s(T) = 6.112 \exp\left(\frac{17.67T}{T + 243.5}\right), \tag{2}$$

$$e(T_d) = 6.112 \exp\left(\frac{17.67T_d}{T_d + 243.5}\right), \tag{3}$$

$$RH = 100\frac{e(T_d)}{e_s(T)}, \tag{4}$$

with RH bounded to the interval $[0, 100]$. Temperatures are in °C and RH is in percent.

Heat stress was summarised using the Wet Bulb Globe Temperature (WBGT). The natural wet-bulb temperature was approximated from air temperature and relative humidity following the empirical formulation of Stull (2011):

$$\begin{aligned} T_w =;& T \tan^{-1}\left[0.151977(RH + 8.313659)^{1/2}\right] + \tan^{-1}(T + RH) \\ &- \tan^{-1}(RH - 1.676331) \\ &+ 0.00391838, RH^{3/2} \tan^{-1}(0.023101, RH) - 4.686035. \end{aligned} \tag{5}$$

Because black-globe temperature is not available from the reanalysis, it was estimated with the empirical regression model of Hajizadeh et al. (2017), which predicts globe temperature from downward shortwave radiation, air temperature and relative humidity:

$$T_g = 0.01498\, R_s + 1.184\, T - 0.0789\, RH - 2.739, \tag{6}$$

where R_s is the hourly mean downward shortwave radiation in W m^{-2}. WBGT was then computed with the standard outdoor weighting:

$$WBGT = 0.7\,T_w + 0.2\,T_g + 0.1\,T. \tag{7}$$

This formulation should be read as an outdoor heat-stress proxy rather than a physically complete WBGT model: T_w follows an empirical fit (Stull, 2011) and T_g an empirical regression calibrated on field measurements (Hajizadeh et al., 2017), rather than a full radiative–convective globe balance. More physically based WBGT formulations using standard meteorological variables are available (Liljegren et al., 2008); we adopt the simpler proxy here because heat is not the dominant hazard in the present case and the Hot class remains near-empty in the results below.

Event-based sampling

For each scheduled match m, we constructed historical analogue realisations by repeating the 2027 calendar date and local kick-off hour in each year from 1996 to 2025. To represent uncertainty around "this point in the season", each match was additionally sampled over a ±2-day window around the scheduled calendar date. The resulting sampling design therefore contains

$$52 \text{ matches} \times 30 \text{ years} \times 5 \text{ date offsets} = 7800 \tag{8}$$

schedule-conditioned realisations.

For each match-year-offset realisation, the nearest available hourly timestamp to the nominal local kick-off time was selected. The match window was defined from one hour before to two hours after this timestamp:

$$W_m = [h_m - 1, h_m + 2]. \tag{9}$$

Within this window we computed maximum WBGT, mean wind speed, maximum gust and accumulated precipitation:

$$WBGT_{\max} = \max_{t \in W_m} WBGT_t, \tag{10}$$

$$G_{\max} = \max_{t \in W_m} G_t, \tag{11}$$

$$P_{\text{match}} = \sum_{t \in W_m} P_t. \tag{12}$$

Two antecedent rainfall indicators were also computed to represent surface wetness and potential saturation before kick-off:

$$P_{24h} = \sum_{t \in (h_m - 24, h_m]} P_t, \tag{13}$$

$$P_{5d} = \sum_{t \in (h_m - 120, h_m]} P_t. \tag{14}$$

The 24-h accumulation captures recent rainfall before the match, whereas the 5-day accumulation is used as a broad proxy for antecedent wetness and surface saturation. These variables are meteorological proxies; they are not direct measurements of pitch water content, traction or drainage performance.

Climate-mode classification

Each October–November season was labelled by ENSO phase using the Ocean Niño Index (ONI) for the OND season. Years with ONI ≥ +0.5 °C were classified as El Niño, years with ONI ≤ −0.5 °C as La Niña, and the remaining years as neutral. The Indian Ocean Dipole was classified using the Dipole Mode Index (DMI) averaged over SON, with positive IOD defined as DMI ≥ +0.4 °C and negative IOD as DMI ≤ −0.4 °C (Saji et al., 1999). Over 1996–2025, the ENSO sample contains 14 La Niña, 6 neutral and 10 El Niño seasons. The IOD sample contains 5 negative, 19 neutral and 5 positive seasons, with the most recent incomplete IOD season excluded from the IOD classification.

Hazard families and match-weather typology

Each realisation was classified using three hazard families: thermal, wet and wind. The thermal family is active when

$$H_T = \mathbf{1}(WBGT_{\max} \geq 26\,^{\circ}\mathrm{C}), \tag{15}$$

the wet family when

$$H_W = \mathbf{1}(P_{\text{match}} \geq 1 \text{ mm or } P_{24h} \geq 5 \text{ mm or } P_{5d} \geq 25 \text{ mm}), \tag{16}$$

and the wind family when

$$H_G = \mathbf{1}(G_{\max} \geq 12 \text{ m s}^{-1}). \tag{17}$$

The number of active hazard families is

$$K = H_T + H_W + H_G. \tag{18}$$

Each realisation is then assigned to one of five mutually exclusive match-weather types:

$$\text{Type} = \begin{cases} \text{Compound}, & K \geq 2, \\ \text{Hot}, & K = 1 \text{ and } H_T = 1, \\ \text{Wet}, & K = 1 \text{ and } H_W = 1, \\ \text{Windy}, & K = 1 \text{ and } H_G = 1, \\ \text{Fair}, & K = 0. \end{cases} \tag{19}$$

The Wet and Compound categories are also combined into a moisture-affected class:

$$\text{Moisture} = \text{Wet} + \text{Compound}. \tag{20}$$

This combined class is used as the main response variable for ENSO and IOD phase contrasts, because the dominant phase signal is expected to arise from rainfall and antecedent wetness rather than from heat.

Aggregation, uncertainty and sensitivity

For each climate-mode phase ϕ, the conditional type distribution was estimated as the frequency of each match-weather type among all schedule-conditioned realisations belonging to years in that phase:

$$P(c|\phi) = \frac{1}{N_\phi} \sum_{i:y_i \in \phi} \mathbf{1}(\mathrm{Type}_i = c), \tag{21}$$

where c is one of Fair, Hot, Wet, Windy or Compound, and N_ϕ is the number of realisations in phase ϕ.

Because the ±2-day samples around a given match are temporally autocorrelated, and because all matches within a given year share the same seasonal climate-mode state, the unit of replication for uncertainty is the year rather than the individual match-day realisation. Uncertainty was therefore estimated using a year-level block bootstrap. Complete years were resampled with replacement, preserving all matches, venues, kick-off windows and date offsets associated with each selected year.

For the phase contrasts, years were resampled independently within the two contrasted phase groups: La Niña versus El Niño for ENSO, and negative versus positive IOD for the IOD. For each bootstrap replicate, the Wet+Compound share was recomputed in both phase groups and the difference between the two means was stored. Confidence intervals are reported as percentile 95% intervals from the bootstrap contrast distribution.

A threshold-sensitivity analysis was performed by varying one threshold at a time around the baseline definition: match rainfall, 24-h rainfall, 5-day rainfall, gust speed and WBGT. The sensitivity analysis evaluates whether the sign and approximate magnitude of the Wet+Compound phase contrasts depend on arbitrary threshold choices.

Results

Tournament structure and analogue sample

The RWC 2027 schedule generates 7800 historical analogue realisations (52 matches × 30 years × 5 date offsets). The matches are unevenly distributed across the venue network: Brisbane hosts the largest number of matches, followed by the Sydney venues and Melbourne, while Newcastle and Townsville host fewer matches. The venue network spans a large latitudinal gradient, from tropical Townsville (19°S) to temperate Melbourne (38°S), and therefore samples distinct spring rainfall, wind and thermal regimes (Fig. 1).

Kick-off times are concentrated in the afternoon and evening, with the largest number of matches around 20:00 local time and relatively few midday starts. This matters for heat and wind exposure because the match-weather typology is evaluated over the local kick-off window rather than from daily mean conditions. Across the 1996–2025 analogue seasons, the ENSO classification yields 14 La Niña, 6 neutral and 10 El Niño springs. The IOD classification yields 5 negative, 19 neutral and 5 positive springs, after excluding the incomplete recent IOD season. The small number of IOD extreme years is therefore an important constraint on the precision of IOD phase estimates (Fig. 2).

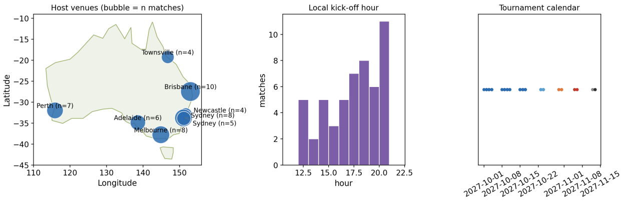

Fig. 1. Host venues (bubble size = number of matches), distribution of local kick-off hours, and tournament calendar.

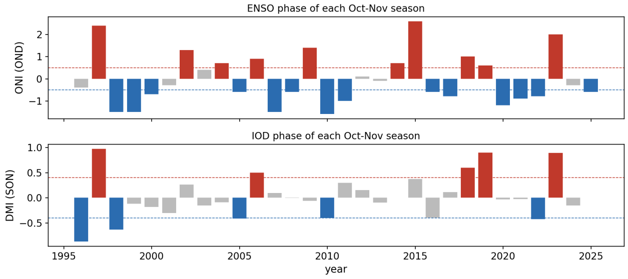

Fig. 2. ENSO phase (ONI, OND) and IOD phase (DMI, SON) of each October–November season, 1996–2025. Dashed lines mark the ±0.5 °C (ONI) and ±0.4 °C (DMI) thresholds.

Baseline match-weather typology

Across all phases, venues and historical analogue years, the baseline typology is dominated by Fair realisations (66.9%). Among the hazardous single-family types, Wet (13.5%) and Windy (13.2%) are the dominant classes, whereas Compound accounts for 6.2% and Hot is almost absent (0.3%) (Fig. 3). The combined Wet+Compound share is therefore 19.7%, meaning that roughly one in five schedule-conditioned realisations is moisture-affected.

The near-absence of the Hot class is important. Although WBGT is computed explicitly for each hourly realisation, the thermal threshold is rarely exceeded during the late-spring tournament window. Heat is therefore retained in the typology for completeness and comparability with other sport-climate studies, but it does not drive the main RWC 2027 phase signal.

The baseline composition varies strongly across venues. Brisbane has the largest moisture-affected share (26.2%), followed by Melbourne (23.4%), Sydney (22.2%) and Newcastle (22.0%). Adelaide (13.9%), Perth (12.2%) and Townsville (6.7%) are less frequently moisture-affected. Windy realisations show a different spatial pattern, peaking at Melbourne (24.4%) and Adelaide (17.4%), while remaining rare at Townsville (1.7%) and Newcastle (5.5%). Thus, the venue ranking depends on the hazard family: Brisbane is most exposed to wet-condition regimes, whereas the southern venues stand out more clearly for wind.

Kick-off timing also structures the baseline typology. Afternoon matches are the least frequently Fair (56.2%) and have the highest Wet (15.4%) and Windy (18.9%) shares. Evening matches are calmer overall, with 73.6% Fair and

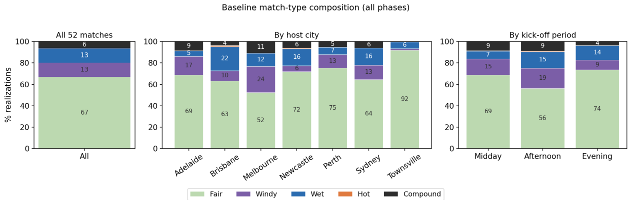

Fig. 3. Baseline match-type composition (all phases): overall, by host city, and by kick-off period.

9.0% Windy realisations. This confirms that the event-based approach captures an exposure structure that would be lost in a daily or seasonal mean climatology.

Climate-mode conditioning of the typology

The match-weather composition shifts systematically with ENSO and IOD phase (Fig. 4). The strongest and most consistent signal concerns moisture-related conditions. Under ENSO, Wet realisations decrease from 17.6% during La Niña springs to 9.1% during El Niño springs, while Compound realisations decrease from 7.3% to 4.8%. Under the IOD, Wet realisations decrease from 19.2% during negative-IOD springs to 9.2% during positive-IOD springs, while Compound realisations decrease from 7.2% to 5.2%.

Combining Wet and Compound realisations, the moisture-affected share rises from about 14% in the dry phases (El Niño and positive IOD) to about 25–26% in the wet phases (La Niña and negative IOD). In practical terms, the same fixed RWC 2027 schedule has roughly twice the probability of encountering moisture-affected playing conditions when embedded in wet-phase large-scale climate states.

The year-level bootstrap confirms that the tournament-wide moisture contrasts are not an artefact of treating match-day realisations as independent. The La Niña–El Niño contrast in Wet+Compound share is +10.9 percentage points (95% CI [+4.1, +17.4]), while the negative–positive IOD contrast is +12.0 percentage points (95% CI [+1.2, +21.7]). Both intervals exclude zero, although the IOD contrast is less precisely estimated because only five negative and five positive IOD seasons are available.

Wind behaves differently from moisture. Windy realisations are somewhat more frequent in the dry phases, reaching 15.3% under El Niño compared with 11.1% under La Niña, and 15.8% under positive IOD compared with 8.8% under negative IOD. This opposite sign indicates that dry-phase conditions are not simply "lower-risk" conditions; rather, they shift the typology away from wet regimes and slightly towards wind-related regimes. Hot realisations remain below 0.5% across all phases, confirming that heat is not the dominant hazard for this tournament timing and venue network.

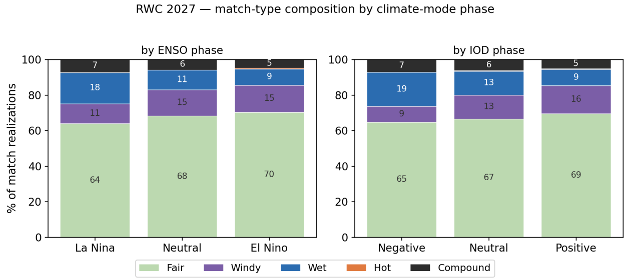

Fig. 4. RWC 2027 match-type composition by ENSO phase (left) and IOD phase (right), estimated from schedule-conditioned historical analogue realisations, 1996–2025.

Venue-level phase sensitivity

The phase sensitivity is strongly venue-dependent (Figs. 5 and 6). Brisbane shows the clearest ENSO signal: the Wet+Compound share falls from 37.1% under La Niña to 14.0% under El Niño, corresponding to a +23 percentage-point La Niña–El Niño contrast. Brisbane also responds to the IOD, but the ENSO contrast is the dominant feature of its phase sensitivity.

Melbourne responds strongly to both modes, with contrasts of approximately +18.5 percentage points for ENSO and +20 points for the IOD. The south-eastern coastal venues are more IOD-sensitive. At Newcastle, the IOD contrast reaches about +13 percentage points, whereas the ENSO contrast is negligible. Sydney and Adelaide also show larger IOD than ENSO contrasts, with Adelaide displaying an IOD contrast of approximately +17.3 points compared with an ENSO contrast of +12.6 points.

By contrast, Perth and Townsville are weakly and non-monotonically sensitive to either mode. Their muted response is consistent with their distinct regional rainfall regimes and with the fact that the dominant ENSO/IOD spring rainfall teleconnections do not project uniformly across the whole Australian venue network. The venue-level results therefore show that the tournament should not be interpreted through a single national phase signal. The relevant climate-mode predictor differs between the north-eastern, south-eastern and western/tropical-northern parts of the schedule.

Threshold sensitivity and Wet-family decomposition

The main phase signal is robust to plausible changes in the hazard thresholds (Fig. 7). When the match-rainfall, 24-h rainfall, 5-day rainfall, gust and WBGT thresholds are varied one at a time, the La Niña–El Niño and negative–positive IOD contrasts in the Wet+Compound share remain positive throughout. Across the tested threshold range, the contrasts remain approximately between +9 and +18 percentage points.

The sensitivity analysis indicates that the Wet+Compound contrast is controlled by the rainfall thresholds rather than by

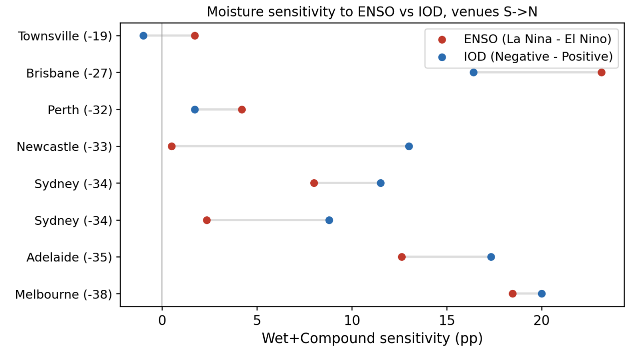

Fig. 5. Moisture (Wet+Compound) sensitivity to ENSO (La Niña−El Niño) and IOD (negative−positive), by venue, ordered by latitude.

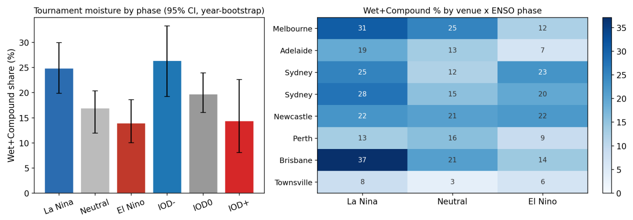

Fig. 6. Operational view. Left: tournament moisture share by phase with 95% year-bootstrap confidence intervals. Right: moisture share by venue × ENSO phase.

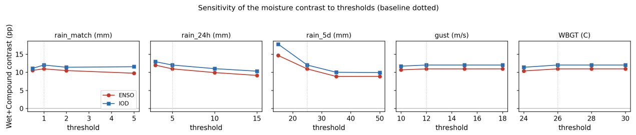

Fig. 7. Sensitivity of the moisture (Wet+Compound) contrast to each indicator threshold, varied one at a time (baseline marked by the dotted line). ENSO: La Niña−El Niño; IOD: negative−positive.

the WBGT or gust thresholds. To clarify what drives the Wet family, we also decomposed the three rainfall triggers used in its definition (Table S1). The triggers are not mutually exclusive, but the decomposition shows that the phase signal is carried mainly by antecedent rainfall. Across both modes, the wet-phase increase is larger for the 24-h and 5-day accumulations than for in-play rainfall: for example, $P_{24\mathrm{h}} \geq 5$ mm rises from 6.7% under El Niño to 13.8% under La Niña, and $P_{5\mathrm{d}} \geq 25$ mm from 6.5% to 12.9%, whereas $P_{\mathrm{m}} \geq 1$ mm rises from 6.0% to 10.1%. The Wet-family phase signal is therefore associated with recent and multi-day antecedent rainfall (and hence surface wetness) rather than with match-time rain alone.

The decomposition also confirms that Compound realisations without an active Wet trigger are negligible ($\leq$0.12class used throughout the analysis is therefore an effectively clean proxy for moisture-affected realisations. This check is descriptive and does not alter the main typology.

Discussion

Climate-mode phase as a missing, forecastable layer

Assessments of climate risk for sporting mega-events usually operate at two time scales. The first is climatological: host cities are screened using long-term mean or extreme conditions, often with a focus on heat exposure for athletes, spectators or tourists (Orr et al., 2022; Craig and Karabas, 2024; Mullan et al., 2025). The second is operational: short-range weather forecasts inform day-to-day decisions once the event is already underway. Our results highlight a third layer between these two scales. For the Rugby World Cup 2027, the distribution of playing-condition regimes is not fixed by the host-city climatology alone; it is also conditioned by the phase of the large-scale climate modes into which the tournament falls.

This matters because the structural exposure of a mega-event is largely fixed years before the event: host cities are selected, stadiums are built or upgraded, the tournament window is chosen, and broadcast-oriented kick-off times are locked in. At the other end of the decision chain, synoptic weather is known only days ahead, when only reactive measures are possible. ENSO and the IOD occupy an intermediate position. Their phase is not known at the time of host selection, but it becomes at least partly predictable at seasonal lead time. ENSO forecasting is operationally mature relative to many other climate modes (Barnston et al., 2012), while IOD prediction remains more model-dependent but can provide useful information several months ahead in modern seasonal prediction systems (Liu et al., 2023). Conditioning exposure on climate-mode phase therefore converts part of the tournament hazard profile from a climatological background assumption into a seasonal preparedness variable.

The contribution of this paper is not that ENSO and the IOD influence Australian climate; that is well established. Rather, the contribution is to translate this large-scale climate variability into the exposure space of a fixed sports schedule. This translation is non-trivial. A tournament is not a seasonal mean over Australia: it is a sequence of matches occurring at specific venues, dates and local kick-off hours. The event-based framework used here therefore asks a more operational question: if the 2027 schedule had occurred under each of the historical October–November climate-mode states, what mix of Fair, Hot, Wet, Windy and Compound regimes would it have encountered? In that sense, the analysis targets the exposure component of climate vulnerability rather than the full impact chain, following the distinction between exposure, sensitivity and adaptive capacity used in sport-climate vulnerability frameworks (Orr and Inoue, 2019).

ENSO and IOD do not act as interchangeable predictors

The tournament-wide signal is clear: moisture-affected realisations (Wet+Compound) are substantially more frequent during La Niña and negative-IOD springs than during El Niño and positive-IOD springs. However, the venue-level structure shows that ENSO and the IOD should not be treated as interchangeable predictors. Brisbane is primarily ENSO-sensitive, while the south-eastern venues show a stronger IOD imprint. Perth and Townsville are comparatively weakly sensitive to either mode. This spatial differentiation is consistent with the known geography of Australian rainfall teleconnections: ENSO has a broad influence on eastern and northern Australian rainfall, while the IOD is particularly relevant for southern and south-eastern spring rainfall and drought risk (Risbey et al., 2009; Ummenhofer et al., 2009; Cai et al., 2009; Ummenhofer et al., 2011).

The need to analyse both modes is strengthened by their covariance. El Niño and positive IOD events often co-occur, and simple index-based attribution can misrepresent the independent contributions of the Pacific and Indian Ocean drivers. Recent modelling work shows that separating ENSO and IOD contributions to Australian precipitation is methodologically difficult: regressing out one mode can underestimate or overestimate the influence of the other (Liguori et al., 2022). We therefore interpret the venue-level ENSO/IOD differences as conditional exposure diagnostics rather than as a strict causal decomposition of the climate system. The practical point remains robust: organisers should not rely on a single generic “Australia” seasonal outlook. The relevant climate predictor differs between the north-eastern, south-eastern and western/tropical-northern parts of the venue network.

This distinction also affects the interpretation of forecast usefulness. A seasonal outlook indicating La Niña conditions would not imply the same increase in moisture-related exposure at all venues. It would be most informative for the north-eastern part of the schedule, especially Brisbane. Conversely, an emerging negative IOD signal would be more relevant for south-eastern venues such as Sydney, Newcastle, Melbourne and Adelaide. This venue-specificity is central to the operational value of the method: the framework does not merely say that a tournament edition may be wetter or drier; it identifies where the schedule is most sensitive to each mode.

Interpretation for rugby: surface, traction and play

The rugby interpretation should be kept deliberately cautious. The analysis does not measure injuries, match outcomes, ball-in-play time, kicking choices or tactical behaviour. It quantifies exposure to weather-regime classes and then interprets the likely rugby relevance of those classes using existing sports-medicine and performance literature. This distinction is important because the relationship between weather, surface condition and rugby outcomes is unlikely to be linear.

The most relevant pathway for the Wet and Compound types is the playing surface. Natural turf conditions depend on rainfall, drainage, soil moisture, evapotranspiration, maintenance and stadium-specific design. Earlier work in the football codes links ground and climatic conditions to injury risk, but the evidence is heterogeneous and sometimes confounded by surface type, seasonality and measurement quality (Orchard, 2002; Twomey et al., 2014). In Australian football, higher rainfall and lower evaporation were associated with a lower risk of non-contact ACL injuries, plausibly through softer surfaces and lower shoe-surface traction (Orchard et al., 1999). In rugby union, Takemura et al. found a seasonal change in ground hardness and injury incidence but did not identify a simple independent ground-hardness effect after accounting for match round (Takemura et al., 2007). In rugby league, harder ground conditions and lower rainfall were associated with match injury risk in semi-professional players (Gabbett et al., 2007). Taken together, these studies justify treating antecedent rainfall and surface saturation as rugby-relevant proxies of exposure, but they do not justify a direct causal claim that wetter conditions necessarily increase or decrease injury risk. This interpretation is supported by the Wet-family decomposition, which shows that the phase signal is driven more by recent and multi-day antecedent rainfall than by in-play rain alone.

For this reason, the Wet and Compound types should be interpreted primarily as changes in the character of playing conditions rather than as injury predictions. Wet or saturated surfaces can reduce traction, increase slipping, affect acceleration and deceleration, and alter handling conditions. However, softer surfaces may also reduce some impact or traction-related injury mechanisms. The direction of total injury risk is therefore ambiguous without match-level injury data and pitch measurements. The safer claim is that wet phases increase the probability that the tournament is played under surface- and handling-relevant constraints, especially when 24-h or 5-day antecedent rainfall contributes to the Wet family.

The Compound category is particularly important because it captures simultaneous degradation of more than one hazard family. A match that is both wet and windy, or wet and thermally stressful, is not simply a marginally worse Wet match; it may involve several simultaneous constraints on footing, handling, kicking, tactical choices and medical logistics. In the present case, Compound remains less frequent than the single-hazard Wet or Windy classes, but it is still phase-sensitive and operationally meaningful. Its main value is not to imply a precise outcome effect, but to identify the subset of match realisations where preparedness should assume interacting rather than isolated weather constraints.

Wind, kicking and the dry-phase signal

The wind signal is weaker than the moisture signal, but it is not irrelevant for rugby. Windy realisations are somewhat more frequent in the dry phases and at the more wind-exposed southern venues. In rugby union, wind can affect territorial kicking, restarts, high balls and goal-kicking. A large analysis of international rugby union goal-kicking showed substantial between-venue variation in kicking success after accounting for distance, angle and kick importance, with venue-related conditions forming part of the explanatory structure (Quarrie and Hopkins, 2015). This supports the rugby relevance of a Windy type, although it does not allow us to isolate wind as the sole mechanism in the present study.

The dry-phase wind signal therefore has a different operational meaning from the wet-phase moisture signal. Wet phases point towards surface, drainage, handling and waterlogging preparedness. Dry phases do not simply mean "benign" conditions; they may shift attention towards wind exposure and kicking-related uncertainty at specific venues. This is one reason why the five-type typology is useful. A binary hazardous/non-hazardous classification would hide the fact that wet and dry phases can produce different kinds of operational concern.

Heat, by contrast, is negligible for this tournament timing and geography. This does not mean that heat is unimportant for sport-climate risk in general. Recent work on football and mega-events shows that heat exposure is a central concern for summer events and for tournaments held in warmer locations (Craig and Karabas, 2024; Mullan et al., 2025). Rather, the RWC 2027 case illustrates that sport-climate assessments should not assume that heat is always the dominant hazard. For a late-spring rugby tournament in Australia, moisture and wind are more relevant to the playing-condition typology than thermal stress. This is a useful counterpoint to a sport-climate literature that remains heavily centred on heat impacts (Orr et al., 2022; Mabon, 2023).

Operational relevance and limits of actionability

The framework does not imply that organisers can change the fundamental exposure of the tournament once the climate-mode phase becomes predictable. By seasonal lead time, the host cities, venues and broad competition window are effectively fixed. What can still change is preparedness. A wet-phase seasonal outlook could justify earlier attention to drainage inspection, surface monitoring, turf protection, contingency planning for waterlogged training grounds, medical and logistical provisioning, and communication with teams and broadcasters about a higher likelihood of wet or compound playing conditions. A dry-phase outlook could shift attention towards wind exposure, surface hardness, irrigation and heat contingencies at the few venues or kick-off windows where these risks remain relevant.

This actionability is modest but real. It sits between two extremes. It is not a long-range siting tool equivalent to climate-change suitability screening, and it is not a substitute for short-range weather forecasting. Instead, it is a seasonal risk-preparedness layer. Its value is highest for aspects of the event that require weeks to months of preparation but do not require changing the host network: turf management, venue staffing, medical readiness, equipment logistics, training-ground allocation, communications, and scenario planning. This positioning is consistent with broader calls in sport-climate research for evidence-informed adaptation rather than generic climate concern (Orr and Inoue, 2019; Orr et al., 2022; Mabon, 2023).

The approach also has value for communication. Tournament stakeholders often understand short-range weather risk but are less familiar with the idea that the same fixed schedule may have different seasonal exposure profiles depending on large-scale climate modes. A phase-conditioned typology provides a simple language: not merely "La Niña is wetter", but "under La Niña, this schedule historically produces a higher share of Wet and Compound match realisations, especially at these venues". That framing is more directly usable by event managers than seasonal rainfall anomalies alone.

Limitations

Several limitations bound these results. First, reanalysis describes the outdoor atmosphere at grid-point scale, not the microclimate or playing surface inside a specific stadium. ERA5-Land provides high-resolution, hourly, land-focused fields and is appropriate for regional-scale exposure analysis (Muñoz Sabater et al., 2021), but it cannot represent stadium drainage, irrigation, hybrid turf, roof state, shading, local shelter or pitch-specific soil conditions. ERA5 gusts are likewise atmospheric estimates, not stadium-measured gusts (Hersbach et al., 2020). The surface interpretation must therefore remain a proxy interpretation: ERA5-Land rainfall is not pitch moisture, and antecedent rainfall is not a direct measurement of traction or hardness.

Second, the WBGT estimate is approximate. The wet-bulb component follows Stull (2011), but the globe-temperature term is represented by an empirical proxy based on air temperature, relative humidity and shortwave radiation rather than by a full heat-budget model or by in-stadium measurements. Physically based WBGT modelling can be more detailed (Liljegren et al., 2008). This limitation should be kept in mind for the exact Hot percentages, but it does not affect the main conclusion because Hot realisations are near-empty and the phase signal is overwhelmingly rain-driven.

Third, the thresholds used to define Hot, Wet, Windy and Compound are operational classification thresholds, not universal physiological or injury thresholds. The sensitivity analysis shows that the moisture contrast remains positive over plausible threshold ranges, which supports the robustness of the main phase signal. However, the exact proportions of Fair, Wet, Windy, Hot and Compound realisations remain threshold-dependent. They should be read as a structured typology of playing-condition regimes, not as fixed natural categories.

Fourth, the historical analogue sample is limited. The ENSO contrast uses more years than the IOD contrast, while the IOD extremes contain only five seasons per phase. The year-level bootstrap accounts for the non-independence of within-year realisations, but it cannot create additional independent climate-mode events. The IOD contrast therefore remains less precisely constrained than the ENSO contrast. Moreover, ENSO and IOD phases covary, so the conditional contrasts reported here should not be interpreted as a clean causal attribution of each mode's independent dynamical effect (Liguori et al., 2022).

Fifth, the 30-year record is treated as a set of quasi-stationary interannual analogues. The secular warming trend over 1996–2025 is not removed, so the historical analogues conflate interannual climate-mode variability with any slow background trend. This is a deliberate scope choice: the secular trend is a distinct axis from the interannual modulation studied here, and heat—the hazard most directly exposed to warming—is in any case near-empty in this late-spring tournament window.

Finally, the paper quantifies exposure, not realised impact. It does not estimate injuries, tactical changes, scoring effects, spectator risk, broadcast disruption or operational costs. The rugby consequences discussed above are plausible pathways grounded in existing literature, but they are not measured in this study. A direct impact analysis would require match-level weather, pitch and outcome data from past rugby competitions, ideally with surface measurements and injury surveillance.

Future work

The most direct extension is an outcome-based companion study linking observed match weather to rugby performance indicators: points, tries, penalties, kicking share, goal-kicking success, ball-in-play time, handling errors, scrums, lineouts and possibly injury reports where available. Such a study would test whether the Wet, Windy and Compound classes identified here translate into measurable differences in play or safety. It would also allow the typology thresholds to be calibrated empirically rather than defined as operational categories.

A second extension is methodological. Future work should test multivariate or probabilistic conditioning rather than discrete phase bins, especially for the IOD where sample sizes are small. It should also explore whether alternative indices, such as regional Indian Ocean predictors or the eastern pole of the IOD, better explain the south-eastern venue signal. Because ENSO and IOD are not independent, future analyses could use model-based separation or conditional regression approaches inspired by recent work on Australian precipitation teleconnections (Liguori et al., 2022).

Finally, the framework should be applied beyond RWC 2027. Other events in teleconnection-sensitive regions—the Brisbane 2032 Olympics, the Australian Open, cricket World Cups, or future football tournaments in monsoon- or ENSO-sensitive regions—could be assessed with the same schedule-conditioned logic. A multi-event synthesis would show whether climate-mode-conditioned exposure is a niche feature of this Australian rugby case or a transferable tool for seasonal preparedness in global sport.

Conclusion

This study shows that the climatic exposure of a sporting mega-event is not fully described by host-city climatology or by the fixed tournament schedule. For the Rugby World Cup 2027 in Australia, conditioning an event-based match-weather typology on ENSO and IOD phase reveals a clear interannual modulation of playing-condition regimes. Moisture-affected realisations (Wet+Compound) are substantially more frequent during La Niña and negative-IOD springs than during El Niño and positive-IOD springs, with year-level bootstrap contrasts of +10.9 percentage points for ENSO and +12.0 percentage points for the IOD. This signal is spatially structured: Brisbane is primarily ENSO-sensitive, the south-eastern venues show a stronger IOD imprint, and Perth and Townsville are comparatively weakly affected by either mode.

The main contribution is methodological as much as empirical. By combining a fixed tournament schedule, historical reanalysis analogues and climate-mode-conditioned classification, the framework identifies a forecastable layer of exposure that lies between long-term climatological screening and short-range weather forecasting. This layer cannot alter the structural decisions already made years before the tournament, such as host cities or stadium locations, but it can inform seasonal preparedness: surface and drainage management, contingency planning for wetter or windier conditions, medical and logistical provisioning, and communication with teams, broadcasters and event organisers.

The analysis remains an exposure assessment. It does not measure the effects of weather on injuries, playing style, match outcomes or spectator safety, and it does not resolve stadium-scale surface conditions, roof effects, irrigation or local shelter. These limitations are important, but they do not weaken the central finding: for events held in regions with strong teleconnections, the realised phase of large-scale climate modes can materially reshape the hazard profile of a specific edition. Future work should connect this exposure framework to observed match outcomes and extend it to other teleconnection-sensitive sporting mega-events.

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ERA5 and ERA5-Land reanalysis data are available from the Copernicus Climate Data Store. The Oceanic Niño Index (ONI) is available from the NOAA Climate Prediction Center, and the Indian Ocean Dipole index used in this study is available from the NOAA Physical Sciences Laboratory. The Rugby World Cup 2027 schedule is publicly available from World Rugby.

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