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Sub-Seasonal Predictability of Heatwave Onset using Coupled Ocean-Atmosphere Teleconnections

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***Abstract*— *Heatwaves are among the deadliest climate extremes, and their impacts on human health, agriculture, energy demand, and infrastructure are strongly dependent on the amount of advance warning available to decision-makers. Weather forecasts provide reliable skill only to about 10–14 days, while seasonal forecasts operate at climatological, not event-scale, resolution, leaving a critical "sub-seasonal" gap of roughly two to six weeks in which actionable heatwave-onset prediction is most needed but least mature. This paper investigates the sub-seasonal predictability of heatwave onset by examining coupled ocean-atmosphere teleconnection patterns, including the El Niño–Southern Oscillation (ENSO), the Madden-Julian Oscillation (MJO), and mid-latitude atmospheric blocking, as sources of extended-range predictive skill. The study reviews observational and reanalysis-based evidence linking specific MJO phases and ENSO states to anomalous ridging, soil-moisture feedbacks, and Rossby wave train propagation associated with heatwave initiation over North America, Europe, and East Asia. A composite and lagged-correlation methodology is described using ERA5 reanalysis, NOAA Optimum Interpolation Sea Surface Temperature (OISST) data, and the Real-time Multivariate MJO (RMM) index, alongside statistical and machine-learning-based predictive frameworks (logistic regression, random forest, and LSTM architectures) applied in the subseasonal-to-seasonal (S2S) prediction literature. Comparative skill metrics reported across studies indicate that heatwave predictability at 3–4 week lead times is substantially enhanced when MJO phase and ENSO state are used as joint predictors relative to climatology alone, though skill remains regionally heterogeneous and highly sensitive to the underlying dynamical driver. The paper concludes by identifying persistent challenges in operational S2S heatwave prediction, including model bias in MJO teleconnection representation, land-atmosphere coupling errors, and the need for regionally tailored predictor combinations.*

***Keywords*— Sub-seasonal Prediction, Heatwave Onset, Ocean-Atmosphere Teleconnections, Madden-Julian Oscillation, ENSO, Atmospheric Blocking, S2S Forecasting, Extended-Range Forecasting.**

I. INTRODUCTION

Heatwaves rank among the most damaging climate extremes globally, causing more weather-related mortality in many regions than any other hazard, alongside substantial agricultural losses, electricity grid stress, and wildfire risk amplification [1]. Unlike hurricanes or floods, heatwaves are frequently under-anticipated because they build gradually from persistent atmospheric ridging rather than a single, rapidly evolving synoptic system, which historically limited the lead time at which their onset could be reliably forecast [2].

Numerical weather prediction (NWP) systems provide useful deterministic skill only out to approximately 10–14 days, beyond which chaotic error growth dominates individual trajectories [3]. Seasonal forecasting systems, by contrast, provide skillful information on monthly-to-seasonal mean anomalies but cannot resolve the timing of individual extreme events within a season. This leaves a forecasting gap spanning roughly two to six weeks, formally designated the sub-seasonal-to-seasonal (S2S) range, in which skill must be derived not from initial-condition memory of the atmosphere alone but from slowly evolving boundary forcings such as sea surface temperature (SST) anomalies, soil moisture, and large-scale tropical convective organization [4].

Coupled ocean-atmosphere teleconnections provide the principal source of this extended-range predictability. The Madden-Julian Oscillation (MJO), an eastward-propagating envelope of tropical convection with a 30–60 day period, has been shown to modulate extratropical circulation through Rossby wave trains that alter the position and persistence of mid-latitude ridges associated with heatwave onset [5]. Specific MJO phases have been linked to increased probability of anomalous warmth and blocking-favorable circulation over North America, with statistically significant lagged relationships extending to three to four weeks [6]. Similarly, the El Niño–Southern Oscillation (ENSO), operating on interannual timescales, modulates the background state of the jet stream and storm tracks, altering the baseline probability of heat extremes in specific regions depending on the phase and strength of the anomaly [7].

Atmospheric blocking, characterized by quasi-stationary high-pressure systems that divert the jet stream and trap warm air masses beneath subsiding air, is now widely recognized as the proximate dynamical mechanism for most major heatwave events, including the 2003 European and 2010 Russian heatwaves [8]. Because blocking onset itself is influenced by upstream tropical forcing via Rossby wave propagation, teleconnection-informed prediction offers a physically grounded route to anticipating blocking, and therefore heatwave, development beyond the deterministic weather forecast horizon [9].

Empirical statistical studies have further demonstrated that Pacific SST patterns alone can provide skillful predictions of eastern United States hot-day frequency at lead times of three to six weeks, using regression frameworks trained on historical SST-temperature relationships rather than dynamical model integration [10]. This finding motivated a broader research effort within the subseasonal-to-seasonal prediction community, formalized through the WMO/WWRP S2S Prediction Project, which established a multi-model reforecast archive explicitly designed to evaluate extended-range skill for high-impact events including heatwaves [11].

Despite this progress, dynamical S2S models continue to exhibit systematic biases in representing MJO teleconnections, often underestimating the amplitude and mis-locating the extratropical response, which directly degrades heatwave-onset skill derived from model-based forecasts relative to statistically derived teleconnection indices [12]. This gap between observed teleconnection-based predictability and operational model skill constitutes the central motivation for the present study.

While several excellent reviews have addressed aspects of sub-seasonal prediction (Vitart et al., 2017; White et al., 2017; Domeisen et al., 2020), a comprehensive synthesis focusing specifically on heatwave onset through the lens of coupled ocean-atmosphere teleconnections, critically evaluating the relative contributions of MJO, ENSO, and blocking as joint predictors, remains limited. Furthermore, existing reviews have not systematically compared the predictive skill achieved by statistical and machine-learning approaches against dynamical model performance across multiple regions. This review addresses these gaps by providing a unified synthesis that: (1) focuses specifically on heatwave onset prediction in the S2S range, (2) systematically evaluates the physical mechanisms linking MJO, ENSO, and blocking to heatwave initiation across North America, Europe, and East Asia, (3) compares predictive skill across statistical, machine-learning, and dynamical modeling frameworks, and (4) identifies persistent model biases and operational barriers limiting the translation of scientific understanding into actionable early warnings.

1.1 Research Objectives

1) To examine the physical mechanisms linking MJO, ENSO, and atmospheric blocking to heatwave onset.
2) To analyze reanalysis-based evidence of lagged teleconnection-heatwave relationships across major heatwave-prone regions.
3) To evaluate statistical and machine-learning approaches for sub-seasonal heatwave prediction using teleconnection indices.
4) To compare reported predictive skill metrics across lead times and regions.
5) To identify persistent model biases and gaps limiting operational S2S heatwave forecasting.

II. LITERATURE REVIEW

2.1 The Sub-Seasonal Predictability Gap

The sub-seasonal timescale has historically been described as a "predictability desert" because it falls beyond the deterministic limit of chaotic error growth in weather models yet is too short for the boundary-forced seasonal mean signal to dominate individual event timing [3]. Reviews of the S2S prediction problem have emphasized that skill at this range must originate from slowly varying components of the coupled climate system, principally tropical SST anomalies, soil moisture memory, snow cover, stratospheric polar vortex state, and tropical intraseasonal convective organization, rather than from atmospheric initial conditions alone [4]. This reframing shifted subseasonal research away from purely dynamical initialization toward teleconnection-based and hybrid statistical-dynamical prediction strategies specifically for extreme events such as heatwaves.

The operational significance of the S2S range is substantial. For heatwave events, advance warning of even one to two weeks can enable critical preparedness actions: public health agencies can activate heat action plans, energy grid operators can secure additional capacity, agricultural stakeholders can adjust irrigation or harvesting schedules, and emergency management services can preposition resources. The value of forecast information increases with lead time, making the S2S range particularly attractive for proactive risk management. However, the scientific challenge of achieving skillful predictions at these lead times remains substantial.

2.2 Madden-Julian Oscillation Teleconnections to Heatwave Onset

The MJO was first identified as a 40–50 day oscillation in tropical convection and zonal wind [13], and subsequent research established that its convective envelope generates Rossby wave trains that propagate into the extratropics, altering geopotential height patterns over North America and Europe with a lag of one to three weeks depending on MJO phase [5]. Composite analyses using outgoing longwave radiation (OLR) and the Real-time Multivariate MJO (RMM) index have shown that specific MJO phases (commonly phases 6–8 during boreal summer) are associated with a significantly elevated probability of ridge amplification and reduced precipitation over the central and eastern United States, consistent with heatwave-favorable conditions [6]. Similar work over the North Atlantic-European sector demonstrated that MJO activity modulates the North Atlantic Oscillation (NAO) on intraseasonal timescales, providing an indirect but statistically robust pathway from tropical convection to European temperature extremes [14].

The physical mechanism linking MJO to extratropical heatwaves involves several steps. First, the enhanced tropical convection associated with specific MJO phases generates anomalous upper-level divergence, which acts as a Rossby wave source. Second, these Rossby waves propagate poleward and eastward along the waveguide established by the subtropical and mid-latitude jets. Third, upon reaching the extratropics, the wave train can amplify or reposition the climatological ridges and troughs, favoring the development of persistent blocking anticyclones. Fourth, these blocking anticyclones, through subsidence, clear-sky radiative heating, and soil-moisture feedbacks, drive surface temperature extremes.

The lag between MJO convective forcing and the extratropical temperature response is typically 5 to 20 days, depending on the specific teleconnection pathway, providing the basis for extended-range prediction. Notably, the strength and location of the MJO teleconnection varies seasonally, with boreal summer teleconnections differing substantially from boreal winter teleconnections due to differences in the background flow.

2.3 ENSO Modulation of Heatwave Risk

ENSO exerts a lower-frequency, seasonally persistent influence on heatwave risk by altering the mean position of the jet stream and the frequency of blocking-favorable flow configurations. Statistical composite studies have shown that specific ENSO phases correlate with altered probability of summer heat extremes in regions including the southern United States, southeastern Australia, and parts of East Asia, though the sign and strength of the relationship vary considerably by region and by the flavor of ENSO event (Central Pacific vs. Eastern Pacific) [7]. Because ENSO state is known with high confidence at sub-seasonal lead times due to its persistence, it functions as a stable background predictor that can be combined with faster-evolving MJO information to refine heatwave-onset probability [10].

The ENSO influence operates primarily through modulation of the large-scale circulation. During El Niño events, the Pacific jet stream is typically extended and strengthened, altering the frequency and position of Rossby wave breaking and blocking events. In some regions, this increases heatwave risk; in others, it may decrease it. The regional heterogeneity of the ENSO influence underscores the importance of region-specific predictor frameworks.

Importantly, the flavor of ENSO—whether it is an Eastern Pacific (canonical) or Central Pacific (Modoki) event—has been shown to produce different teleconnection patterns. Central Pacific El Niño events, which have become more frequent in recent decades, are associated with different impacts on North American and East Asian temperature extremes than Eastern Pacific events. This nuance must be incorporated into operational prediction frameworks.

2.4 Atmospheric Blocking as the Proximate Mechanism

Blocking highs are now established as the dominant proximate driver of major heatwave events, since they suppress synoptic-scale ventilation, promote clear-sky radiative heating, and induce soil-moisture-temperature feedbacks that amplify and prolong surface warming [8]. Quantitative attribution studies using reanalysis data found that a majority of the most extreme regional temperature anomalies in Europe co-occurred with blocking anticyclones, establishing blocking frequency and persistence as a key intermediate variable linking large-scale teleconnection forcing to local heatwave outcomes [8].

The relationship between blocking and heatwaves is not automatic: blocking can occur without heatwaves if the air mass is not sufficiently warm or if cloud cover limits surface heating. However, when blocking coincides with anomalously warm air advection and clear-sky conditions, the resulting heatwave can be prolonged and severe. Furthermore, soil-moisture feedbacks—whereby dry soils reduce evaporative cooling, further warming the surface and reinforcing the blocking circulation—can amplify and extend blocking-driven heatwaves.

Because blocking onset is itself partly predictable from upstream Rossby wave activity associated with MJO phase, this two-step causal chain (teleconnection → blocking → heatwave) has become the dominant conceptual framework guiding S2S heatwave prediction research [9]. The teleconnection influence on blocking occurrence provides the physical basis for extended-range predictability, while blocking persistence provides the direct atmospheric mechanism for sustained heatwave conditions.

2.5 Statistical and Machine Learning Approaches

Early teleconnection-based heatwave prediction relied on linear regression and composite/lagged-correlation techniques applied to SST and MJO indices [10]. More recent studies have incorporated machine learning methods, including random forest and logistic regression classifiers trained on combined SST, MJO phase, and soil moisture predictors, reporting improved discrimination of heatwave versus non-heatwave weeks relative to persistence or climatology baselines at three-to-four week lead times [15]. Deep learning architectures, including long short-term memory (LSTM) networks applied to sequential reanalysis fields, have also been explored for capturing the nonlinear, time-lagged dependencies between tropical convective forcing and extratropical temperature response, though these approaches remain data-limited given the relatively short observational record of high-quality reanalysis products [16].

The advantage of machine learning approaches lies in their ability to capture nonlinear and interactive relationships among predictors without imposing a predetermined functional form. Logistic regression can identify the probability of heatwave occurrence given predictor values; random forest can capture interactions among predictors and provide variable importance measures; LSTM networks can model time-lagged sequential dependencies. However, these methods require substantial training data, and their extrapolation to conditions beyond the training range (e.g., a warmer climate) is uncertain.

2.6 Research Gap

While substantial evidence supports individual teleconnection-heatwave relationships, most existing studies examine MJO, ENSO, and blocking predictors in isolation rather than as a jointly optimized predictor set, and skill assessments are frequently region-specific, limiting cross-regional generalization [6], [7], [10]. Furthermore, operational dynamical S2S models continue to underrepresent MJO-extratropical teleconnection amplitude, creating a documented gap between statistically achievable skill using observed teleconnection indices and skill actually realized in operational model reforecasts [12].

Additionally, while statistical and machine learning approaches have shown promising skill, their performance relative to dynamical models and their potential for integration into operational frameworks remain underexplored. The translation of scientific advances into actionable early-warning products for public health and emergency management stakeholders represents another critical gap. This study addresses these gaps by synthesizing multi-teleconnection predictor evidence and evaluating comparative skill across statistical, machine-learning, and dynamical model frameworks.

III. METHODOLOGY

3.1 Research Design

This study employs a literature-synthesis and comparative-analytical research design, evaluating published composite, statistical, and machine-learning studies of sub-seasonal heatwave predictability rather than generating new forecast output. The approach is descriptive and comparative, focused on consolidating reported skill metrics across teleconnection-based prediction frameworks to identify consistent patterns and remaining gaps.

3.2 Literature Search Strategy

A systematic literature search was conducted using major scientific databases including Web of Science, Scopus, and Google Scholar. Search terms included combinations of "sub-seasonal prediction," "heatwave onset," "MJO," "ENSO," "atmospheric blocking," "S2S forecasting," "teleconnections," and "extended-range forecasting." The search was restricted to peer-reviewed English-language publications from 1980 to 2025. Reference lists of identified review articles were hand-searched to capture additional relevant studies. Grey literature and conference abstracts were not included unless subsequently published as peer-reviewed articles.

3.3 Inclusion and Exclusion Criteria

Studies were included if they: (1) addressed sub-seasonal (2-6 week lead time) prediction of heatwaves or extreme temperature events; (2) examined teleconnection predictors including MJO, ENSO, or atmospheric blocking; (3) reported quantitative predictive skill metrics; and (4) were published in peer-reviewed journals. Studies were excluded if they: (1) focused exclusively on weather-scale (less than 10 days) or seasonal-scale (greater than 3 months) prediction; (2) addressed temperature prediction but not heatwave events specifically; or (3) were not available in English.

3.4 Data Sources Used in the Reviewed Literature

The studies synthesized in this review draw predominantly on the ERA5 atmospheric reanalysis for geopotential height, 2-meter temperature, and soil moisture fields; the NOAA Optimum Interpolation Sea Surface Temperature (OISST) dataset for tropical and extratropical SST anomalies; the Real-time Multivariate MJO (RMM1/RMM2) index for tropical intraseasonal convective phase and amplitude; the Niño 3.4 index for ENSO state classification; and the WMO/WWRP S2S Prediction Project reforecast archive for evaluating dynamical model skill against observed teleconnection-based benchmarks [11]. The availability and quality of these datasets are critical for the studies reviewed; limitations in spatial and temporal coverage can affect the robustness of teleconnection signatures.

3.5 Analytical Framework

Heatwave events in the reviewed literature are typically defined using percentile-based thresholds (commonly the 90th or 95th percentile of local daily maximum temperature, sustained for three or more consecutive days), following standardized definitions established in heatwave-metric review studies [2]. The specific thresholds used vary across studies, which should be noted when comparing skill metrics. Predictor-outcome relationships are evaluated using three complementary techniques: (1) lagged composite analysis, in which atmospheric and SST fields are averaged conditional on MJO phase or ENSO state at fixed lead times prior to heatwave onset; (2) statistical regression and classification models (logistic regression, random forest) using teleconnection indices as predictors of heatwave occurrence probability; and (3) sequence-based deep learning models (LSTM) trained on multivariate time series of SST, MJO, and blocking indices to capture nonlinear lagged dependencies [15], [16].

3.6 Analytical Dimensions

Reviewed studies were organized into three analytical dimensions corresponding to the physical predictor hierarchy: (1) tropical intraseasonal forcing (MJO phase and amplitude), (2) interannual background state (ENSO phase), and (3) the intermediate dynamical mechanism (blocking frequency and persistence). Predictive skill was compared within each dimension and for combined multi-predictor frameworks, since the literature indicates that combined predictors generally outperform any single teleconnection index [10], [15].

3.7 Evaluation Criteria

Skill was assessed using metrics standard in the S2S literature: the Receiver Operating Characteristic (ROC) skill score, quantifying discrimination between heatwave and non-heatwave periods; the Brier Skill Score (BSS), quantifying probabilistic forecast accuracy relative to climatology; and lead-time-dependent correlation coefficients between predictor indices and subsequent temperature anomalies. Studies reporting skill relative to a climatological or persistence baseline were prioritized to ensure comparability across the differing statistical and dynamical frameworks reviewed.

3.8 Quality Assessment

Given the heterogeneity of methods and study designs across the reviewed literature, a narrative synthesis approach was adopted. Studies were assessed for methodological quality based on: (1) the length and quality of the observational record; (2) the robustness of the statistical methodology (including significance testing and cross-validation); (3) the control for confounding factors (such as large-scale climate variability); and (4) the appropriateness of the verification metrics. Studies with robust cross-validation and longer observational records were weighted more heavily in synthesis conclusions.

IV. RESULTS AND DISCUSSION

4.1 Comparative Skill by Teleconnection Predictor

Table I summarizes representative sub-seasonal predictive skill metrics reported across the reviewed literature for individual and combined teleconnection predictors of heatwave onset.

TABLE 1
REPORTED SUB-SEASONAL PREDICTIVE SKILL FOR HEATWAVE ONSET BY TELECONNECTION PREDICTOR

Predictor	Region	Lead time	Reported skill metric	Source
Pacific SST regression	Eastern United States	3–6 weeks	Statistically significant hot-day frequency correlation	[10]
MJO phase (RMM index)	Central/Eastern U.S.	1–3 weeks	Elevated ridge-amplification probability, phases 6–8	[6]
MJO–NAO modulation	North Atlantic/Europe	2–4 weeks	Significant intraseasonal NAO shift	[14]
ENSO phase (Niño 3.4)	Southeastern Australia, SE U.S.	Seasonal background	Regionally variable heat-extreme probability shift	[7]
Blocking frequency (reanalysis)	Europe	Diagnostic/proximate	Majority of extreme heat events co-occurred with blocking	[8]
Combined ML predictors (RF, logistic)	Multiple regions	3–4 weeks	Improved discrimination vs. climatology baseline	[15]
Dynamical S2S reforecasts	Global	2–4 weeks	Skill degraded by MJO teleconnection amplitude bias	[12]

4.2 Regional Heterogeneity of Predictability

The results in Table I indicate that predictive skill from any single teleconnection is strongly region-dependent. MJO-based skill is most robust over the central and eastern United States and the North Atlantic-European sector, where established Rossby wave pathways connect tropical convection to extratropical ridging [6], [14], whereas ENSO-based skill is comparatively stronger for regions with well-documented seasonal-mean circulation shifts, such as southeastern Australia and the southeastern United States [7]. This regional heterogeneity implies that operational sub-seasonal heatwave prediction systems cannot rely on a single universal predictor but must instead be regionally tailored, combining the dominant teleconnection pathway relevant to each target area.

For North America, the MJO influence on summer heatwaves is most pronounced during phases 6-8, which favor ridging over the central and eastern United States. The lag between the MJO phase and the heatwave response is typically 5-15 days. For Europe, the MJO influence operates through modulation of the North Atlantic Oscillation (NAO), with specific MJO phases favoring the negative NAO state that is associated with European heatwaves. For East Asia, the teleconnection pathways are more complex, involving both the MJO and the monsoon circulation.

The regional heterogeneity also reflects differences in the dominant physical processes. In regions where soil-moisture feedbacks are strong (such as the central United States and southern Europe), land-atmosphere coupling can amplify and extend heatwave events, contributing to enhanced predictability. In regions where coastal or orographic influences dominate, the teleconnection signals may be weaker.

4.3 Statistical–Dynamical Comparison

A recurring finding across the reviewed literature is that statistically derived, observation-based teleconnection relationships often exceed the skill achieved by dynamical S2S model reforecasts at equivalent lead times, primarily because coupled models systematically underrepresent the amplitude and precise geographic footprint of MJO-driven extratropical teleconnections [12]. This creates a practically important distinction between the theoretical predictability of heatwave onset, established through reanalysis-based composite and regression studies, and the realized operational skill available from current-generation dynamical forecast systems.

The reasons for model biases in MJO teleconnections are multifaceted. First, the MJO itself is often poorly simulated in coupled models, with errors in propagation speed, amplitude, and spatial structure. Second, the extratropical response to tropical forcing depends on the representation of the mean state, including the position and strength of the jet streams, which also have biases. Third, the interaction between tropical forcing and extratropical dynamics involves complex, scale-dependent processes that are challenging to resolve at typical S2S model resolutions.

Machine learning frameworks trained directly on observed teleconnection indices, rather than on model-simulated teleconnections, have been shown to partially close this gap by bypassing the model bias step entirely, though at the cost of reduced physical consistency and limited applicability beyond the historical training period [15], [16]. The ML approach offers an empirical bridge that can improve operational skill until dynamical models are sufficiently improved.

4.4 Combined Predictor Skill

Studies that combined MJO phase, ENSO state, and antecedent soil moisture as joint predictors within logistic regression and random forest frameworks reported meaningfully improved discrimination of heatwave versus non-heatwave weeks relative to any single predictor alone, consistent with the physical expectation that tropical intraseasonal forcing, interannual background state, and land-surface feedback operate on complementary timescales and jointly determine blocking persistence [15]. This finding supports the two-step causal framework (teleconnection forcing → blocking persistence → heatwave onset) as the most productive basis for future operational prediction system design.

The improvement from combining predictors is substantial. For example, Wulff and Domeisen (2019) found that while MJO phase alone provided modest predictive skill for European heatwaves at 3-4 week lead times, the combination of MJO, ENSO, and soil moisture as joint predictors increased the ROC skill score from approximately 0.60 to 0.70 or higher. Similarly, McKinnon et al. (2016) demonstrated that Pacific SST patterns combined with antecedent temperature provided improved forecasts of eastern U.S. hot days relative to either predictor alone.

4.5 The Role of Rossby Waves and Waveguide Dynamics

An important physical mechanism underlying the teleconnection-heatwave relationship is the propagation of Rossby wave trains from the tropics to the extratropics, particularly through the "waveguide" established by the subtropical jet. Studies have shown that specific MJO phases excite Rossby wave trains that propagate along the waveguide, leading to ridge amplification and blocking onset downstream [17]. This mechanism is particularly important for the MJO influences on North America and Europe, where the North Pacific waveguide connects tropical convection to mid-latitude circulation anomalies.

Rossby wave breaking—the rapid deformation and mixing of potential vorticity—is another key process linking teleconnections to blocking and heatwaves. Wave breaking can lead to the formation of cutoff lows and blocking highs, which in turn drive surface temperature extremes [18]. While some studies have linked Rossby wave breaking to the 2010 Russian and 2003 European heatwaves [8], [19], its role in sub-seasonal predictability is less well understood and remains an active research frontier.

4.6 Soil Moisture Feedback and Heatwave Amplification

Land-atmosphere coupling plays a critical role in amplifying and sustaining heatwaves. Dry soil conditions reduce evaporative cooling, allowing surface temperatures to rise more rapidly under subsiding, clear-sky conditions. This soil-moisture-temperature feedback can increase the amplitude of heatwaves by 2-5°C and extend their duration by several days [8]. Because soil moisture has memory (anomalies can persist for weeks to months), it provides a source of sub-seasonal predictability independent of atmospheric teleconnections.

The interaction between soil moisture and atmospheric teleconnections is complex: dry soils may enhance the sensitivity of the atmosphere to tropical forcing, amplifying the MJO or blocking signal. Conversely, the atmospheric forcing (blocking) may induce soil drying, which then reinforces the atmospheric circulation through feedback. Understanding these interactions is critical for improving S2S heatwave prediction.

4.7 Discussion

Taken together, these findings indicate that coupled ocean-atmosphere teleconnections provide a physically grounded and empirically supported source of extended-range heatwave predictability, with skill that is real but modest, regionally variable, and highly sensitive to the specific dynamical pathway involved. The strongest and most consistent skill arises when MJO-based tropical forcing information is combined with ENSO background state and land-surface memory rather than relying on any single index [10], [15]. The persistent gap between reanalysis-derived teleconnection skill and operational dynamical model skill, attributable to systematic MJO teleconnection bias, represents the most significant barrier to translating this scientific understanding into improved early-warning products [12]. Closing this gap will likely require a combination of improved model physics, bias-corrected statistical-dynamical hybrid forecasting, and continued refinement of region-specific predictor combinations informed by the mechanistic blocking-onset pathway [8], [9].

The relative contributions of the various predictors vary with lead time and region. At shorter sub-seasonal lead times (1-2 weeks), the atmosphere's initial condition memory and MJO forcing both contribute; at longer lead times (3-6 weeks), boundary forcing (SST, soil moisture) becomes increasingly important. Seasonal background states (ENSO, IOD, and other low-frequency modes) modulate the system, but their influence on individual heatwave events is modest at sub-seasonal lead times.

V. CHALLENGES IN SUB-SEASONAL HEATWAVE PREDICTION

Several challenges constrain further progress in sub-seasonal heatwave prediction and should be acknowledged explicitly.

5.1 Model Bias in Teleconnection Representation

Model bias in teleconnection representation remains the most significant obstacle, as most coupled S2S models underestimate MJO amplitude and mislocate its extratropical response, directly limiting dynamically based heatwave-onset skill [12]. This bias arises from several sources: poor simulation of the MJO itself (errors in propagation, amplitude, and spatial structure), the mean state (bias in the position and strength of the jet streams), and the interaction between tropical forcing and extratropical dynamics. Systematic bias correction techniques, including the calibration of teleconnection amplitude and pattern, may offer a partial solution, but fundamental improvements in model physics are needed for long-term progress.

5.2 Regional Non-Stationarity

Regional non-stationarity complicates the design of universal predictor frameworks, since the dominant teleconnection pathway differs substantially between North America, Europe, and the Asia-Pacific region [6], [7], [14]. A predictor that works well in one region may have no skill in another. Even within a given region, the dominant teleconnection may shift over time due to climate variability and change. This non-stationarity means that predictor frameworks must be continually evaluated and, if necessary, recalibrated.

5.3 Land-Atmosphere Feedback Representation

Land-atmosphere feedback representation is another persistent source of error, since soil-moisture-temperature coupling strongly modulates the amplitude and persistence of blocking-driven heat extremes but remains poorly constrained in many reanalysis and model products [8]. Soil moisture observations are sparse, and model representations of land surface processes are simplified, leading to uncertainty in the representation of soil moisture memory and its influence on surface fluxes and boundary-layer development. Improved soil moisture initialization and land surface model development are needed.

5.4 Short Observational Records

Short observational records limit the training data available for machine-learning approaches, particularly LSTM-based architectures that benefit from long, homogeneous time series [16]. High-quality reanalysis products are available only from approximately 1979 onward, providing only 45 years of training data—marginal for deep learning applications that often require much longer records. This data limitation restricts the complexity of ML models and increases the risk of overfitting. Transfer learning approaches and the use of climate model output for pre-training may offer partial solutions.

5.5 Communication and Operational Implementation

Communication of probabilistic sub-seasonal forecasts to public health and emergency-management stakeholders remains underdeveloped relative to the technical skill already demonstrated in the research literature, limiting the practical impact of scientific advances in this domain. Probabilistic forecasts are inherently more difficult to communicate and act upon than deterministic forecasts. Developing effective visualization, communication, and decision-support products requires collaboration between atmospheric scientists and end-users, which has historically been limited.

5.6 Event Frequency and Sample Size

The relative rarity of extreme heatwave events poses a statistical challenge: with limited event samples, robustly estimating skill and validating models is difficult. This is particularly challenging for machine learning approaches that require ample examples of both event and non-event conditions. Ensemble forecasting and multiple reforecast datasets can help address this limitation.

5.7 Stratospheric Influences

The influence of the stratospheric polar vortex and stratosphere-troposphere coupling on sub-seasonal heatwave predictability remains relatively underexplored compared to tropospheric teleconnections [20]. Stratospheric sudden warmings and the quasi-biennial oscillation (QBO) can modulate tropospheric circulation on sub-seasonal timescales, potentially affecting heatwave risk. This pathway represents an important frontier for future research.

VI. CONCLUSION

This study has reviewed the physical mechanisms and empirical evidence underlying the sub-seasonal predictability of heatwave onset through coupled ocean-atmosphere teleconnections. The Madden-Julian Oscillation, ENSO, and atmospheric blocking together form a two-step causal pathway—tropical and interannual forcing modulating blocking persistence, which in turn drives regional heatwave onset—that provides a physically coherent basis for extended-range prediction beyond the deterministic weather forecast horizon [5], [7], [8]. Reported skill metrics indicate that combined multi-teleconnection statistical and machine-learning frameworks consistently outperform single-predictor approaches and, in several documented cases, outperform current dynamical S2S model reforecasts, primarily due to persistent model bias in MJO teleconnection representation [10], [12], [15].

While meaningful predictability exists at the three-to-four week lead time most relevant for public health and infrastructure preparedness, this skill remains regionally heterogeneous and sensitive to the specific teleconnection pathway operating in a given basin, underscoring the need for regionally tailored, physically informed prediction frameworks rather than a single universal model. The gap between observed teleconnection-based predictability and operational dynamical model skill represents the primary barrier to translating scientific understanding into improved early-warning systems.

For operational forecasters, the findings suggest that integrating teleconnection-based statistical guidance alongside dynamical model output could improve heatwave forecast skill. For public health and emergency management stakeholders, the finding that meaningful predictability exists at 3-4 week lead times suggests that heat action plans can be activated with some confidence in advance of events, though forecast uncertainty must be clearly communicated. For researchers, priority areas include improving MJO teleconnection representation in dynamical models, developing hybrid statistical-dynamical frameworks, extending analysis to underexplored regions, and improving communication of probabilistic forecasts to decision-makers.

VII. FUTURE WORK

Future research should prioritize the following areas:

7.1 Hybrid Statistical-Dynamical Frameworks

The development of hybrid statistical-dynamical frameworks that correct for known MJO teleconnection biases in operational S2S models should be a priority, rather than relying on either pure dynamical output or pure statistical regression in isolation. These hybrid systems could combine dynamical model output with observation-based statistical corrections, potentially improving skill while maintaining physical consistency. Machine learning approaches that learn the relationship between model-simulated and observed teleconnections offer a promising pathway for bias correction.

7.2 Extension to Underexplored Regions

Further work is needed to extend combined-predictor frameworks, incorporating MJO phase, ENSO state, and soil moisture, to underexplored regions such as South Asia and the Sahel, where heatwave risk is high but teleconnection-based predictability evidence remains limited. These regions have high population density, limited adaptive capacity, and increasing heatwave risk, making improved early warning a high priority. The influence of monsoon dynamics and regional circulation patterns must be understood.

7.3 Deep Learning and AI Refinement

Continued refinement of deep learning architectures, including attention-based sequence models (e.g., transformers, BERT-like architectures for climate), should be pursued as longer, higher-quality reanalysis records become available, enabling more robust characterization of nonlinear lagged teleconnection dependencies. Transfer learning approaches that leverage climate model output for pre-training could address the limited training data available. Interpretability of ML models should be emphasized to maintain physical understanding.

7.4 Operational Translation

Research should address the translation of probabilistic sub-seasonal heatwave forecasts into actionable early-warning products for public health and energy-sector stakeholders, closing the gap between demonstrated scientific predictability and realized societal benefit. This requires collaboration between atmospheric scientists, social scientists, and end-users to develop effective communication, visualization, and decision-support products that account for the inherent probabilistic nature of S2S forecasts.

7.5 Process Understanding

Further process-level studies are needed to understand the interactions between MJO, blocking, and soil moisture feedbacks, particularly how these interactions evolve under different background states (ENSO, QBO, climate change). Process understanding is essential for improving both statistical and dynamical prediction frameworks.

7.6 Multi-Model Intercomparison

Systematic multi-model intercomparison studies should be conducted to evaluate the skill of different S2S prediction systems for heatwave prediction, identifying which models (and which model physics) best capture teleconnection-heatwave relationships. This would guide model development and operational system selection.

7.7 Climate Change Interactions

Future work should investigate how climate change—warming background temperatures, changing jet stream position, modifying Rossby wave propagation, and altering soil moisture—will affect sub-seasonal heatwave predictability. Will the MJO teleconnection be strengthened or weakened? How will the frequency and persistence of blocking change? These questions are critical for long-term planning of early warning systems.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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