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• Review •

Advancing Asian Monsoon Climate Prediction under Global Change: Progress, Challenges, and Outlook※

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ABSTRACT

Predicting monsoon climate is one of the major endeavors in climate science and is becoming increasingly challenging due to global warming. The accuracy of monsoon seasonal predictions significantly impacts the lives of billions who depend on or are affected by monsoons, as it is essential for the water cycle, food security, ecology, disaster prevention, and the economy of monsoon regions. Given the extensive literature on Asian monsoon climate prediction, we limit our focus to reviewing the seasonal prediction and predictability of the Asian Summer Monsoon (ASM). However, much of this review is also relevant to monsoon predictions in other seasons and regions. Over the past two decades, considerable progress has been made in the seasonal forecasting of the ASM, driven by an enhanced understanding of the sources of predictability and the dynamics of seasonal variability, along with advanced development in sophisticated models and technologies. This review centers on advances in understanding the physical foundation for monsoon climate prediction (section 2), significant findings and insights into the primary and regional sources of predictability arising from feedback processes among various climate components (sections 3 and 4), the effects of global warming and external forcings on predictability (section 5), developments in seasonal prediction models and techniques (section 6), the challenges and limitations of monsoon climate prediction (section 7), and emerging research trends with suggestions for future directions (section 8). We hope this review will stimulate creative activities to enhance monsoon climate prediction.

Key words: Asian summer monsoon, monsoon climate prediction, climate predictability, predictability sources, seasonal prediction models, seasonal prediction techniques, artificial intelligence

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Article Highlights:

- Progress in comprehending the physical basis for monsoon climate prediction, and advancements in seasonal prediction

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※ This paper is a contribution to the special topic on Global and Regional Monsoons: State of the Art and Perspectives.

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models/techniques.

- Significant findings regarding the sources of predictability and impacts of global warming and external forcings on monsoon predictability.
- Challenges/limitations in predicting the Asian monsoon climate, along with emerging research trends and future recommendations.

1. Introduction

The massive Asian monsoon system represents the most complex interactions among Earth's atmosphere, hydrosphere, cryosphere, and biosphere, including human activities. It is one of the most significant climate multiplexes globally. The monsoon climate is characterized by a seasonal reversal of winds and a marked annual precipitation contrast between a wet summer and a dry winter (Webster, 2006). The Asian monsoons include the Indian or South Asian (SA), East Asian (EA), Maritime Continent (MC), and western North Pacific (WNP) regional monsoons. This system significantly influences the weather and climate conditions across much of Asia. In recent decades, Asian monsoon prediction has garnered increasing attention (e.g., Rao et al., 2019), thanks to rapid advancements in enhancing existing approaches' performance and deepening the understanding of the system's physical processes.

Predicting seasonal variations of the Asian monsoon, particularly monsoon rainfall along with the associated floods and droughts, is central to monsoon science and has a profound socioeconomic impact (e.g., Gadgil and Rupa Kumar, 2006). Skillful seasonal forecasts prove valuable across many societal sectors (Doblas-Reyes et al., 2013). Accurate predictions assist farmers in planning their planting and harvesting, optimizing crop yields, and reducing the risk of crop failure. Effectively predicting monsoon rainfall aids in managing water resources and ensuring adequate water supply for drinking, irrigation, and industry. Improved prediction capabilities enhance preparedness and risk management strategies for extreme weather events such as floods, droughts, and heatwaves, which helps reduce human and economic losses. Accurate forecasts facilitate better planning and resource allocation in various sectors, including energy, transportation, and tourism, thereby mitigating financial risks. Overall, enhanced understanding and proficient prediction of the Asian monsoon support improved resilience and adaptation strategies in response to climate variability and change.

Despite advances in climate science, the seasonal prediction of Asian summer monsoon precipitation and extreme events remains one of the "grand challenges" in the field over the past century (Webster et al., 1998; Chang et al., 2005; Rajeevan et al., 2012). In the past two decades, significant progress has been made in the seasonal prediction of the ASM due to a better understanding of the key sources of predictability, the physical processes determining seasonal anomalies, and the development of sophisticated models and technologies. Both statistical and dynamical models have seen substantial improvements, offering enhanced prediction accuracies.

This article begins with a retrospective review of the understanding of the physical basis for climate prediction (section 2). Accurate seasonal prediction of the ASM requires in-depth knowledge of the sources of predictability, which implicates complex interactions among atmospheric, oceanic, land, and snow/ice surface processes under natural and anthropogenic external forcings. Therefore, section 3 summarizes the current knowledge on the primary sources of Asian monsoon predictability, while section 4 discusses additional predictability sources, emphasizing the progress made in the past two decades. Section 5 reviews the impacts of global change and external forcing on monsoon predictability. Section 6 presents advances in prediction models and techniques. Section 7 discusses the challenges and limitations of monsoon climate prediction. The final section deliberates emerging research trends and provides recommendations for the way forward. All sections are well suited for studying other regional monsoon predictions, including section 3, where the methodology and theoretical perspectives can also be applied to examine sources of predictability for other monsoons.

2. Physical basis for climate prediction revisited

2.1. *Physical basis for empirical–statistical prediction: Teleconnection theory*

Blanford (1884) found that the snowfall in the Himalayas during the previous winter preceded anomalies in summer monsoon rainfall over India. Two years later, the Indian Meteorological Department (IMD) began issuing its first long-range forecast for summer monsoons, marking the start of empirical–statistical methods in climate prediction (Kang and Shukla, 2006).

The empirical forecast relies significantly on studies of atmospheric teleconnections. Wallace and Gutzler (1981) provided a thorough review of these studies. Sir Gilbert Walker (1925) and Walker and Bliss (1932) discovered the "Southern Oscillation", a seesaw of surface pressure between Darwin and Easter Island, as well as the North Atlantic Oscillation (NAO) and the North Pacific Oscillation, thereby formally establishing the concept of "teleconnection". Walker's pioneering work has led to a surge in the study of teleconnection patterns since the 1980s, revealing the Pacific–North American (PNA) pattern (Wallace and Gutzler, 1981), the Pacific–Japan (PJ) pattern (Nitta, 1987;

Huang and Wu, 1989), the connection between the East Asian Summer Monsoon (EASM) and the Indian Summer Monsoon (ISM) (Liang, 1988; Kripalani et al., 1997), the Pacific–East Asia teleconnection (Wang et al., 2000), the East Asia–North America teleconnection (Lau and Weng, 2002), and the Silk Road teleconnection (Enomoto et al., 2003). The most notable boreal summer teleconnections include the Circumglobal Teleconnection (CGT), a zonally oriented wave train along the westerly waveguide (Ding and Wang, 2005), and a West Pacific–North America teleconnection, a wave train arising from the West Pacific monsoon trough and following a great circle to North America (Ding et al., 2011).

Hoskins and Karoly's (1981) groundbreaking work established the physical basis for atmospheric teleconnections. Their Rossby wave train theory illustrates that the ray path of stationary Rossby wave propagation on a sphere follows great circles, varying with background mean flows. Rossby waves, a type of rotational wave most prominent at high latitudes, are primarily generated by atmospheric divergence, which is more pronounced in the tropics. This enables Rossby waves triggered in the tropics to propagate to higher latitudes. Similarly, waves triggered in high latitudes, such as those caused by a stronger-than-normal flow over a mountain range or warm sea surface temperature (SST) region, can impact the tropics. Hoskins and Ambrizzi (1993) further demonstrated that a westerly jet can act as a partial waveguide, channeling Rossby wave trains.

In the tropics, where upper-tropospheric easterlies prevail, the idea that tropical convection triggers stationary Rossby waves seems unlikely at first glance. However, two mechanisms can explain how deep tropical heating may activate stationary Rossby waves in easterly flows. Sardeshmukh and Hoskins (1988) showed that poleward easterlies and strong vorticity advection by the divergent wind in the subtropical region can efficiently generate stationary Rossby waves. Wang and Xie (1996) elaborated on an easterly vertical shear mechanism. The basic-state easterly vertical wind shear can produce barotropic Rossby waves and emanate them from the equator to the extratropics.

A second teleconnection theory was proposed by Simmons et al. (1983), who demonstrated that a rapidly growing mode can correlate with barotropic instability of the horizontally varying climatological background state, resulting in patterns resembling the PNA pattern. They suggested that the low-frequency variability of the Northern Hemisphere's wintertime general circulation is linked to disturbances that derive kinetic energy from the basic state through barotropic instability. Indeed, as Ding et al. (2011) demonstrated, linear barotropic mechanisms, including energy propagation and barotropic instability of the basic-state flow, also contribute to shaping and maintaining the boreal summer CGT. Recent studies further indicate that land–atmosphere interactions and eddy-mean flow feedbacks are crucial for sustaining specific atmospheric teleconnection modes with circumglobal features (Teng et al., 2019, 2022; Meehl et al., 2022).

2.2. *Bjerknes' ENSO theory lays a cornerstone for the modern dynamical climate prediction*

The cause of the Southern Oscillation remained a mystery until Bjerknes' pioneering work discovered the underlying processes linking it to El Niño and La Niña (Bjerknes, 1969). Bjerknes established that the equatorial surface winds, driven westward along the equator by the zonal SST gradient, create cold upwelling ocean water in the eastern Pacific, thereby re-enhancing the surface easterlies. This positive feedback (known as Bjerknes feedback) ultimately led to the development of the El Niño–Southern Oscillation (ENSO). Bjerknes' idea lays a cornerstone for modern ENSO prediction. Meanwhile, the equatorial wave theory advanced by Matsuno's (1966) and Gill's (1980) theory on the atmospheric response to a heat source laid a sound foundation for understanding the dynamic processes governing atmospheric and oceanic coupling processes.

Cane and Zebiak made the first ENSO prediction using a coupled tropical ocean–atmosphere model of intermediate complexity (Cane and Zebiak, 1985; Zebiak and Cane, 1987). This work stimulated the development in the 1990s of complex coupled ocean–atmospheric general circulation models (CGCMs) for dynamic prediction (e.g., Ji et al., 1996; Stockdale et al., 1998). In the first decade of the 21st century, ensemble forecasting involved multiple model runs with slightly varied initial conditions to provide a range of possible outcomes, helping to estimate uncertainty in predictions (Kang and Shukla, 2006). Subsequently, multimodel ensemble (MME) prediction systems were developed to assess predictability and forecast uncertainties (Kang et al., 2004; Palmer et al., 2004).

2.3. *From Charney's boundary-forced predictability to monsoon–warm ocean interaction theory*

Charney and Shukla (1981) hypothesized that the predictability of the Indian monsoon relies on the influence of boundary conditions at the Earth's surface. For boundary conditions to significantly impact monsoon rainfall prediction, the surface anomaly must be large and persistent, while the seasonal mean response (the signal) should be sufficiently pronounced and distinguished from intrinsic internal variability (the noise) (Kang and Shukla, 2006). This hypothesis underlies the simulations and experiments conducted using atmospheric general circulation models (AGCMs) driven by SST anomalies.

However, Wang et al. (2004) found that, given the strongest 1997/98 El Niño forcing, eleven AGCMs forced by specified observed SST anomalies failed to simulate Asian monsoon precipitation anomalies. They uncovered that treating the monsoon as a slave to SST forcing in the monsoon oceans leads to this failure, pointing to a strategic weakness in AMIP (Atmospheric Model Intercomparison Project) type simulations and predictions. Gadgil and Srinivasan (2011) confirmed that AGCMs have limited skill in capturing the interannual variability of ISM rainfall.

Using observed data and multimodel seasonal hindcast experiments, Wang et al. (2005) revealed that the SST over the precipitating summer monsoon regions is generally a passive response to the atmosphere rather than a forcing factor. The warm pool SST is primarily controlled by surface heat fluxes, with solar radiation and surface evaporation dominating. The atmospheric anomalies regulate SST by altering cloud amounts and surface wind speed, thus dominating local SST variations. Wu and Kirtman (2007) reached similar conclusions. These studies established monsoon–warm ocean feedback as a crucial process and source of monsoon climate predictability, shifting the "boundary-forced predictability" paradigm to "coupled monsoon–ocean predictability."

Likewise, predicting monsoon anomalies with an AGCM forced by predicted SST, i.e., the "two-tier approach" (Bengtsson et al., 1993), does not work in the monsoon–warm ocean region. Studies have emphasized the need for coupled ocean–atmosphere models to achieve more accurate ISM rainfall predictions (Kumar et al., 2005; Preethi et al., 2010). The concept of treating the monsoon and warm ocean as a coupled system has been elaborated upon in previous studies (Webster et al., 1999, 2002; Wang et al., 2000, 2003). Collectively, these works highlight that ocean–atmosphere coupling is essential for driving and modulating the Asian monsoons.

3. Primary sources of predictability of the ASM: ENSO

3.1. *Observed ENSO–ASM relationship*

ENSO serves as the primary source of predictability for both global climate and the Asian Monsoon (Yang and Lau, 2006). Based on instrumental observations (1901–2017), the total amount of Asian land precipitation during a monsoon year, from May to the following April, robustly correlates with the Niño-3.4 SST index, displaying a correlation coefficient of $r = -0.86$ (Wang et al., 2020a). This significant correlation indicates a 4.5% decrease in total Asian land rainfall for each 1°C increase in SST in the Niño-3.4 region (5°S–5°N, 120°–170°W). This result implies that the total amount of Asian land precipitation strongly correlates with ENSO intensity.

However, the significant response of the Asian monsoon to ENSO shows considerable regionality and seasonality. Wang et al. (2020a) identified six subregions that exhibit significant correlations with ENSO over the past 116 years, with correlation coefficients (absolute value) greater than 0.5 ($p < 0.001$) (Fig. 1). Negative correlations mean an El Niño causes drought conditions, while La Niña typically leads to opposite but weaker effects. The MC rainfall shows the strongest negative correlation with the peak-phase Ocean Niño Index (ONI; $r = -0.81$) from May(0) to November(0). The prominent negative correlations ($r = -0.79$) shift to Southeast Asia from October(0) to May(1). Negative correlations also occur over India ($r = -0.59$) from June(0) to October(0) and in Northern China ($r = -0.50$) from June(0) to October(0). On the other hand, positive correlations are seen in the East Asia subtropical frontal zone from November (0) to April(1) ($r = 0.62$) and central Asia ($r = 0.5$) from Oct(0) to May(1). The ENSO impacts decrease with latitude.

The ASM responses vary with different flavors of El

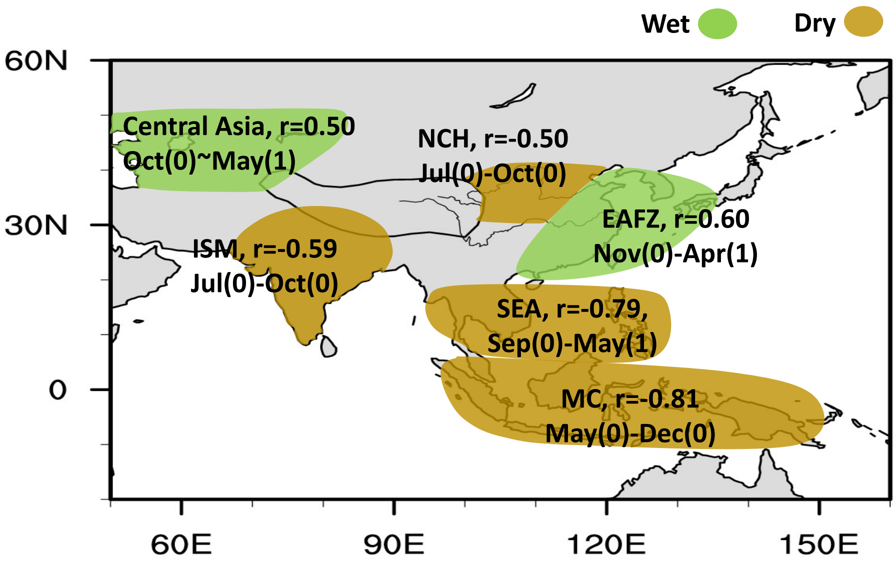

Fig. 1. The impact of El Niño on Asian precipitation. Here, r denotes the correlation coefficient between the D(0)JF(1) ONI and each regionally averaged precipitation anomaly during the corresponding marked period; the number 0 (1) indicates the developing (decaying) year of El Niño. ISM denotes Indian summer monsoon, NCH denotes northern China, EAFZ denotes East Asian front zone, SEA denotes southern East Asia, and MC denotes Maritime Continent. Adopted from Wang et al. (2020a).

Niño. El Niño events have recently been classified as Eastern Pacific (EP) and Central Pacific (CP) El Niño based on the maximum warming locations during their peak phase in boreal winter (Ashok et al., 2007; Kug et al., 2009; Yeh et al., 2009). However, ASM variability is not directly related to the SST anomaly (SSTA) patterns in the peak phase of El Niño. Therefore, it is essential to classify El Niño based on its development and decay characteristics during boreal summer. By cluster analysis of the onset and amplification processes, Wang et al. (2019) classified 33 El Niño events from 1901 to 2017 into Super [or Strong Basin-wide (SBW)], moderate EP, and CP El Niño events (Fig. 2). Each type exhibits distinct development processes, coupled dynamics, precursors, and hydroclimate impacts.

The ASM shows significantly different responses to El Niño diversity during its developing and decaying summer (Wang et al., 2020b). During the developing summer, the three types of El Niño SST anomalies are remarkably different, not only in spatial structures but also warming intensities (Fig. 2). Therefore, during May–June(0), the early onset of the super El Niño events induces significant dryness over the Asian monsoon, but not the moderate EP (MEP) and CP events. During July–August(0), the CP warming significantly reduces rainfall over northern India and northern China; in contrast, the MEP warming causes deficient rainfall over central-western India and the Yangtze River Valley. With the strong warming, the SBW events severely reduce land precipitation over the regions affected by both the moderate CP (MCP) and MEP warming. Likewise, the three types of El Niño decay show conspicuously distinctive SSTAs and thus exert remarkably different impacts on boreal summer land precipitation (Wang et al., 2020b).

3.2. *Predictable modes of the interannual variability of the ASM precipitation*

To reveal the sources of the summer monsoon rainfall predictability over the entire Asian monsoon domain, Wang et al. (2015a) identified three principal modes of variability during June, July, and August (Figs. 3a–c) from 1979 to 2010. These modes are associated with (1) the developing central Pacific El Niño–La Niña (Fig. 3d), (2) the WNP anticyclonic anomaly associated with the decaying El Niño (Fig. 3e), and (3) the Indian Ocean Dipole (IOD) SSTA (Fig. 3f). The first two modes represent ENSO impacts, accounting for about 32% of the total variance. Their origins will be discussed in subsection 3.3. The ECMWF model can

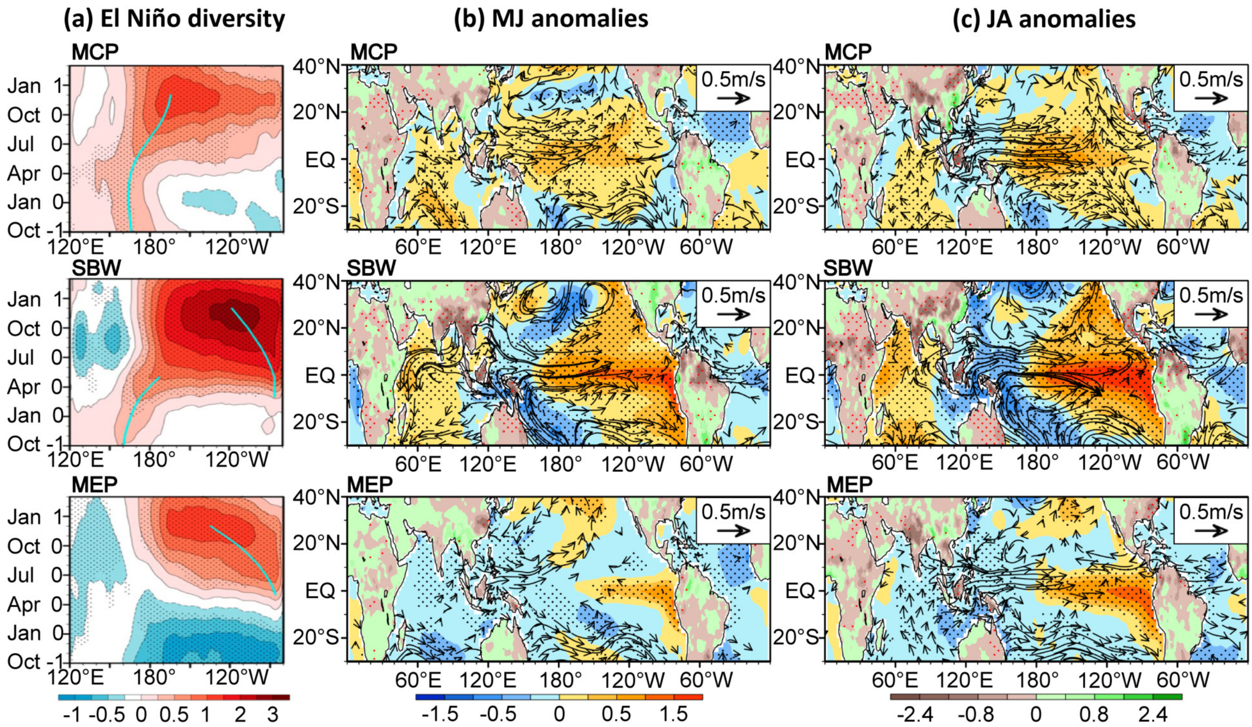

Fig. 2. Asian Monsoon response to El Niño diversity during its developing phases. (a) Composite longitude–time diagrams of the equatorial SSTA averaged between 5°S and 5°N for Super [or Strong Basin-wide (SBW)] El Niño (7 events), moderate EP (MEP) El Niño (14 events), and moderate CP El Niño (9 events). The stippling denotes regions where the SSTA signal (group mean) is larger than the noise (the standard deviation of each member from the group mean). The green lines outline the propagation tracks of maximum SSTAs. The time ordinate is from October of the year prior to El Niño (−1) to the March after the El Niño year (1). Climate anomalies associated with three types of El Niño during (b) May(0) to June(0) and (c) July(0) to August(0). The color shading over land represents the composite precipitation anomaly in units of mm d^{-1}. The color shading over the ocean denotes the composite SSTA in units of °C. The arrows denote composite 850-hPa wind anomalies in units of m s^{-1}. The stippling and thick arrows denote the regions where the anomalies are significant at the 95% confidence level. The data used are from 1901 to 2017. Adapted from Wang et al. (2019).

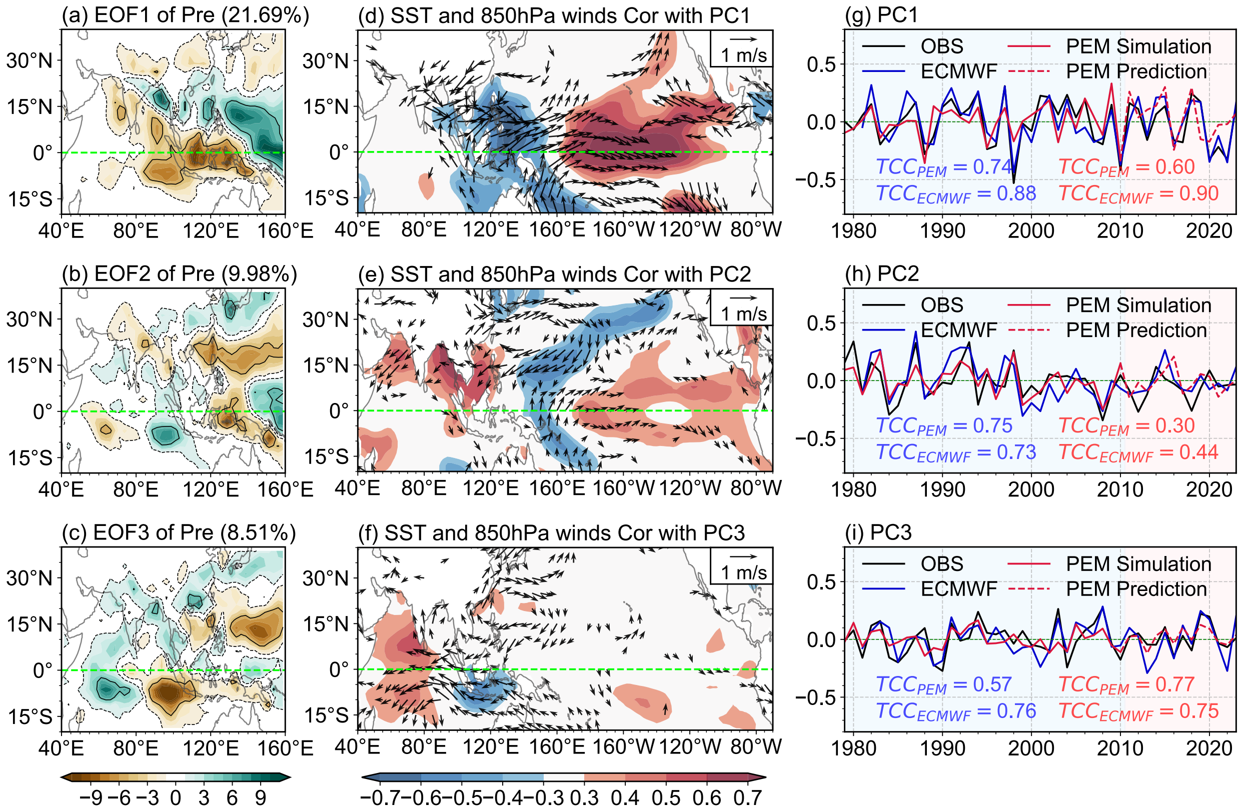

Fig. 3. (a–c) Spatial distribution of the first three leading empirical orthogonal function (EOF) modes of JJA precipitation derived from 1979 to 2010. The black dashed and solid lines represent the ±1 and ±5 contour lines. (d–f) Corresponding correlation maps for the three modes with the simultaneous SST and 850-hPa wind anomalies. The green dashed lines in (a–f) indicate the position of the equator. (g–i) Corresponding principal components (PCs) of the first three EOF modes from observations (black lines), the physical–empirical model (PEM; red lines, see section 6.2), and the European Centre for Medium-Range Weather Forecasts (ECMWF) fifth-generation seasonal forecast model (SEAS5) (blue lines). The SEAS5 seasonal forecasts are initialized on the 1st of each month, utilizing the ensemble mean from 51 members. The ECMWF predicted PCs are derived by projecting the JJA precipitation (initialized from 1 June) onto the observed EOF modes. Values after 2010 represent real-time validations. The light blue (red) shaded area indicates the training period of 1979–2010 (independent prediction period of 2011–23) for PEM.

realistically predict these modes (Figs. 3g–i), suggesting that the achievable predictability of the ASM in the model could arise from these three primary pathways.

To examine whether the sources of ASM predictability have remained effective in the recent 13 years, we assessed the performance of the three corresponding principal components' forecasting skills from 2011 to 2023. The first principal component (PC1) remains effective. PC3 shows a higher temporal correlation coefficient (TCC) skill, suggesting an increasing role of the Indian Ocean Dipole in ASM variability. However, the TCC drops significantly for PC2 due to its weakened correlation with the western Pacific SSTA. This breakdown is speculated to be linked to three consecutive multi-year La Niña events (2010–11, 2016–17, and 2020–22) and the record global warming post-2011. Nevertheless, the precise reasons require further studies.

3.3. *Mechanisms by which ENSO impacts the ASM*

3.3.1. *How a developing ENSO affects the ASM*

Figure 4a illustrates how a developing El Niño affects the first mode of ASM rainfall variability. The El Niño warming changes the Pacific SST gradients. The equatorial Kelvin and Rossby waves act as efficient agents to adjust atmospheric circulation anomalies, causing the zonal shift of the Walker cell, resulting in the decreased rainfall over the MC and enhanced precipitation in the central Pacific. Second, the dipole precipitation heating anomalies at the equator excite an off-equatorial Rossby wave response. The enhanced heating near the dateline generates an ascending low-level cyclone over the Philippines, weakening the western North Pacific subtropical high (WNPSH) and EASM. On the other hand, the anomalous cooling associated with the suppressed rainfall over the MC generates descending Rossby anticyclones propagating westward and northward, forming the anticyclonic anomalous ridge extending from the MC to India, weakening the ISM. The northward propagation of the Rossby wave is due to the effect of the strong easterly vertical wind shear (Wang and Xie, 1996; Xie and Wang, 1996), thus weakening the Indian monsoon. Third, the reduced precipitation heating over India excites a

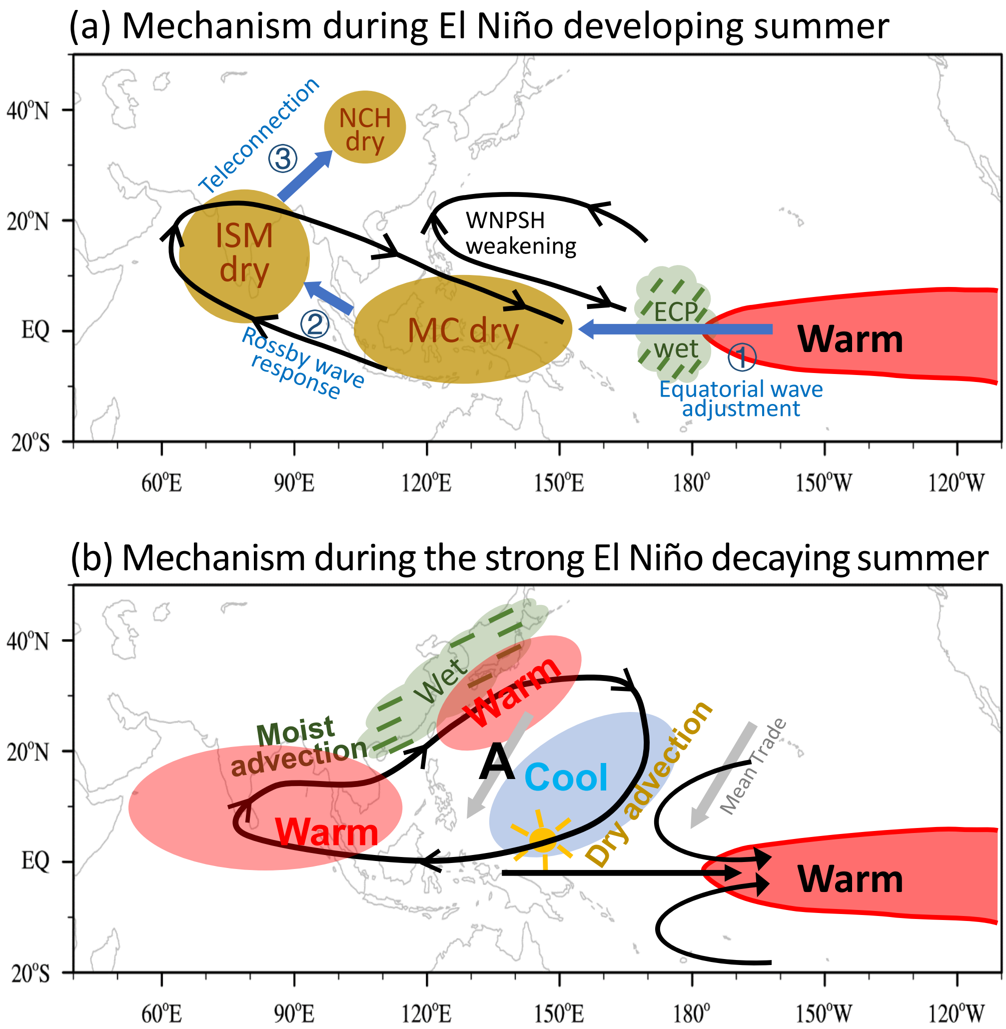

Fig. 4. Schematic diagrams illustrating how El Niño impacts Asian monsoon precipitation. (a) The chain teleconnection mechanism during the developing summer of El Niño [JASO(0)] [modified from Wang et al. (2017)]. (b) The interaction mechanism between the WNPSH and the Indo-Pacific warm pool during the decaying summer of El Niño [MJJA(1)]. ISM denotes Indian summer monsoon, NCH denotes northern China, MC denotes Maritime Continent, and ECP denotes eastern-central Pacific. Adapted from Wang et al. (2013).

barotropic Rossby wave train, forming a high pressure anomaly over EA and reducing the North China rainfall. This ISM–EASM teleconnection was named the “Silk Road teleconnection” by Enomoto et al. (2003).

3.3.2. *How a decaying El Niño affects the ASM*

Strong and moderate El Niño events affect the ASM differently during the decaying phase, as illustrated in Fig. 5. During a strong El Niño, the anomalous western Pacific anticyclone (WPAC) develops and peaks from January to March. It carries to the next summer regardless of the El Niño decay, causing floods in the Yangtze River Valley in June and July. In contrast, a weak El Niño cannot excite the anomalous WPAC. The anomalous WPAC emerges in July and August due to the rapid transition to a La Niña status. Note that a moderate El Niño cannot maintain the WPAC as the air–sea interaction is weak (Wang et al., 2000, 2013). This is why the ENSO-induced monsoon–ocean feedback mechanism has weakened in recent years as moderate CP El Niño has dominated.

The maintenance of the anomalous WPAC during the decay of strong El Niño events results from the thermodynamic interaction between the anomalous WPAC and the underlying warm ocean. Wang et al. (2000) pioneered an air–sea interaction theory to elucidate how the positive feedback between the anomalous WPAC and the underlying dipolar SST anomaly extends ENSO’s impacts on the EASM during ENSO’s decaying phase. This theory has been further extended to the anomalous WPAC interaction with the underlying Indo-Pacific warm pool (Fig. 3b) (Wang et al., 2013; Li et al., 2017b). First, to the southeast of the WPAC, the SST is cooler because the anomalous northeasterly winds

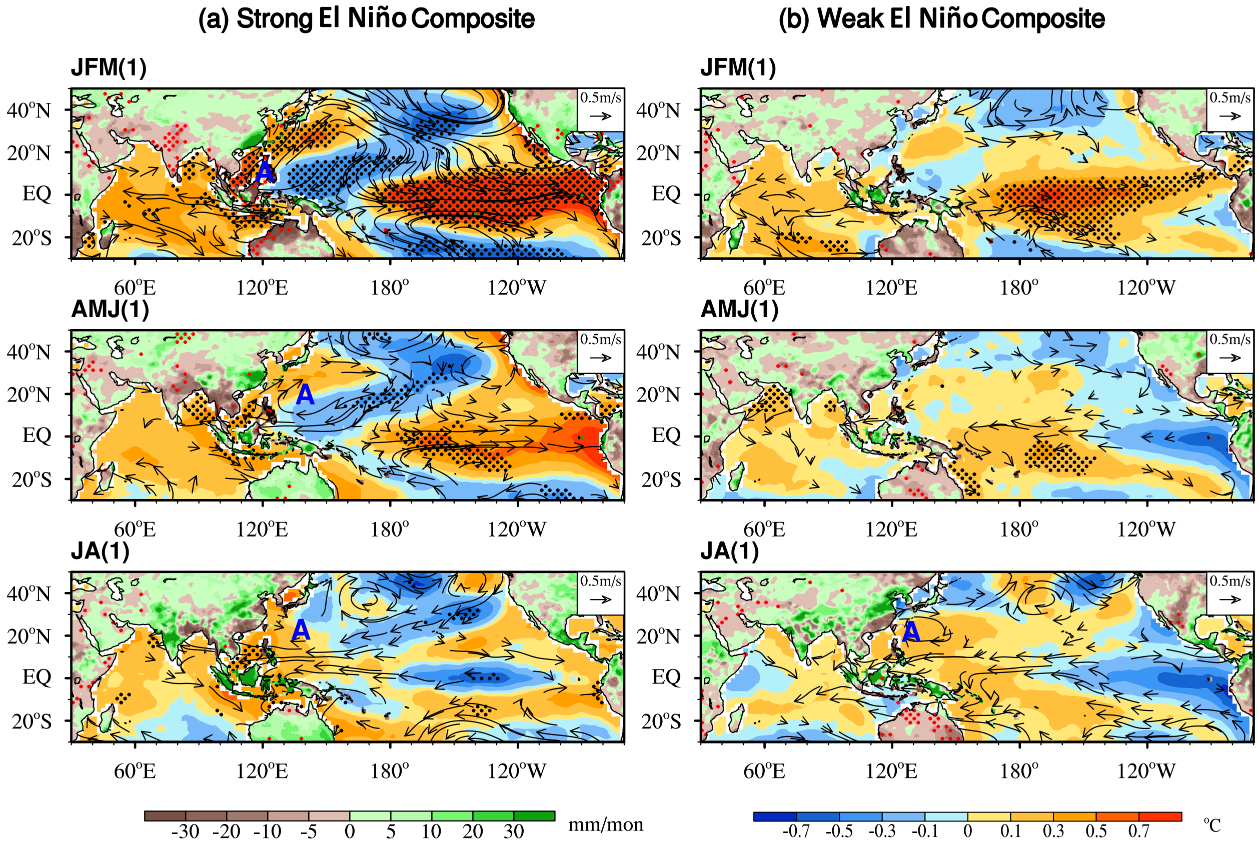

Fig. 5. Impacts of decaying El Niño on Asian precipitation: Contrasting the composite anomalies between (a) strong and (b) weak El Niño events for January–February–March (JFM), April–May–June (AMJ), and July–August (JA). Color shading denotes SSTAs over oceans and precipitation anomalies over land. Vectors represent low-level wind anomalies at 850 hPa. The dotted area indicates a statistically significant level at 0.10. Strong El Niño years: 1957, 1965, 1972, 1982, 1991, 1997, 2009, 2015. Weak El Niño: 1963, 1968, 1969, 1976, 1994, 2002, 2004, 2006.

strengthen the mean easterlies, thereby enhancing evaporation and entrainment. The anomalous northeasterly winds also advect dry air from the north, reducing moist static energy and convective instability. Conversely, the resultant ocean cooling and reduced static energy, in turn, reduce in situ precipitation heating, hence generating descending Rossby waves that reinforce the WPAC in their westward decaying journey. This WPAC–ocean interaction theory has been confirmed by numerical experiments with CGCMs (e.g., Lau and Nath, 2003; Lau et al., 2004; Lau, 2003; Chowdary et al., 2010; Xiang et al., 2013). Using coupled climate model experiments, Kosaka et al. (2013) demonstrate that the PJ pattern in the WNP is the atmospheric manifestation of an air–sea coupled mode spanning the Indo-western Pacific warm pool. The PJ pattern forces the Indian Ocean via a westward-propagating atmospheric Rossby wave. In response, the Indian Ocean SST feeds back and reinforces the PJ pattern via a tropospheric Kelvin wave.

During the mature and decaying phase of intense El Niño events, the WPAC ridge extends westward to the Bay of Bengal, increasing downward solar radiation flux and reducing evaporation cooling, which warms the northern Indian Ocean (NIO) (Du et al., 2009). Note that the NIO warming cannot feed back to the WPAC without precipitation heating accompanying the warming. Whether the Indian Ocean can affect the WPAC depends on the precipitation anomaly, not solely on the SST anomaly. Some AGCM experiments forced by Indian Ocean SST anomalies may lead to flawed conclusions since warming without a precipitation anomaly cannot drive the atmosphere. The effect of the Indian Ocean SSTAs on the WPAC should be demonstrated through experiments with coupled ocean–atmospheric models (e.g., Lau et al., 2004; Chowdary et al., 2010; Xiang et al., 2013).

Xie et al. (2009b) emphasized the oceanic processes determining the equatorial Indian Ocean warming. This Indian Ocean warming does not rely on WPAC-induced warming. This independent Indian Ocean warming can generate anomalous precipitation heating, exciting an easterly equatorial Kelvin wave over the far western Pacific. The associated anticyclonic shear vorticity can enhance the anomalous WPAC—a process known as the “Indian Ocean Capacitor” or “Indo-Pacific Ocean Capacitor” mechanism (Xie et al., 2009a; Xie and Kosaka, 2016). In this mechanism, the Indian Ocean dynamics act as a memory, feeding back to the atmosphere at a later stage, and the monsoon–warm ocean interaction can delay its impacts.

Lau and Nath (2000) revealed that the monsoon–ocean interaction mechanism also functions during the ENSO development phase. The ISM–ocean interaction tends to offset the remote impacts of ENSO by warming the northern Indian Ocean. During boreal summer, positive feedback between Indian Ocean SST and the anomalous Southeast Indian Ocean anticyclone contributes to the development of the IOD (Li et al. 2003). This positive feedback relies on summer monsoon mean circulation and switches to negative feedback under winter monsoon circulation, leading to the rapid decay of the IOD and the formation of Indian Ocean basin warming (Wang et al., 2003). The change in the atmosphere –ocean feedback in the Indian Ocean suggests that the annual variations of the monsoon flow play a vital role in regulating the monsoon–warm pool ocean interaction.

4. Additional regional and remote sources of predictability

This section discusses additional sources of predictability beyond ENSO. The Asian monsoon is driven by two relatively independent heat sources, one over the Bay of Bengal and the other over the Philippine Sea, resulting in distinct annual and interannual variations of the South Asian and East Asian summer monsoons (Wang et al., 2001), as well as the unique features of East Asian monsoon variability (Tao and Chen, 1987; Ding and Sikka 2006). The additional predictability is often found on regional scales, and some originates from the mid and high latitudes.

4.1. *IOD*

The third predictable mode of ASM precipitation (Fig. 2f) corresponds to an SST pattern resembling the IOD or the Indian Ocean zonal mode discovered by Saji et al. (1999) and Webster et al. (1999). A positive IOD (cooling in the east) usually brings enhanced monsoon rains over India, while a negative IOD has the opposite effect (Ashok et al. 2004, 2007). Indian Ocean SSTAs are considered a critical ISM driver (e.g., Ashok et al., 2001; Ummenhofer et al., 2011; Chowdary et al., 2015). Gadgil et al. (2004) showed that significant anomalies of the ISM rainfall are linked to the Equatorial Indian Ocean Oscillation, the atmospheric component of the IOD. In recent decades, the influence of the IOD on mean ISM rainfall and extreme rainfall events has strengthened along with the decaying ENSO impact (Krishnaswamy et al., 2015).

However, ENSO substantially influences the Indian Ocean SST variability. Thus, understanding how the Indian Ocean SST affects ISM variability independently is a complex problem. A model study suggested that the Indian Ocean SST does not force the monsoon circulation and precipitation change if the influences of the Pacific Ocean are removed (Crétat et al., 2017). ENSO can also induce the IOD. The 1997 El Niño is an example. The increased rainfall over India caused by the El Niño-induced IOD offset the drought caused by the El Niño, thus resulting in a normal monsoon.

The Indian Ocean may feed back to the ISM rainfall by modulating the ENSO–ISM rainfall relationship during the decaying phase of El Niño, accompanied by basin-wide warming in the Indian Ocean (Terray et al., 2021). Whenever the ENSO–ISM correlation is low (high), the IOD–ISM correlation is high (low). Because the two phenomena have positive and negative events, their influence on ISM rainfall may vary depending on the phase and amplitude of the IOD and ENSO (Saji et al., 1999; Ashok et al., 2001).

4.2. *Land–atmosphere interactions and effects of the Tibetan Plateau*

Land–atmosphere interactions act as a driver in shaping regional variations of the ASM from year to year. Anomalous land surface conditions may provide a "memory" that affects the following season's monsoon. Yang and Lau (1998) found that with enhanced snow and soil moisture in the Asian continent during previous cold seasons, the ASM becomes moderately weaker, and the antecedent land surface processes mainly influence the early part of the summer monsoon. The enhanced winter snow covers over northern China and southern Mongolia tend to increase the summer rainfall over northeastern China and the Korean Peninsula, while decreasing the rainfall over the subtropical East Asia–Pacific region (Lu et al., 2020).

The land surface processes in the mid–high latitudes of Eurasia, the midlatitudes of East Asia, and the Indochina Peninsula also contribute to the variability of the EASM (Chen, 2022). For example, nonuniform summer warming in the midlatitudes of East Asia has been identified as a driver of the decadal weakening of extratropical cyclone activity (Zhang et al., 2020), which can further lead to decadal-scale weakening of the EASM through synoptic wave–mean flow interaction (Chen et al., 2017, 2019). Meanwhile, spring soil wetness or dryness over the Indochina Peninsula can significantly influence the summer monsoon circulation via land–atmosphere interaction and the associated anomalous surface thermal forcing (Gao et al., 2019; Zhu et al., 2021). Xue et al. (2004) discussed how land surface processes affect the onset and variability of the EASM.

The barrier effect of the Himalayas, along with thermal heating and the dynamical uplift effects of the Tibetan Plateau, has long been recognized as the key driver of the ASM in the mean state (Yanai and Wu, 2006; Boos and Kuang 2010). Spring land surface warming over the Tibetan Plateau could enhance the EASM (Xue et al., 2022). Increased winter snow cover in the western Tibetan Plateau and the Himalayas facilitates above-normal summer rainfall between the Yellow and Yangtze River basins through the snow–hydrology feedback effect (Xiao and Duan, 2016). Zha and Wu (2023a), using MODIS snow cover data over the past 20 years, identified a new critical region where winter snow cover on the Tibetan Plateau influences the EASM and rainfall in the middle and lower reaches of the Yangtze River. Snow cover in this key region played a crucial role in the extreme mei-yu event of 2020, contributing to 43% of rainfall anomalies, surpassing the combined influence of the three major oceans (Zha and Wu, 2023b).

The differential heating between the continents and oceans during the summer months creates pressure gradients that drive the ASM circulation. In the preceding months, reduced snow cover over the Himalayas and the Tibetan Plateau may strengthen the ISM by promoting more land heating and increasing the meridional temperature gradients. Enhanced Indian Ocean warming could weaken the land–sea thermal contrast, dampen the monsoon Hadley circulation, and reduce South Asian rainfall (Roxy et al., 2015). Compared to the effect of the tropical oceans, soil moisture and heat flux from the land surface are equally crucial in altering the land–ocean thermal contrast.

4.3. *Remote influences from the Atlantic and the extratropical Pacific*

Studies indicate the potential influence of the Atlantic Zonal Mode (AZM) on the ISM (Kucharski et al., 2007, 2008, 2009; Nair et al., 2018). The AZM induces a Kelvin wave-like response in tropospheric temperature that propagates eastward to reach the Indian Ocean and modulates the mid-tropospheric land–sea thermal gradients and, consequently, the ISM (Pottapinjara et al., 2014, 2021). The ISM–AZM relationship has strengthened in recent decades due to the increase in the eastern equatorial Atlantic Ocean SSTAs (Sabeerali et al., 2019).

The tripolar SSTAs associated with the North Atlantic Oscillation (NAO) in winter and spring can persist into the next summer, affecting the EASM by exciting extratropical Rossby wave trains (Wu et al., 2009; Li et al., 2018b). Negative SSTAs over the equatorial Atlantic may increase rainfall over Central India by strengthening the Somali Jet and lower-level convergence (Kucharski et al., 2007; Sahastrabuddhe et al., 2019). Positive spring Atlantic Meridional Mode SSTAs in the tropical North Atlantic Ocean may strengthen anomalous cyclonic circulation and convection over the Sahel region, which, in turn, modulates the winds over the western Indian Ocean, cooling the SST there and strengthening the monsoon circulation and rainfall over India (Vittal et al., 2020).

Contrasting SSTAs between the Indo-Pacific warm pool and the North Pacific Ocean may significantly impact the variability of the EASM by modulating the western Pacific subtropical high (WPSH) (Zheng et al., 2014; Yu et al., 2019). The spring SSTAs in the tropical eastern Indian Ocean may serve as a valuable precursor for the EASM by altering perturbation potential energy (Huyan et al., 2017).

4.4. *High-latitude processes*

With Arctic amplification rapidly occurring and slow warming observed in the Southern Ocean over recent decades, researchers are increasingly focusing on how global climatic phenomena in the midlatitudes and polar regions affect monsoon patterns. Notably, the leading circulation modes at the two poles, the Northern Annular Mode and the Southern Annular Mode (SAM), have exhibited different long-term behaviors over recent decades, which may exert diverse impacts on the monsoon.

Studies of the climatic impacts of the Arctic sea-ice–atmosphere system suggest a potential link between Arctic sea-ice anomalies and East Asian summer precipitation and heatwaves (Wu et al., 2009; Chen et al., 2021, 2024; Zhang et al., 2021, 2024a; Liu et al., 2023b). However, no consensus exists on whether and how Arctic sea ice influences the EASM. On one hand, Arctic sea ice in spring may act as a memory mechanism, storing signals from the NAO in the preceding winter and affecting precipitation in Northeast Asia in early summer (Zhang et al., 2021). On the other hand, model experiments suggest that the reduction of Arctic sea ice could significantly impact atmospheric circulation in high-latitude regions, but it is not the leading cause of the recently increased precipitation over northern China and has little influence on summer precipitation in the Yangtze River basin and southern China (Wu et al., 2023). Zuo et al. (2016) demonstrated that a model using autumn Arctic sea-ice anomalies as predictors shows considerable skill in predicting winter temperature anomalies over a large part of China. Additionally, soil moisture anomalies over North Eurasia may act as a new precursor, providing an additional source of predictability for better forecasting of summer rainfall in northern East Asia (Sang et al., 2022).

A positive correlation was observed between ISM rainfall and the preceding February–March SAM during 1983–2013 (Prabhu et al., 2016). A negative (or positive) phase could result in equatorial central Pacific warming (or cooling), which simultaneously weakens (or strengthens) the Indian subcontinent's monsoonal rainfall. Dou et al. (2017) established a direct link between the May SAM and ISM rainfall in June–July from 1979–2015. They proposed that the May SAM triggers a southern IOD SST anomaly pattern through anomalous circulation, modulating cross-equatorial flows and moisture transport. Dwivedi et al. (2022) pointed out that the SAM–ISM rainfall relationship experienced non-stationarity in June and July due to changes in the southern IOD (SIOD) SSTA pattern. The Atlantic Multidecadal Oscillation (AMO) may modulate the SIOD SSTA pattern, contributing to the multidecadal swings of the SAM–ISM rainfall relationship. The SAM may also indicate the predictability of the South China Sea summer monsoon by inducing cross-hemispheric propagation of the Rossby wave (Liu et al., 2018a). Further studies of these polar-monsoon teleconnections are essential to gain a more comprehensive understanding of high-latitude-origin impacts on monsoon climate or vice versa (Grunseich and Wang 2016).

5. Impacts of external forcing on monsoon predictability

Anthropogenic and natural external forcing, including greenhouse gases (GHGs), aerosols, ozone, volcanic eruptions, urbanization, and vegetation changes, can significantly alter the climate. Climate change can modify long-established atmospheric circulation patterns and SST distributions, affecting the timing, intensity, and spatial distribution of monsoons. The monsoon system may show nonlinear responses to climate change drivers, leading to unexpected shifts and increased variability in its behavior. Understanding these components and their interactions is crucial for accurate monsoon prediction, enabling better preparation and adaptation strategies in affected regions.

5.1. *GHG warming impacts on extreme weather and climate predictability*

5.1.1. *Changes in seasonal predictability due to global warming*

The ASM is substantially influenced by regional and global radiative forcing induced by changes in CO_2 emissions (Turner et al., 2007). Recent studies using CMIP6 (phase 6 of the Coupled Model Intercomparison Project) model projections have shown the impacts of global warming on Asian monsoon rainfall and its variability across a wide range of time scales (e.g., Ha et al., 2020; Jin et al., 2020; Choudhury and Pradhan, 2022). There is high confidence that land monsoon rainfall will increase in South and East Asia. Despite considerable variations between different areas, the rainy season is likely to be lengthened in the Northern Hemisphere due to a late retreat (especially over East Asia) (Moon and Ha, 2020).

The GHG-induced warming trend adds a robust source of surface air temperature (SAT) predictability. Wang et al. (2012) pointed out that the temperature prediction skill is much higher than the precipitation prediction skill, primarily owing to global warming–related increasing trends in SAT. Furthermore, the warming SAT has increased the intensity and frequency of droughts and heatwaves in China over the past half-century, with an accelerated rate observed after the 1980s. At the same time, dust weather activity has become less frequent in northern China due to weakened cold surge activity, reinforced precipitation, and improved vegetation conditions.

The variability of monsoon rainfall is found to increase under the RCP (Representative Concentration Pathway) 8.5 scenario from daily to decadal time scales (Brown et al., 2017). The most significant fractional increases in monsoon rainfall variability appear in South Asia at all sub-annual time scales and in East Asia at annual-to-decadal time scales. Future changes in rainfall variability are significantly positively correlated with changes in mean wet season rainfall in each monsoon domain and across most time scales. The EASM rainfall variability is projected to increase (Xue et al., 2023; Katzenberger and Levermann, 2024). The increased variability may imply that monsoon rainfall will be less predictable as part of the internal variability is unpredictable.

Future changes in ISM predictability, influenced by its teleconnection with various remote drivers, remain highly uncertain. While some studies indicate that the ENSO–ISM relationship will remain stable, others foresee a weakened relationship. Some also suggest that competition will arise between circulation changes and moisture availability over the ISM region (Li and Ting, 2015; Azad and Rajeevan, 2016; Roy et al., 2019; Schulte et al., 2021).

5.1.2. *Extreme precipitation changes*

Significant increases in extreme precipitation linked to observed global warming have emerged over the past century. The annual maximum daily rainfall has risen by approximately 8% per °C in the South Asian monsoon (Zhang and Zhou, 2019). A rising trend has been detected in the annual maximum daily rainfall and the number of extremely wet days based on daily precipitation in Seoul, Korea, since 1778 (Wang et al., 2006). In the central Indian subcontinent, a substantial shift towards heavier precipitation in shorter-duration spells occurred from 1950 to 2015 (Goswami et al., 2006; Rajeevan et al., 2008; Roxy et al., 2017; Singh et al., 2019). The anthropogenic influence has notably contributed to the observed shift towards heavy precipitation in eastern China (Ma et al., 2017) and western Japan (Kawase et al., 2020). The increase in extreme hourly rainfall has been significantly correlated with rapid urbanization in the Pearl River Delta and Yangtze River Delta of coastal China (Wu et al., 2019a; Jiang et al., 2020). The urban heat island effect enhances instability and facilitates deep convection. Significant spatial variability in the trends of extreme rainfall in India due to urbanization and changes in land use and land cover has also been identified (Ali and Mishra, 2017). These observed increases in extreme precipitation suggest a crucial role of GHG-induced warming.

Climate model projections suggest high confidence that the frequency and intensity of monsoon extreme rainfall events will increase, alongside an increasing risk of drought in some monsoon regions (Wang et al., 2020a). Heavy rain will increase considerably faster than the mean precipitation, particularly in Asia (Kitoh, 2017). Unlike mean precipitation changes, heavy and intense rainfall is more closely controlled by environmental moisture content constrained by the Clausius–Clapeyron relationship and convective-scale circulation changes. Extreme precipitation in the Asian monsoon region exhibits the highest sensitivity to warming (Zhang et al., 2018). CMIP6 models project a change in extreme 1-day rainfall of +58% over South Asia and +68% over East Asia in 2065–2100 compared to 1979–2014 under the SSP (Shared Socioeconomic Pathway) 2-4.5 scenario (Ha et al., 2020). Model experiments also indicate a threefold increase in the frequency of rainfall extremes over the Indian subcontinent under future global warming of 1.5°C–2.5°C (Bhowmick et al., 2019). Due to more rapidly increasing evaporation, CMIP6 model projections for 2015–2100 under the SSP2-4.5 and SSP5-8.5 scenarios indicate that the western part of East Asia will face a more rapid increase in drought severity and risks than the eastern part (Moon and Ha, 2020). Projections of future extreme rainfall changes in the densely populated and fast-growing coastal zones are critical. The increase in monsoon extreme rains and tropical cyclones, together with rising sea levels, will exacerbate impacts, particularly along coastal regions of the Indian subcontinent (IPCC, 2022).

5.1.3. *Mechanisms accounting for precipitation changes due to GHG warming*

Three main physical processes through which GHG radiative forcing affects monsoon rainfall were summarized in Wang et al. (2020c). First, GHG warming raises atmospheric humidity, which increases monsoon rainfall. However, the specific humidity increase is not driven solely by local temperature thermodynamics; rather, it is regulated by the climatological mean circulation and the projected warming patterns of tropical SST. Second, GHG warming creates vertical differential heating, resulting in top-heavy heating that stabilizes the atmosphere and suppresses ascent, partially offsetting the effect of increased humidity on precipitation intensity. The net thermodynamic effect is smaller than the humidity increase effect alone. Third, GHGs induce horizontal differential heating, leading to robust "Northern Hemisphere warmer than Southern Hemisphere" and "land warmer than ocean" patterns, as well as El Niño-like warming. The differential warming pattern drives changes in atmospheric circulation, playing a critical dynamic role in determining monsoon circulation and related rainfall changes.

5.2. *Aerosol impacts on monsoon variability and prediction*

Li et al. (2016) comprehensively reviewed studies on Asian aerosols, monsoons, and their interactions. They pointed out that, on a continental scale, aerosols reduce surface insolation and weaken the land–ocean thermal contrast, thus inhibiting the development of monsoons. Locally, aerosol radiative effects alter the thermodynamic stability and convective potential of the lower atmosphere, reducing temperatures, increasing atmospheric stability, and weakening wind and atmospheric circulation. The Indian landmass has exhibited cooling due to aerosols, while the western Indian Ocean has experienced a significant warming trend, which reduced the ISM rainfall historically (Roxy et al., 2015). The Northern Hemisphere monsoon is more sensitive to anthropogenic aerosols than to GHGs (Cao et al., 2022).

Recent studies suggest that anthropogenic aerosol emissions have weakened the ASM since the end of the 1980s (e.g., Bonfils et al., 2020). Model experiments indicate that changes in anthropogenic aerosols dominate rainfall decreases in northern China (Tian et al., 2018). The abrupt reduction of emissions during the COVID-19 pandemic provides a unique opportunity to assess aerosol forcing on monsoons, as the 2020 mei-yu precipitation is found to have been strengthened through an increase in shortwave radiation in northern China (Yang et al., 2022). Remote dust aerosols from the Middle East may strengthen the southwesterly monsoon winds and enhance summer rainfall over central-eastern India (Jin et al., 2014; Vinoj et al., 2014).

Aerosols can affect Asian monsoons by changing ENSO. Analysis of 500-year reconstructions has shown enhanced mei-yu following historical volcanic eruptions, as these events tend to excite the occurrence of El Niño (Liu et al., 2022). Furthermore, the increase in biomass aerosol from the 2019–20 Australian wildfire has been argued to have favored the occurrence of the multi-year La Niña events from 2020 to 2022 by increasing the cloud albedo over the southeastern subtropical Pacific Ocean (Fasullo et al., 2023). This multi-year La Niña should impact the EASM differently than a traditional one.

Stratospheric ozone over the Tibetan Plateau, through Rossby wave breaking, brings ozone-rich dry air into the upper tropical troposphere. This alters the atmospheric radiative balance, impacts temperature and circulation patterns, and inhibits the formation of deep convective clouds, thereby prolonging dry spells over the Tibetan Plateau and North India (Fadnavis and Chattopadhyay, 2017; Roy et al., 2021). Zhu and Wu (2023) showed that variations in the Tibetan Plateau ozone valley from May to July quantitatively contributed to up to 15% of East Asian summer precipitation anomalies.

6. Advances in prediction models and techniques

Over the past five decades, seasonal prediction techniques have advanced significantly. Current tools for seasonal prediction include dynamic and statistical–empirical models. Advances in computing power, data collection, and understanding of climate systems continue to enhance the effectiveness of these forecasting tools.

6.1. *Dynamic model prediction*

Dynamic models effectively capture interactions among various components of climate systems and are more physically adaptable to changing climate conditions. Coupled atmosphere–ocean models initialized in May are statistically significant in predicting Indian monsoon rainfall (DelSole and Banerjee, 2017). These dynamic prediction systems can forecast Indian summer rainfall one month in advance. Some individual models demonstrate correlation skill values as high as 0.6, comparable to the MME mean (Jain et al., 2019). Liang et al. (2022) reviewed the seasonal prediction of the ASM using the China Meteorological Administration Climate Prediction System Version 3, which excels in many aspects.

Critical developments in climate model prediction can be categorized into improvements in model resolution, representation of physical processes, integration of data assimilation techniques, and the application of machine learning.

Higher-resolution models better represent regional features such as orography and coastlines, both spatially and temporally, which are crucial for accurate monsoon predictions. For instance, the National Centers for Environmental Prediction (NCEP) Global Forecast System, version 2 coupled forecast system model (CFSv2), improved the skill in predicting ISM rainfall, significantly outperforming its lower-resolution version (Ramu et al., 2016).

Advances in the representation of physical processes such as cloud microphysics, land–surface interactions, and ocean–atmosphere coupling have significantly improved the accuracy of monsoon simulations. Palmer (2001) proposed nonlocal stochastic–dynamic parametrization, which has been widely used. Recent advancements in microphysics, snow schemes, and convection parameterization in the CFS model have considerably increased the forecasting skill for ISM rainfall (Pokhrel et al., 2016). Rajeevan et al. (2012) also found that improved physics and dynamics enhanced the performance of both the MME and individual models. Recent studies by Bao et al. (2019) and Liu et al. (2024b) highlighted the critical role of explicit convective parameterization in improving the prediction of large-scale climate events such as El Niño, the IOD, and the Madden–Julian Oscillation (MJO). They integrated a Resolving Convective Precipitation scheme, introducing microphysical processes in convective precipitation and notably enhancing the EASM prediction skill. Orographic parameterization is crucial for improving EASM seasonal prediction by resolving small-scale processes that affect atmospheric circulation. Studies show that schemes like the Turbulent Orographic Form Drag and Gravity Wave Drag can significantly reduce wet biases in precipitation simulations over the Central Himalayas and Tibetan Plateau (Wang et al., 2020d; Xie et al., 2021). Enhancing parameterizations related to the Tibetan Plateau seasonal warming and land–atmosphere interactions, including the representation of surface fluxes and precipitation patterns, can improve the simulated EASM variability.

Improving the initialization of models has also enhanced the levels of prediction skill. Dynamic models necessitate high-quality initial conditions and boundary data. Consequently, enhanced data assimilation methods can integrate more comprehensive satellite datasets and ground-based observations. The operational use of CGCMs requires continued refinement in model initialization and a better understanding of stochastic influences (Delsole and Shukla, 2009). Statistical methods, including the perturbed-parameter ensembles method (Murphy et al., 2014), are employed to initialize dynamic models. Additionally, statistical methods correct biases in dynamic model outputs (Lee et al., 2011).

Ensemble methods are effective techniques for combining model runs from single or multiple models to produce a range of possible outcomes (e.g., Krishnamurti et al., 2000). Krishnamurti et al. (1999) proposed a superior ensemble approach, which stimulated a surge of MME studies on seasonal prediction. Notably, Lee et al. (2013) found that the prediction skill for East Asian summer rainfall via an MME with better-performing models was significantly higher than that from an all-inclusive operational MME, suggesting the importance of excluding poor models when forming the ensemble group. The probability forecast increases the robustness of predictions and, more importantly, provides information about forecast uncertainty, a critical component of climate forecasting, thereby enhancing reliability (Ramu et al., 2023).

The skill levels of models in predicting seasonal anomalies correlate positively with their performance in simulating the climatology of precipitation (Lee et al., 2010). Models with a more accurate representation of the ENSO–monsoon relationship tend to demonstrate higher prediction skill (Jain et al., 2019; Yan and Guo, 2023). Conversely, models showing a weak relationship between the IOD and Indian rainfall anomalies may limit the prediction skill for the local monsoon circulation and Indian rainfall (Johnson et al., 2017). In contrast to the high skill level observed in the seasonal prediction of Indian summer rainfall, the skill for predicting East Asian summer rainfall remains relatively low (Takaya et al., 2021; Wang et al., 2021), likely due to the sensitivity of EASM variations to multiple processes originating not only from the tropics but also from higher latitudes and upstream Tibetan Plateau regions (Richter et al., 2024).

6.2. *Empirical prediction models and hybrid dynamic–empirical models*

The IMD adopted the Statistical Forecasting System in 2007, based on ensemble techniques that combine multiple models using eight key predictors. This approach has improved the forecast accuracy (Rajeevan et al., 2007). Recently, a probabilistic prediction system has further enhanced the prediction skill for ISM rainfall by advancing new predictors and techniques (Ramu et al., 2023). However, challenges remain in forecasting extreme years and addressing non-stationarity in predictor relationships.

The PEM approach has been developed to overcome the limited sample size in climate prediction (Wang et al., 2013; Yim et al., 2014). Building PEMs emphasizes understanding the sources of predictability. Establishing a PEM involves four steps: identifying major empirical modes of variability (often EOFs) or rainfall/circulation indices; detecting and confirming sources of variability based on a physical understanding of the lead–lag relationships between the predictors and predictand (usually involving numerical experiments); constructing PEMs using only physically meaningful predictors; and estimating predictability using the predictable mode analysis method (Wang et al., 2015a).

The PEM method has been used to predict the EASM circulation index (Wu et al., 2009), WNP subtropical high index and associated tropical storm days in the subtropical WNP (Wang et al., 2013), the All-India rainfall index (Wang et al., 2015b), May–June rainfall over South China (Yim et al., 2014) and East Asia (Xing et al., 2017), July–August precipitation in Southeast Asia (Xing et al., 2016) and extratropical EA (Yim et al., 2016), summer rainfall in arid and semiarid Northwest China (Xing and Wang, 2017), the anomaly patterns of ISM rainfall (Li and Wang, 2016), summer rainfall over the west-central India and peninsular India (Li et al., 2017a), and continental East Asian summer rainfall (Ma et al. 2025). PEM has also been applied to seasonal prediction of extreme weather events, including summer extreme precipitation days over East China (Li and Wang, 2018a), peak summer heatwave days over the Yangtze–Huaihe River basin (Gao et al., 2019), and July precipitation in central China (Li et al., 2023). Rigorous post-publication, real-time verification of the prediction skill in the above works have shown that some predictions are skillful. For instance, the EASM index prediction (Wu et al., 2009) achieved a temporal correlation skill of 0.51 during the post-publication, 17-year period from 2007 to 2023. However, some predictions have suffered from nonstationary predictors. For example, the May–June EA precipitation pattern prediction in the domain (20°–45°N, 100°–130°E) achieved an impressive average spatial pattern correlation skill of 0.47 from 2016 to 2021 but dramatically dropped to −0.66 for 2022 and −0.02 for 2023.

Combining dynamic and statistical models is a promising way to improve seasonal forecasts (Ren et al., 2023). Statistical methods can help enhance forecasting skill by integrating diverse sources of information. Wang and Fan (2009) combined dynamic model predictions and observed spatial patterns of historical "analog years", resulting in an improved prediction skill for EA and WNP summer precipitation. The combined dynamic–statistical approach can generate more accurate and flexible predictions but requires careful calibration and validation against observed data. Kim and Webster (2010) provided an example of using hybrid models that blend dynamic and statistical approaches to enhance the predictability of hurricane over North Atlantic. Utilizing a dynamic–empirical model, Wang et al. (2018) demonstrated a promising pathway for making decadal predictions of Northern Hemispheric land monsoon rainfall. Liu et al. (2018b) employed a simple statistical downscaling method based on predictable circulation data, which offers an efficient tool to improve the raw rainfall forecast skill in China. In a recent study aimed at achieving high prediction skill for ENSO, Zhao et al. (2024) coupled a dynamic prediction model, the Extended Nonlinear Recharge Oscillator Model, with the statistical relationship between ENSO and other climate modes, resulting in skillful ENSO forecasts at lead times of up to 16–18 months. To address the poor simulation of the Boreal Summer Intraseasonal Oscillation (BSISO) in dynamic prediction models, Bach et al. (2024) employed statistical predictions of the BSISO to correct the prediction of Asian summer monsoon precipitation in dynamic prediction systems, achieving significant improvement.

6.3. *Comparison of prediction models*

Comparison of strengths:

• Dynamic models are based on the fundamental laws of fluid dynamics and thermodynamics, which allow for a detailed representation of the atmosphere and ocean. They can integrate observations and data from various sources and capture complex interactions within the climate system, making them useful for long-term climate projections.

• Empirical models use historical data to identify patterns and relationships, which can be valuable in areas with rich historical climate records. These models are typically easier to develop, understand, and apply in practical settings.

• Dynamic–empirical models combine the physical foundations of dynamic models with the data-driven elements of empirical models to enhance accuracy. These models can be adapted to account for both the underlying physical processes and the statistical relationships. They often show improved predictive capabilities compared to solely dynamic or empirical methods in various contexts.

Comparison of weaknesses:

• Dynamic models incorporate physical parameterizations, resulting in uncertainties due to differing representations of physical processes. Their outcomes are sensitive to initial conditions, which can lead to forecast uncertainty. Furthermore, they demand substantial computational resources.

• Empirical models may fail to capture critical physical processes. The non-stationarity of predictors can hinder their performance under changing climate conditions. Furthermore, they might not be suitable for predicting extreme events, particularly in regions with sparse or unreliable historical data.

• Dynamic–empirical models are more challenging to develop, requiring expertise in the understanding of the physical processes that link predictors and outcomes. They may demand extensive datasets for calibration and validation, which can be difficult in data-scarce regions. Furthermore, they are subject to uncertainties from both dynamic and empirical components.

In summary, each method has unique advantages and challenges, and the best approach often depends on the specific context of the climate prediction task, including the studied regions, the available data, and the forecast time scale. Researchers typically combine these models to enhance predictability and reliability.

6.4. *Mining new sources of predictability and exploring new methods for seasonal prediction*

Wang et al. (2013) used the central Pacific's May-minus-March SSTA to predict the summer WPSH, demonstrating that the SST tendency represents a new source of predictability as it signifies the direction of SSTA development. In addition, the central Pacific SST tendency between April and May addresses the declining prediction skill for the ISM in recent decades (Wang et al., 2015b). DelSole and Banerjee (2017) confirmed that predictors based on the tendency of SST during spring exhibit skill during both recent and historical periods, and may thus provide more skillful predictions of monsoon rainfall than predictors based on a single month. The May-minus-March SST tendency has been used for predicting mei-yu rainfall (Zhou et al., 2019; Qiao et al., 2021; Li et al., 2023) and heatwave days in the Yangtze River basin (Gao et al., 2018). This tendency predictor has also been utilized in land–air and sea ice–air couplings, such as the rapid spring Eurasian snowmelt favoring intense southern China summer rainfall (Xu and Li, 2024), and the early retreat of Arctic sea ice along the Eurasian coast in May tending to strengthen the mei-yu rainfall (Chen et al., 2024). SST tendency predictors are particularly useful because SSTAs prior to the forecast period ("persistence" predictors) may become ineffective in predicting the ASM when ENSO is transitioning rapidly across spring predictability barriers (Webster and Yang, 1992).

New sources of predictability for extreme precipitation, such as floods and excessive precipitation, have been actively explored alongside the significant climate warming in recent years. The extreme IOD in the autumn of 2019, which occurred independently of a strong El Niño and marked the second such occurrence after the strongest event in 1675 during the last millennium (Abram et al., 2020), is recognized as a significant factor contributing to the extreme flooding of the Yangtze River in the summer of 2020 (Takaya et al., 2020; Zhou et al., 2021b). A wintertime negative-phase NAO and associated North Atlantic tripolar SSTAs can increase the number of heatwave days in the Yangtze River basin during the following summer via both the tropical pathway (Qiao et al., 2018) and the extratropical pathway (Gao et al., 2018).

Atmospheric teleconnection provides new sources of predictability. Recent extreme upstream forcings in the CGT, such as the diabatic heating related to extreme rainfall in Pakistan, have been identified to significantly enhance heatwaves in the Yangtze River basin (Tang et al., 2023b; Fu et al., 2024). Above-normal shortwave radiation in northern Russia may generate a Ural anticyclone anomaly and a downstream wave train along the South Asian jet stream, promoting heatwaves in East Asia (Liu et al., 2023a).

The atmosphere could influence the ocean's memory. Khatri et al. (2024) proposed an ocean memory framework to reveal the atmosphere's influence on ocean temperatures. They demonstrated how the NAO could impact decadal fluctuations in the subpolar North Atlantic Ocean temperatures.

Additionally, the stratospheric Quasi-Biennial Oscillation (QBO) westerly phase can induce the "southern flood–northern drought" pattern of the EASM through subtropical wave–flow feedback, and a statistical model that includes the QBO can effectively predict this pattern at least three months in advance (Zhang et al., 2024b).

Changing the predictor from seasonal mean anomalies to year-to-year increments represents a new method in seasonal prediction. Fan et al. (2008) proposed predicting the year-to-year increment instead of seasonal mean rainfall anomalies in the middle–lower reaches of the Yangtze River Valley. This approach has been applied to other predictands, such as typhoon frequency over the WNP (Fan and Wang, 2009). Recently, based on EOF decomposition of multi-factor fields, Feng et al. (2020) employed a "similar error correction" method to enhance model prediction.

7. Challenges and limiting factors in monsoon prediction

Why is seasonal prediction so challenging? Webster (2006) noted about 20 years ago, "A combination of modeling problems and empirical non-stationarity has plagued monsoon prediction on an interannual time scale. Empirical forecasts have to contend with the specter of statistical non-stationarity while numerical models lack simulation fidelity". His assertion is still valid today. In particular, the sources of predictability are changing under global warming and the influence of multidecadal variations. Here, we re-elaborate on the main challenges by highlighting four factors: dynamic model deficiencies, non-stationary monsoon variability, inherent uncertainties arising from complex multiscale interactions, and data quality and availability.

7.1. *Dynamic modeling*

Systematic model biases in monsoon climates have persisted through the CMIP generations (e.g., Sperber et al., 2013), despite model improvements from CMIP3 to CMIP6 due to steady increases in horizontal resolution and enhanced parameterizations. Biases in variability arise in historical monsoon simulations, hindering accurate seasonal prediction and attribution of present-day monsoon changes (Herman et al., 2020; Marvel et al., 2020). Biases in evapotranspiration affect the Bowen ratio (Yin et al., 2013) and, consequently, atmospheric boundary layer height and humidity.

The missing or poorly resolved processes include the lack of organized convection (e.g., mesoscale convective systems) at coarse model resolutions, a poorly simulated diurnal cycle in the tropics due to failures in convective parameterization (Willetts et al., 2017), inadequate simulation of orographic processes, and imperfect land–atmosphere coupling stemming from underdeveloped parametrizations and a scarcity of observations of land–atmosphere exchanges (e.g., Turner et al., 2019). Features such as local convection can lead to considerable variability in rainfall distribution, meaning that dynamic models may not perform adequately. Correctly simulating the effects of aerosols on monsoon rainfall necessitates improved cloud microphysics schemes (Yang et al., 2017; Chu et al., 2018). Accurately modeling the interactions among the atmosphere, oceans, and land, especially the dynamic feedback processes, is challenging.

To date, summer monsoon seasonal precipitation over land and outside the deep tropics has remained a significant challenge in climate science, particularly over EA (Takaya et al., 2021). In EA, the diverse spatiotemporal structures of the EASM responses to El Niño complicate dynamic models that aim to predict summer rainfall. These differing responses are partly due to the varying intensities and evolutions of ENSO events and the gradual northward migration of the EA rainfall anomalies from June to August, which can obscure the El Niño-induced JJA mean anomalies (Wang et al., 2017). Therefore, to accurately forecast rainfall over continental EA, dynamic models must not only predict the strength, location, and evolution of El Niño but also the subseasonal migration of the subtropical EASM rain bands. The conventional practice of predicting JJA mean precipitation anomalies may require reassessment. Considering the seasonal evolution of rainfall, forecasting the mean rainfall in May–June and July–August could be more effective.

7.2. *The non-stationarity in monsoon prediction*

7.2.1. *Changes in ENSO properties*

Non-stationarity often arises from changing sources of predictability. As the primary source of predictability for the ASM, ENSO onset, propagation, structure, and intensity have changed since the 1970s (Wang, 1995; An and Wang, 2000).

The changes in ENSO intensity have profoundly impacted ASM variability and predictability. The impacts of ENSO on northern China, Central Asia, and the EA subtropical frontal zone have all increased with ENSO amplitude since 1901, especially after the 1950s (Wang et al. 2020a). Kumar et al. (1999) found a weakening since the late 1970s of the ISM–ENSO anticorrelation during the developing phase. However, the relationships between ENSO and the WNPM, EASM, and MC monsoon (Chang et al. 2004) have all been enhanced during ENSO's developing, mature, and decaying phases, suggesting the overall coupling between the Asian–Australian monsoon system and ENSO has strengthened due to intensified ENSO (Wang et al., 2008).

Changes in ENSO diversity also profoundly affect ASM variability and predictability. El Niño events have recently been classified as EP and CP El Niño based on the maximum warming locations during their peak phase in boreal winter (Ashok et al., 2007; Kug et al., 2009; Yeh et al., 2009). However, ASM variability is not directly related to the SSTA patterns in the peak phase of El Niño. Therefore, it is essential to classify El Niño based on its development and decay characteristics during boreal summer (Wang et al., 2020b). Through cluster analysis of the onset and amplification processes, Wang et al. (2019) classified 33 El Niño events from 1901 to 2017 into Super (or SBW), moderate EP, and CP El Niño events. Each type exhibits distinct development processes, coupled dynamics, precursors, and hydroclimate impacts.

The ASM shows significantly different responses to El Niño diversity during its developing and decaying summer (Wang et al. 2020b). During the developing summer, the three types of El Niño SSTAs are remarkably different, not only in spatial structure but also warming intensities (Fig. 5). Therefore, during May–June(0), the early onset of Super El Niño events induces significant dryness over the Asian monsoon, but not the moderate MEP and CP events. During July–August(0), CP warming significantly reduces the rainfall over northern India and northern China; in contrast, MEP warming causes deficient rainfall over central-western India and the Yangtze River Valley. With strong warming, SBW events severely reduce the land precipitation over regions affected by both MCP and MEP warming. Likewise, the three types of El Niño decay show conspicuously distinctive SSTAs and thus exert remarkably different impacts on boreal summer land precipitation (Wang et al. 2020b). Therefore, changing El Niño diversity is a prominent source of the nonstationary ENSO–ASM relationship.

Since 1970, moderate EP events have nearly disappeared, while moderate CP and Super El Niño events have become dominant, both developing from the western Pacific (Wang et al., 2019). In addition, 10 multiyear La Niña events over the past century have shown an increasing trend, with eight of these occurring after 1970. Notably, five out of the six La Niña events since 1998 have been multiyear La Niña events (Wang et al., 2023). The multiyear La Niña events during this period followed either a Super El Niño or a CP El Niño. The impacts of multiyear La Niña events differ from single-year La Niña events through a prominent onset rate and cumulative intensity or persistence, which affects the ASM differently.

The ENSO–ISM rainfall connection is more stable in northern Central India and the southern Indian peninsula, while it has undergone significant epochal changes in Central India and eastern Central India (Seetha et al., 2020; Kumar and Singh, 2021; Mahendra et al., 2021). The failures in ISM rainfall prediction primarily stem from the inability of models to capture the evolving CP ENSO, the rapid deepening of the Asian low, and the intensification of North and South Pacific highs during boreal spring (Wang et al., 2015b).

The relationship between precipitation on the Indochina Peninsula and ENSO underwent changes around the late 1970s and 1990s, linked to shifts in the timing of ENSO developments and the tropical Indo-Pacific SSTA patterns (Wu and Zhu, 2021). Similarly, a strengthening of the negative correlation between El Niño and the subsequent spring precipitation over the Indochina Peninsula has been observed since the early 1990s, attributable to more intense and longer-lasting positive SSTAs in the tropical central Pacific after the early 1990s. Due to the changing equatorial Pacific SSTAs, more precipitation fell in August on the Indochina Peninsula during La Niña developing years from 1959 to 1979, but in El Niño developing years from 1983 to 2003 (Wu et al., 2023).

7.2.2. *Influences of decadal-to-multidecadal variations*

The ISM rainfall is associated with the AMO (Goswami et al., 2006; Zhang and Delworth, 2006; Wang et al., 2009; Luo et al., 2011, 2018b; Krishnamurthy and Krishnamurthy, 2016). However, this relationship is unstable over time (Malik et al., 2017; Luo et al., 2018a). This nonstationary relationship is supported by CESM (Community Earth System Model) large-ensemble simulations and attributable to internal climatic processes (Ahmad et al., 2022). In that study, it was suggested that subtropical WNP SSTs play a substantial role in modulating the ISM's linkage with the AMO. The AMO may influence precipitation over the Indochina Peninsula in May and June by modulating the El Niño-related air–sea interaction over the WNP (Fan et al., 2019). During positive AMO phases in July and August, anomalous wave trains induced by the warmer-than-normal North Atlantic Ocean result in positive pressure anomalies over southern China, leading to suppressed precipitation over the Indochina Peninsula.

The summer rainfall over eastern China changed during the second half of the 20th century, following a "south-flood–north-drought" pattern. This pattern is characterized by decreased rainfall in the north and an increase in the south (Gong and Ho, 2002; Yu et al., 2004; Ding et al., 2008). The weakening tendency of the EASM circulation and the decrease in summer rainfall over northern China are considered to be part of the interdecadal variability driven by the phase switch of the Pacific Decadal Oscillation (PDO) from negative to positive in the late 1970s (Hu, 1997; Zhou et al., 2008; Qian and Zhou, 2014). The PDO affects EA summer rainfall by modulating the tropical Walker circulation and the midlatitude jet stream (Dong and Lu, 2013; Ueda et al., 2015; Xu et al., 2015; Zhu et al., 2015). Additionally, numerical experiments suggest that the forcing both from the equatorial central Pacific and the atmosphere–ocean interaction in the WNP is essential for the decadal variability of EA summer rainfall (Li and Wang, 2018b).

Severe floods often occur in the post-El Niño summer (Wang and Zhao, 1981; Zhang et al., 1999; Wu et al., 2003; Wang et al., 2020a). However, due to the subseasonal northward march of the subtropical rainband from May to August (Tao and Chen, 1987; Chang et al., 2000; Wang and Zhang, 2002; Ding and Chan, 2005), rainfall over the Yangtze River basin shows relatively low correlation with ENSO, suggesting the seasonal mean rainfall forecast cannot capture hydrological hazards (Wang et al., 2017).

In summary, it is essential to explore the reasons behind the changes in predictability sources. Examining the evolving characteristics of the primary sources of predictability throughout the historical period, as well as projected future changes, aids in anticipating potential modifications to the impacts of predictability. Utilizing advanced artificial intelligence (AI) capable of capturing nonlinear relationships may assist in addressing non-stationarity.

7.3. *Inherent uncertainties arising from complex scale interactions*

Weather and climate systems are inherently chaotic, setting limits on predictability. Minor uncertainties in initial conditions can lead to significant differences in predicted outcomes. Complex multi-scale interactions add uncertainties to seasonal forecasts (Chen et al., 2023). The ENSO cycle is inherently irregular, posing a great challenge for monsoon climate prediction.

The chaotic and stochastic nature of ENSO limits its predictability and, consequently, the predictability of the ASM. Nonlinear ENSO theory demonstrates that the intrinsic interannual oscillation of the coupled system is fundamentally chaotic when the basic states of the tropical atmosphere and ocean vary annually (Wang and Fang, 1996). Wang et al. (1999) further developed a stochastically forced nonlinear dynamic model for ENSO to explain its irregularity. The model's irregular ENSO can arise from (a) stochastic forcing–excited resonance, (b) stochastic forcing–perturbed coupled nonlinear oscillation, and (c) stochastic transition between a warm and a cold stable, steady state.

Atmospheric internal dynamics can generate unpredictable monsoon variations. For instance, Wu et al. (2019b) found that several climate models' pre-industrial and historical simulations can reproduce the north–south contrasting pattern in interdecadal summer rainfall changes over eastern China. These changes are not accompanied by the PDO signal in the Pacific Ocean, indicating that changes in GHG and aerosol emissions, as well as PDO effects, are not necessary for the occurrence of this pattern. This decadal variability pattern was also identified in climatological annual varying SST forced atmospheric model simulations, suggesting a possible role of atmospheric internal variability.

Midlatitude baroclinic eddies, acting as stochastic forcing, may generate unpredictable low-frequency variability. Regional variability is influenced by various geographic features. The Asian monsoon spans a region with mountains, plateaus, and marginal seas. These features affect local and regional climate patterns, making general predictions challenging. Intraseasonal oscillations such as the MJO and BSISO play a crucial role in modulating monsoon circulation, alternating between active and break monsoon cycles. The timing and distribution of monsoon rainfall can vary significantly within a season, impacted by intraseasonal oscillations. Predicting the effects of these subseasonal variations presents a substantial challenge (Liu et al., 2024a).

7.4. *Data quality and availability*

Reliable, high-resolution data are essential for accurate predictions. However, data gaps, especially over oceans and in less accessible regions, can introduce uncertainties. Accurate modeling requires integrating data from multiple sources and scales, making the task challenging but vital for climate prediction. Both dynamic and statistical models need constant updates to incorporate new data and adapt to ongoing climate changes. It remains a continual challenge to keep models accurate under changing conditions. The limited training datasets from observations inhibit the realization of AI technology's full potential in climate prediction.

8. Emerging research trends and recommendations

Enhancing model accuracy and refining our understanding of evolving climate drivers—especially the complex interactions between the ocean, atmosphere, land, cryosphere, and biosphere—will enhance future monsoon predictions in a warming climate. These improvements are vital for tackling the challenges posed by increasing variability and extreme events caused by anthropogenic climate change.

8.1. *Emerging research trends in monsoon prediction*

Emerging research trends in monsoon prediction leverage advancements in technology and scientific understanding to tackle existing challenges and limitations. Here is an overview of some emerging research directions in ASM climate prediction.

8.1.1. *Utilizing AI in seasonal prediction*

Recently, data-driven and machine-learning approaches have increasingly been applied to analyze large climate datasets, identify patterns of climate variability, mine new sources of predictability, and improve weather and climate predictions. These technologies can manage complex and nonlinear relationships often present in climate systems, providing new insights that traditional models may miss.

Using AI for weather forecasting and climate prediction has made significant progress. In climate prediction, artificial neural networks and genetic algorithms have been applied to the prediction of ENSO (e.g., Ham et al., 2019), the ISM (e.g., Dash et al., 2024), and the EASM (e.g., Tang and Duan, 2021). However, AI has limitations similar to those of empirical models, particularly regarding limited datasets and the prediction of extreme events that never occurred in historical data. To overcome the scarcity of observational data and consider physical constraints, transfer learning from historical dynamic model simulations was used to build a deep-learning prediction model for skillful ENSO forecasts (Ham et al., 2019). It is essential to understand the mathematical principles, their scope of application, and their advantages and limitations behind the AI algorithms. An era is approaching with booming AI climate modeling and prediction.

8.1.2. *Focusing on extreme events and exploring new sources of predictability*

Climate change is associated with increased extreme weather events, which can complicate predictions by introducing new dynamics and potential feedback loops. In recent years, the exploration of new sources of predictability for extreme climate events has surged. For instance, extreme heat events have frequently occurred in various regions of East Asia, with a trend of further increase projected for the future (Li et al., 2018a; Luo and Lau, 2019, 2020; Yeh et al., 2021; Ma and Yuan, 2023; Zhou et al., 2023). The strengthening and westward extension of the WPSH are direct causes of extreme summer heat in eastern China (Tang et al., 2023a; Zhang et al., 2024a; Huang et al., 2024), and its interannual variation is not solely influenced by ENSO variability. Enhanced convection over the Indian Ocean can directly impact the WPSH or modulate the frequency, intensity, and duration of extreme heat events in eastern China by strengthening the South Asian high in the upper troposphere (Luo and Lau, 2019). Through a comparative analysis of strong and weak gradient La Niña events, Zhang et al. (2024a) emphasized that, beyond the traditional understanding of the influence of SST variability in the central equatorial Pacific, strong gradient La Niña events lead to an intensified response of the WPSH through enhanced convection over the MC attributable to warm anomalies in the western Pacific. ENSO events with significant zonal SST gradients can largely explain the occurrence of regional and global monsoons and Eurasian heatwaves (Zhang et al., 2019).

8.1.3. *Improving subseasonal prediction*

Subseasonal predictions aim to forecast weather conditions over several weeks, thus bridging the gap between short-term weather forecasts and long-term climate predictions. These forecasts are crucial for managing agriculture, water resources, and disaster risk. Researchers are improving models that capture subseasonal variations influenced by factors like the MJO (Madden and Julian 1972) and BSISO (Wang and Xie, 1997). This involves refining model physics and incorporating high-resolution datasets. These research trends aim to address existing challenges in subseasonal prediction, offering more accurate, reliable, and timely forecasts of extreme events.

A new approach has been proposed for the subseasonal prediction of the EASM (Liu et al., 2024a). It involves identifying opportunities and barriers, and clarifying the capabilities and limitations of models in predicting intraseasonal events, thereby achieving more accurate predictions of disastrous weather and climate events. To optimize subseasonal prediction products in state-of-the-art systems, the goal is to discern which predictions are reliable and whether they can identify precursors indicating predictive accuracy. To this end, the exploration of event-oriented predictability aims to narrate the story behind the forecast of each rainfall event. This approach should also apply to seasonal prediction. Identifying predictable and unpredictable modes used for the South Asian summer monsoon, along with their contributions from tropical SST change and internal atmospheric variability (Zhang et al., 2022), should provide information about the types of monsoon changes that can be predicted.

8.2. ***Recommendations***

Future directions in monsoon prediction involve enhancing existing capabilities and addressing current limitations through strategic initiatives. The following recommendations are aimed at improving the precision and reliability of monsoon predictions by building robust infrastructure, facilitating the exchange of knowledge and data, and fostering a collaborative environment among stakeholders.

8.2.1. *Enhancing observational networks*

The density and geographic coverage of weather stations should be increased, particularly in remote and under-monitored regions such as the Tibetan Plateau, to capture more comprehensive data on local weather conditions. Investment should be made in advanced technologies such as automatic observation stations, satellites, radars, and ocean buoys, to provide high-resolution, real-time data on atmospheric, oceanic, and land-surface conditions. Furthermore, data from citizen science projects and local weather networks should be incorporated, as these can provide valuable ground-level insights and improve the coarseness of data available for models.

8.2.2. *Developing better models and dynamic prediction systems*

It has been suggested that convection-permitting regional simulations more realistically represent short-timescale rainfall processes and their responses to forcing (Kendon et al., 2019). Future models could be improved by explicitly resolving deep convection to address common problems across monsoon systems.

Climate prediction is a probabilistic forecast, and the estimation of uncertainty in weather and climate prediction is encapsulated by the word "predictability" (Palmer and Hagedorn, 2006). No forecast is complete without a forecast of forecast skill (Tennekes et al., 1987). Thus, the large-ensembles method is a practical approach to understanding a climate signal's spread or degree of uncertainty. Such large ensembles include perturbed-parameter ensembles (Murphy et al., 2014) or traditional initial-condition ensembles, such as CanESM2 (Sigmond and Fyfe, 2016; Kirchmeier-Young et al., 2017) or MPI-ESM (Maher et al., 2019). Better ensemble prediction design is expected to increase the value of prediction products.

8.2.3. *Bridging the gap between research and operational forecasting*

Better communication and collaboration should be fostered between researchers and operational forecasters to ensure that the latest scientific advancements are quickly and effectively integrated into forecasting practices. Also, tools and platforms should be created that make complex model outputs more accessible and usable for users in climate services and decision-making, such as farmers, city planners, and emergency responders. Finally, ongoing education and training should be provided for operational meteorologists to keep them updated on the latest tools, techniques, and findings in climate science and monsoon research.

8.2.4. *International and interdisciplinary collaboration and data sharing*

International cooperation through initiatives to address the transboundary nature of the monsoon system and its impacts is encouraged. The extended-range probabilistic forecasts of Bangladesh's Ganges and Brahmaputra floods provide an example in this regard (Webster et al., 2010). Moreover, standardized data-sharing protocols should be established that ensure timely and efficient information exchange across borders, enhancing the quality and scope of shared datasets. Multinational research projects that leverage diverse expertise and resources to tackle complex challenges associated with monsoon prediction and climate change impacts should be supported. Collaboration across disciplines, such as meteorology, oceanography, hydrology, agriculture, and energy sectors, is essential for developing applications that effectively utilize seasonal predictions.

Addressing the challenges discussed in the previous section requires improved data collection methods, refined models, bridging the gap between research and operational forecasting, and integrating cross-disciplinary approaches to enhance our understanding of the monsoon system as well as our predictive capabilities and services. These recommended efforts are crucial for mitigating the impacts of monsoon variability and climate change, ultimately leading to more resilient communities and sustainable development in regions affected by the Asian monsoon.

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