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Evaluation on Indian Summer Monsoon in High Resolution Prototypes of Unified Forecast System (UFS)

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सार – भारतीय ग्रीष्मकालीन मानसून (आईएसएम) दक्षिण एशिया में कृषि, जल संसाधनों और आपदा तैयारियों को अत्यधिक प्रभावित करता है। वायुमंडलीय गतिकी, संवहन, भू-सतही प्रक्रियाओं, महासागरीय परिस्थितियों और क्षेत्रीय स्थलाकृति के अंतर्संबंधों के कारण इसके परिसंचरण, वर्षा वितरण और दैनिक परिवर्तनशीलता का सटीक पूर्वानुमान लगाना चुनौतीपूर्ण बना हुआ है। यह अध्ययन 10 जून से 8 सितंबर 2020 के दौरान एनओए की एकिकृत पूर्वानुमान प्रणाली (यूएफएस) की पांच पीढ़ियों - एचआर1, एचआर2, एचआर3ए, एचआर3बी, एचआर4 और एचआर5 - से छह उच्च-रिज़ॉल्यूशन कॉन्फिगरेशन का मूल्यांकन करता है। अधिकांश परिसंचरण, वर्षा सूचकांक और स्थानिक वर्षा मूल्यांकन में दिन-10 के पूर्वानुमानों का उपयोग किया गया है, जबकि सप्ताह-1 और सप्ताह-2 के समय विश्लेषण दिन और रात की वर्षा में होने वाले पूर्वाग्रहों का आकलन करते हैं। वायुमंडलीय परिसंचरण के लिए ईआरए5 और जीएफएसवी16 विश्लेषणों और वर्षा के लिए सीएमओआरपीएच और जीपीसीपी विश्लेषणों के आधार पर पूर्वानुमानों का मूल्यांकन किया गया है। प्रदर्शन का आकलन चार गतिशील मानसून सूचकांकों, तीन वर्षा-आधारित सूचकांकों, स्थानिक परिसंचरण और वर्षा पैटर्न तथा दैनिक वर्षा चक्र का उपयोग करके किया जाता है। उच्च-रिज़ॉल्यूशन कॉन्फिगरेशन व्यापक मानसून परिसंचरण के व्यापक लौकिक विकास को पुनः प्रस्तुत करते हैं। पूर्वी एशियाई-पश्चिमी उत्तरी प्रशांत मानसून सूचकांक के लिए, HR4, ERA5 के साथ उच्चतम सहसंबंध (GFSv16 के लिए 0.425 की तुलना में 0.651) देता है, जबकि HR1, GFSv16 में 5.352 m s^{-1} से RMSE को घटाकर 3.524 m s^{-1} कर देता है। हालांकि, कोई भी कॉन्फिगरेशन एकसमान रूप से श्रेष्ठ नहीं है, और गतिशील भारतीय मानसून सूचकांक का प्रदर्शन आम तौर पर GFSv16 के तुलनीय है। वर्षा सूचकांक प्रमुख अंतर-मौसमी भिन्नताओं को पकड़ते हैं, हालांकि व्यक्तिगत वर्षा घटनाओं में त्रुटियां बनी रहती हैं। भारतीय महाद्वीप वर्षा सूचकांक के लिए, HR2 CMORPH ($3.766 \text{ मिमी दिन}^{-1}$) और GPCP ($3.686 \text{ मिमी दिन}^{-1}$) की तुलना में सबसे कम RMSE देता है। HR5 मध्य और उत्तरी भारत तथा हिमालयी क्षेत्र में अधिक वर्षा और पश्चिमी एवं दक्षिणी भारत में कम वर्षा दर्शाता है। ये विन्यास देखे गए दैनिक चक्र के व्यापक चरण को पुनः प्रस्तुत करते हैं, लेकिन दिन के समय और मध्यरात्रि के बाद वर्षा के चरम पर थोड़ी जल्दी अधिकतम वर्षा और अत्यधिक वर्षा का अनुकरण करते हैं। कुल मिलाकर, नए उच्च-रिज़ॉल्यूशन UFS विन्यास क्षेत्रीय वर्षा और संवहनी परिवर्तनशीलता में कमियों को बनाए रखते हुए मध्यम-श्रेणी के मानसून पूर्वानुमान के कुछ पहलुओं में सुधार करते हैं।

ABSTRACT. The Indian Summer Monsoon (ISM) strongly influences agriculture, water resources, and disaster preparedness across South Asia. Accurate prediction of its circulation, rainfall distribution, and diurnal variability remains challenging because of interactions among atmospheric dynamics, convection, land-surface processes, ocean conditions, and regional topography. This study evaluates six high-resolution configurations from five generations of NOAA's Unified Forecast System (UFS)—HR1, HR2, HR3a, HR3b, HR4, and HR5—during 10 June–8 September 2020. Most circulation, rainfall-index, and spatial-precipitation evaluations use day-10 forecasts, while week-1 and week-2 composites assess daytime and nighttime precipitation biases. Forecasts are evaluated against ERA5 and GFSv16 analyses for atmospheric

circulation and CMORPH and GPCP for precipitation. Performance is assessed using four dynamical monsoon indices, three rainfall-based indices, spatial circulation and precipitation patterns, and the diurnal rainfall cycle. The high-resolution configurations reproduce the broad temporal evolution of the large-scale monsoon circulation. For the East Asian–western North Pacific Monsoon Index, HR4 gives the highest correlation with ERA5 (0.651 versus 0.425 for GFSv16), while HR1 reduces RMSE to 3.524 m s^{-1} from 5.352 m s^{-1} in GFSv16. However, no configuration is uniformly superior, and performance for the Dynamic Indian Monsoon Index is generally comparable to GFSv16. The rainfall indices capture the principal intraseasonal variations, although errors remain in individual rainfall events. For the Indian Continent Precipitation Index, HR2 gives the lowest RMSE against CMORPH ($3.766 \text{ mm day}^{-1}$) and GPCP ($3.686 \text{ mm day}^{-1}$). HR5 shows wet biases over central and northern India and the Himalayan region and dry biases over western and southern India. The configurations reproduce the broad phase of the observed diurnal cycle but simulate a slightly early maximum and excessive precipitation during the daytime peak and after midnight. Overall, the newer high-resolution UFS configurations improve selected aspects of medium-range monsoon prediction while retaining deficiencies in regional precipitation and convective variability.

Key words – Indian summer monsoon, Unified forecast system, High-resolution forecasting, Monsoon indices, Medium-range prediction, Diurnal precipitation variability.

1. Introduction

The Indian Summer Monsoon (ISM), occurring primarily from June to September, is the principal rainy season over most of India and contributes approximately 80% of the country's annual rainfall. Monsoon rainfall plays a central role in agricultural production, water-resource availability, disaster management, and the Indian economy. Excessive rainfall may cause floods, landslides, infrastructure damage, and loss of life, whereas deficient rainfall and prolonged dry spells may lead to drought, water shortages, and reduced crop productivity. Reliable prediction of the ISM is therefore essential for agricultural planning, water-resource management, disaster preparedness, and socioeconomic decision-making (Gadgil and Gadgil, 2006; Kumar *et al.*, 2013; Mohanty *et al.*, 2019).

The ISM is a complex and spatially heterogeneous system governed by interactions among large-scale atmospheric circulation, ocean–atmosphere coupling, land-surface processes, regional topography, and convection. Its seasonal development is associated with the strengthening of the land–sea thermal contrast, establishment of cross-equatorial flow, development of the Somali low-level jet and monsoon westerlies, and northward migration of the tropical convergence zone. Moisture transport from the Arabian Sea and Bay of Bengal supports widespread rainfall over the Indian subcontinent, while regional rainfall patterns are strongly influenced by the Western Ghats, Himalayan foothills, Tibetan Plateau, and other areas of complex terrain (Webster *et al.*, 1998; Gadgil, 2003; Mohanty *et al.*, 2019).

The ISM also exhibits substantial variability across interannual, intraseasonal, synoptic, and diurnal timescales. Interannual variability is characterized by persistent and spatially extensive rainfall anomalies during major drought and flood years. Within the monsoon season, alternating active and break phases produce substantial changes in rainfall over the monsoon core region and surrounding

areas. Monsoon depressions and other synoptic systems originating over the Bay of Bengal further contribute to rainfall over eastern, central, and northern India (Krishnamurthy and Shukla, 2000; Rajeevan *et al.*, 2010; Mohanty *et al.*, 2019; Paul *et al.*, 2025).

In addition to seasonal and intraseasonal variability, monsoon precipitation exhibits a pronounced diurnal cycle. The timing and magnitude of rainfall are influenced by surface heating, land–sea thermal contrasts, boundary-layer evolution, moisture transport, regional topography, and the organization of convection. Errors in the simulated timing or intensity of convection can produce systematic biases in accumulated precipitation. Evaluating the diurnal rainfall cycle therefore provides information that cannot be obtained solely from seasonal or daily rainfall totals (Sen Roy and Balling, 2007).

Despite continuing advances in observations, data assimilation, numerical modeling, and computational capability, accurate simulation and prediction of the ISM remain challenging. Forecast skill over tropical and monsoon regions is limited by multiscale interactions among atmospheric circulation, clouds, convection, radiation, moisture, land-surface processes, and ocean–land–atmosphere feedbacks. These processes operate over a wide range of spatial and temporal scales, and forecast errors generally increase with lead time as the direct influence of the atmospheric initial conditions decreases (Nageswararao *et al.*, 2022).

Global coupled models continue to exhibit systematic biases in the representation of the ISM, including errors in the spatial distribution and seasonal evolution of rainfall, delayed monsoon onset, and limitations in representing intraseasonal variability (Sperber *et al.*, 2013). Operational numerical weather prediction systems may also exhibit deficiencies in important onset-related circulation features. For example, although the operational high-resolution Global Forecast System can reproduce several characteristics associated with monsoon onset over Kerala,

it may underestimate the amplitude of the low-level southwesterly winds (Sarkar and Narbar, 2025). Such circulation errors can affect moisture transport from the surrounding oceans and influence the timing, location, and intensity of rainfall over India.

Increasing horizontal resolution and improving physical parameterizations are important approaches for reducing monsoon-model biases. Higher resolution provides a more detailed representation of coastlines, terrain, mesoscale circulation, and rainfall associated with complex orography. Previous studies have shown that increased horizontal resolution can improve the representation of rainfall over the Western Ghats, while improvements in convection and related physical parameterizations can reduce precipitation and near-surface temperature biases over South Asia (Rajendran *et al.*, 2012; Anand *et al.*, 2018). However, improvements are not necessarily uniform across all variables, regions, and forecast lead times. Process-oriented evaluations are therefore required to determine which aspects of the monsoon system benefit from increased resolution and updated model physics.

Considerable progress in monsoon modeling and prediction has been achieved by major international operational and research centers. Coupled ensemble prediction systems, such as the European Centre for Medium-Range Weather Forecasts seasonal forecasting system SEAS5 and the UK Met Office Global Seasonal Forecast System 5, GloSea5, incorporate higher-resolution atmospheric and ocean models, improved initialization procedures, and updated physical parameterizations (MacLachlan *et al.*, 2015; Johnson *et al.*, 2019). International initiatives such as the Sub-seasonal to Seasonal Prediction Project have further supported the development and systematic comparison of forecasts produced by multiple operational centers (Vitart *et al.*, 2017). For the Indian summer monsoon, SEAS5 and GloSea5-GC2 have demonstrated useful skill in predicting large-scale circulation and monsoon onset, although challenges remain in predicting regional rainfall and smaller-scale features (Johnson *et al.*, 2017; Chevuturi *et al.*, 2019, 2021). Persistent deficiencies also remain in the representation of regional precipitation and intraseasonal monsoon variability (Keane *et al.*, 2021; Chevuturi *et al.*, 2021). These continuing challenges highlight the importance of process-oriented evaluations of newly developed forecasting systems.

The Unified Forecast System (UFS), developed by NOAA in collaboration with the broader research community, is a community-based Earth-system modeling framework designed to support forecast applications across weather-to-seasonal timescales using shared scientific

components, software infrastructure, and model architecture (Tallapragada, 2018; Uccellini *et al.*, 2022). Its atmospheric component employs the Finite-Volume Cubed-Sphere dynamical core, which provides a scalable framework for hydrostatic and nonhydrostatic global atmospheric prediction, including applications at convection-allowing resolutions (Harris *et al.*, 2021). The common UFS framework is intended to strengthen collaboration between research and operational communities and accelerate the transition of scientific advances into operational forecast systems.

A sequence of early coupled UFS prototypes, designated P1–P8, was developed and evaluated for future global, ensemble, and seasonal prediction applications. Evaluations showed that most week-1 and week-2 benchmark anomaly-correlation scores improved relative to the Climate Forecast System, version 2, although exceptions and persistent systematic biases remained (Stefanova *et al.*, 2022). More recently, several high-resolution UFS configurations have been developed for global deterministic medium-range weather prediction. These configurations incorporate changes in horizontal resolution, model physics, configuration settings, coupling strategy, and initialization procedures. However, systematic process-oriented assessments of these newer configurations with respect to Indian Summer Monsoon circulation, precipitation, and diurnal variability remain limited.

The present study extends previous broad evaluations of UFS forecast performance by providing a process-oriented assessment focused specifically on the ISM. Five generations of high-resolution UFS prototypes are considered. Because the third generation was tested in two distinct configurations, HR3a and HR3b, a total of six configurations—HR1, HR2, HR3a, HR3b, HR4, and HR5 are evaluated. The analysis covers the 2020 monsoon period from 10 June to 8 September. Most evaluations of circulation indices, rainfall indices, and spatial precipitation patterns use day-10 forecasts, while additional week-1 and week-2 composites are examined to assess daytime and nighttime precipitation biases.

The forecasts are evaluated using ERA5 and GFSv16 analyses for atmospheric circulation and CMORPH and GPCP products for precipitation. Four dynamical indices the East Asian–western North Pacific Monsoon Index (Wang *et al.*, 2008), Webster–Yang Monsoon Index (Webster and Yang, 1992), South Asian Monsoon Index (Goswami *et al.*, 1999), and Dynamic Indian Monsoon Index (Wang and Fan, 1999) are used to assess the intensity and temporal evolution of the large-scale monsoon circulation. Three rainfall-based indices the Webster–Yang Precipitation Index (Webster and Yang, 1992), South Asia

Precipitation Index (Goswami *et al.*, 1999), and Indian Continent Precipitation Index (Goswami *et al.*, 1999) are used to examine rainfall variability over selected monsoon domains. The evaluation also considers spatial circulation and precipitation differences between the periods before and after 25 July 2020, regional precipitation biases, and the timing and magnitude of the diurnal rainfall cycle. Together, these diagnostics provide a comprehensive assessment of the strengths and limitations of the high-resolution UFS configurations.

The primary objective of this study is to evaluate the ability of the six high-resolution UFS configurations to represent major characteristics of the 2020 ISM. Specifically, the study examines their performance in simulating: (i) the temporal evolution and intensity of the large-scale monsoon circulation; (ii) rainfall intensity and variability over selected monsoon domains; (iii) circulation and precipitation differences across the selected monsoon transition date; (iv) spatial precipitation patterns and regional biases; and (v) daytime, nighttime, and diurnal precipitation variability over the Indian subcontinent. Particular attention is given to whether the newer HR4 and HR5 configurations improve the representation of monsoon circulation and precipitation relative to the earlier configurations and the operational GFSv16.

The remainder of the paper is organized as follows. Section 2 describes the high-resolution UFS configurations, retrospective forecast design, reference datasets, monsoon indices, and evaluation methodology. Section 3 presents the results for the dynamical and rainfall-based indices, circulation and precipitation differences across the selected transition date, spatial precipitation biases, and diurnal rainfall variability. Section 4 summarizes the principal findings, remaining model deficiencies, and implications for future UFS development.

2. Data and methodology

2.1. UFS configurations and forecast design

As the Unified Forecast System has evolved, five generations of high-resolution UFS prototypes have been developed and tested, incorporating changes in horizontal resolution, physical parameterizations, model dynamics, coupling configuration, and model settings. Because the third generation was evaluated using two distinct configurations, HR3a and HR3b, a total of six configurations—HR1, HR2, HR3a, HR3b, HR4, and HR5—are examined in this study. HR1, HR2, and HR3a use the C786 horizontal grid, corresponding to an

approximate grid spacing of 13 km, whereas HR3b, HR4, and HR5 use the C1152 grid, corresponding to approximately 9 km. All configurations employ 127 vertical levels. The horizontal resolution and principal physics and dynamics updates of the six configurations are summarized in Table 1. The UFS Weather Model source code is available through the UFS Community GitHub repository at <https://github.com/ufs-community/ufs-weather-model>.

The forecasts were initialized at 00UTC from June 1, 2020 through August 30 with every 3 days, and integrated a maximum lead time of 384 hours. The verification period extends from 10 June to 8 September 2020, providing a total of 31 forecast cases. Forecast fields were compared with the corresponding analyses and observational products at their valid times. Unless otherwise stated, the circulation-index, rainfall-index, and spatial precipitation evaluations use forecasts at lead Day-10, or 240 h. The daytime and nighttime precipitation analysis uses separate week-1 and week-2 forecast composites.

Lead Day-10 was selected to evaluate model performance near the upper end of the deterministic medium-range forecast period. At this lead time, errors associated with atmospheric dynamics, physical parameterizations, moisture transport, convection, and land-atmosphere interactions have had sufficient time to develop. Day-10 therefore provides a stringent assessment of whether improvements in the high-resolution configurations persist beyond the early forecast period, when forecasts are more strongly influenced by their initial conditions. A systematic assessment of forecast performance as a function of lead time is beyond the scope of the present study.

2.2. Verification datasets and preprocessing

Precipitation forecasts were evaluated primarily against the bias-corrected Climate Prediction Center Morphing Technique Precipitation Climate Data Record (CMORPH; Xie *et al.*, 2017). CMORPH has a native spatial resolution of approximately 8 km and a temporal resolution of 30 min. For this study, the CMORPH data were accumulated to 3-hourly and daily totals and mapped to a common 0.25° analysis grid for comparison with the forecasts.

The Global Precipitation Climatology Project Daily Precipitation Analysis Climate Data Record, Version 1.3 (GPCP Daily; Huffman *et al.*, 2001; Adler *et al.*, 2017), was used as an additional independent precipitation reference. GPCP Daily provides global daily precipitation estimates at 1° × 1° resolution. It was used for the

TABLE 1

Horizontal resolution and principal physics and dynamics updates of the high-resolution UFS configurations evaluated in this study

Configuration	Grid (approx. spacing)	Principal physics and dynamics updates
HR1	C768 (~13 km)	Prognostic saSAS cumulus closure; Thompson microphysics and cloud-cover tuning; unified cloud–radiation interaction; Noah-MP fixes and enhancements; uGWD.v0 gravity-wave-drag physics; MERRA2 aerosol treatment.
HR2	C768 (~13 km)	Noah-MP optimization, including surface/soil parameter and diagnostic updates; wind-shear and TKE-dependent entrainment updates in convection and PBL mass-flux schemes; unified precipitation-type/product diagnostics; prognostic-closure correction and CAPE-related entrainment enhancement; semi-implicit solver update; minor Thompson microphysics updates; continued uGWD.v0 physics.
HR3a	C768 (~13 km)	Low-sun-angle shortwave-radiation correction; reduced dynamical splitting (n_{split}); implicit Rayleigh damping of vertical motion; transition to uGWD.v1, including non-stationary gravity-wave drag and updated orographic GWD/TOFD; Noah-MP optimization; convection-parameter configuration updates; unified boundary-condition/grid-generation update.
HR3b	C1152 (~9 km)	Same principal physics and dynamics package as HR3a, evaluated at the higher C1152 horizontal resolution.
HR4	C1152 (~9 km)	High-wind ocean momentum-roughness limit and related surface-layer refinements; sea-ice skin-temperature correction and land-surface updates; revised orographic gravity-wave drag, including TOFD and mountain-blocking treatment; damping and time-stepping updates; FV3 omega/dzdt-related update; updated MERRA2 aerosol climatology; convective-cloud-liquid/radiation coupling update.
HR5	C1152 (~9 km)	Cumulus-convection refinements and bug fixes, including prognostic updraft-fraction and TKE-transport/interface updates; Noah-MP land updates including soil-organic-matter effects on soil thermal conductivity, aquifer/hydrologic treatment, snow-aging and potential-evaporation fixes; cloud–radiation interaction update, including land cloud-number concentration and convective-cloud ice-radius changes; orographic gravity-wave-drag retuning for grids <10 km, including reduction of the effective grid-size parameter for C1152.

evaluation of daily area-averaged rainfall indices and was not used for the diurnal precipitation analysis. When required for comparison, GPCP was mapped to the common analysis grid; this interpolation does not increase the effective spatial resolution of the original product.

Atmospheric circulation was evaluated using the ERA5 reanalysis produced by the European Centre for Medium-Range Weather Forecasts (Hersbach *et al.*, 2020) and the operational GFSv16 analysis (NOAA, 2021). Zonal and meridional winds at 850 and 200 hPa were analyzed on a 0.25° grid and compared with the UFS forecasts at corresponding valid times. ERA5 was used as the primary independent reference for the time-series evaluation of the dynamical indices, whereas the GFSv16 analysis was used for selected spatial comparisons within the NCEP modeling framework.

All forecast, analysis, and observational fields were compared at common valid times. The same geographical domains were applied to every dataset when calculating the monsoon indices. Angle brackets in the equations below denote the spatial average over the specified latitude–longitude domain.

2.3. Calculation of monsoon indices

A suite of dynamical and rainfall-based monsoon indices was used to quantify the structure, intensity, and temporal variability of the Indian Summer Monsoon. The dynamical-index domains are shown in Fig. 1, and the rainfall-index domains are shown in Fig. 2. In the equations below, u_{850} and u_{200} denote zonal wind at 850 and 200 hPa, respectively; v_{850} and v_{200} denote meridional wind at the same levels; and P denotes daily accumulated precipitation. Unless otherwise stated, the indices were calculated from day-10 forecasts and the corresponding reference datasets at the same valid times.

2.3.1. Dynamical monsoon indices

The East Asian–western North Pacific Monsoon Index (EAWNPI; Wang *et al.*, 2008) is calculated as the difference between the 850-hPa zonal wind averaged over the southern and northern domains shown in Fig. 1.

$$\text{EAWNPI}(t) = \langle u_{850}(t) \rangle [5^{\circ}\text{--}15^{\circ}\text{N}, 90^{\circ}\text{--}130^{\circ}\text{E}] - \langle u_{850}(t) \rangle [20^{\circ}\text{--}30^{\circ}\text{N}, 110^{\circ}\text{--}140^{\circ}\text{E}] \quad (1)$$

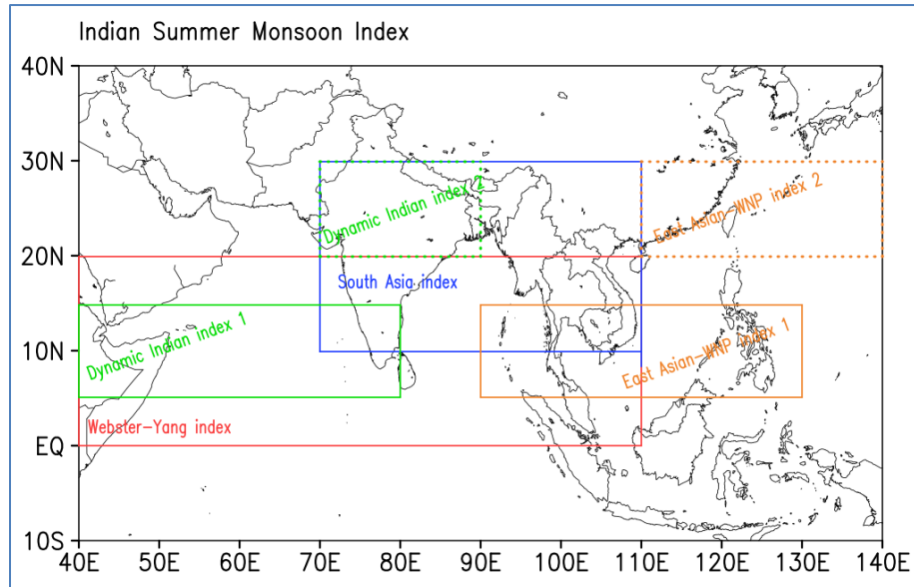


Fig. 1. Domains used to calculate the dynamical monsoon indices

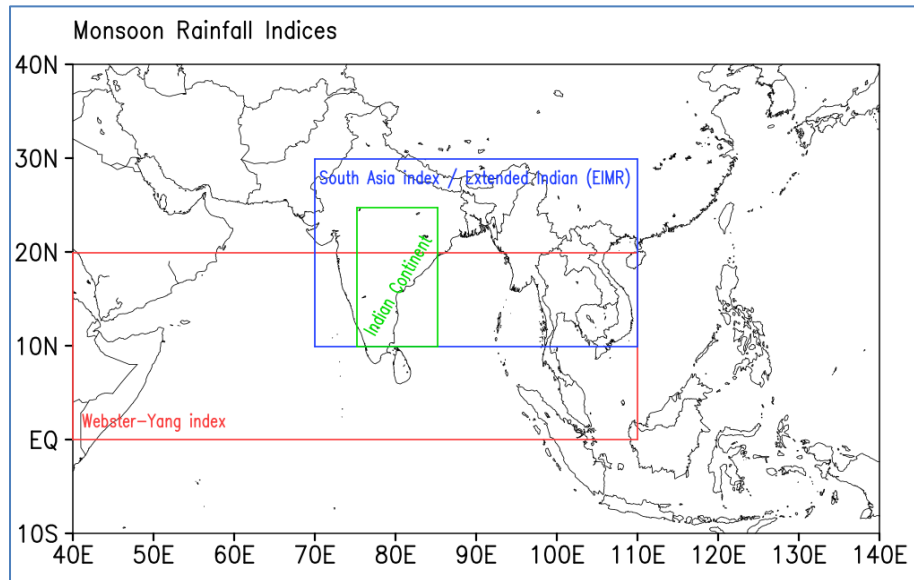


Fig. 2. Domains used to calculate monsoon rainfall indices

Positive values indicate a stronger contrast between the tropical western North Pacific westerlies and the subtropical East Asian circulation.

The Webster–Yang Monsoon Index (WYI; Webster and Yang, 1992) measures the vertical shear of the zonal wind over the broad South Asian monsoon region:

$$\text{WYI}(t) = \langle u_{850}(t) - u_{200}(t) \rangle [0^\circ\text{--}20^\circ\text{N}, 40^\circ\text{--}110^\circ\text{E}] \quad (2)$$

The South Asian Monsoon Index (SAMI; Goswami

et al., 1999) represents the vertical shear of the meridional wind over South Asia:

$$\text{SAMI}(t) = \langle v_{850}(t) - v_{200}(t) \rangle [10^\circ\text{--}30^\circ\text{N}, 70^\circ\text{--}110^\circ\text{E}] \quad (3)$$

The Dynamic Indian Monsoon Index (DIMI; Wang and Fan, 1999) measures the low-level zonal-wind contrast between the southern Arabian Sea and the northern Indian region:

$$\text{DIMI}(t) = \langle u_{850}(t) \rangle [5^\circ\text{--}15^\circ\text{N}, 40^\circ\text{--}80^\circ\text{E}] - \langle u_{850}(t) \rangle [20^\circ\text{--}30^\circ\text{N}, 70^\circ\text{--}90^\circ\text{E}] \quad (4)$$

2.3.2. Rainfall-based monsoon indices

Three rainfall-based indices were calculated as domain-averaged daily precipitation. The Webster–Yang Precipitation Index (WYPI) uses the geographical domain of the Webster–Yang circulation index:

$$\text{WYPI}(t) = \langle P(t) \rangle [0^\circ\text{--}20^\circ\text{N}, 40^\circ\text{--}110^\circ\text{E}] \quad (5)$$

The South Asia Precipitation Index (SAPI) represents area-averaged precipitation over the broad South Asian monsoon region defined by Goswami *et al.* (1999):

$$\text{SAPI}(t) = \langle P(t) \rangle [10^\circ\text{--}30^\circ\text{N}, 70^\circ\text{--}110^\circ\text{E}] \quad (6)$$

The Indian Continent Precipitation Index (ICPI) represents area-averaged precipitation over the central Indian continental domain:

$$\text{ICPI}(t) = \langle P(t) \rangle [10^\circ\text{--}25^\circ\text{N}, 75^\circ\text{--}85^\circ\text{E}] \quad (7)$$

The rainfall indices are expressed in mm day^{-1} and were not standardized. Positive differences between a forecast index and the corresponding observational index indicate excessive domain-averaged precipitation in the forecast.

3. Results and discussion

3.1. Indian summer monsoon Indices

Four dynamical monsoon indices the East Asian–western North Pacific monsoon index (EASMI), Webster–Yang Monsoon Index (WYI), South Asian Monsoon Index (SAMI), and Dynamic Indian Monsoon Index (DIMI)—were used to evaluate the ability of the high-resolution UFS configurations to represent the structure, intensity, and temporal evolution of the Indian Summer Monsoon circulation. All indices presented in this section were calculated from forecasts at lead day 10 (240 h) for the period from 10 June to 8 September 2020. The UFS results were evaluated primarily against ERA5, while the operational GFSv16 forecast and analysis were included as additional references. The geographical domains used to calculate the four indices are shown in Fig. 1.

3.1.1. East Asia–WNP monsoon Index

The East Asian–western North Pacific Monsoon Index measures the horizontal shear of the lower-tropospheric zonal wind between the southern tropical region ($5^\circ\text{--}15^\circ\text{N}$, $90^\circ\text{--}130^\circ\text{E}$) and the northern subtropical region ($20^\circ\text{--}30^\circ\text{N}$, $110^\circ\text{--}140^\circ\text{E}$). Positive values indicate

stronger 850-hPa westerly winds over the southern region relative to the northern region, whereas negative values indicate a weakening or reversal of this circulation contrast.

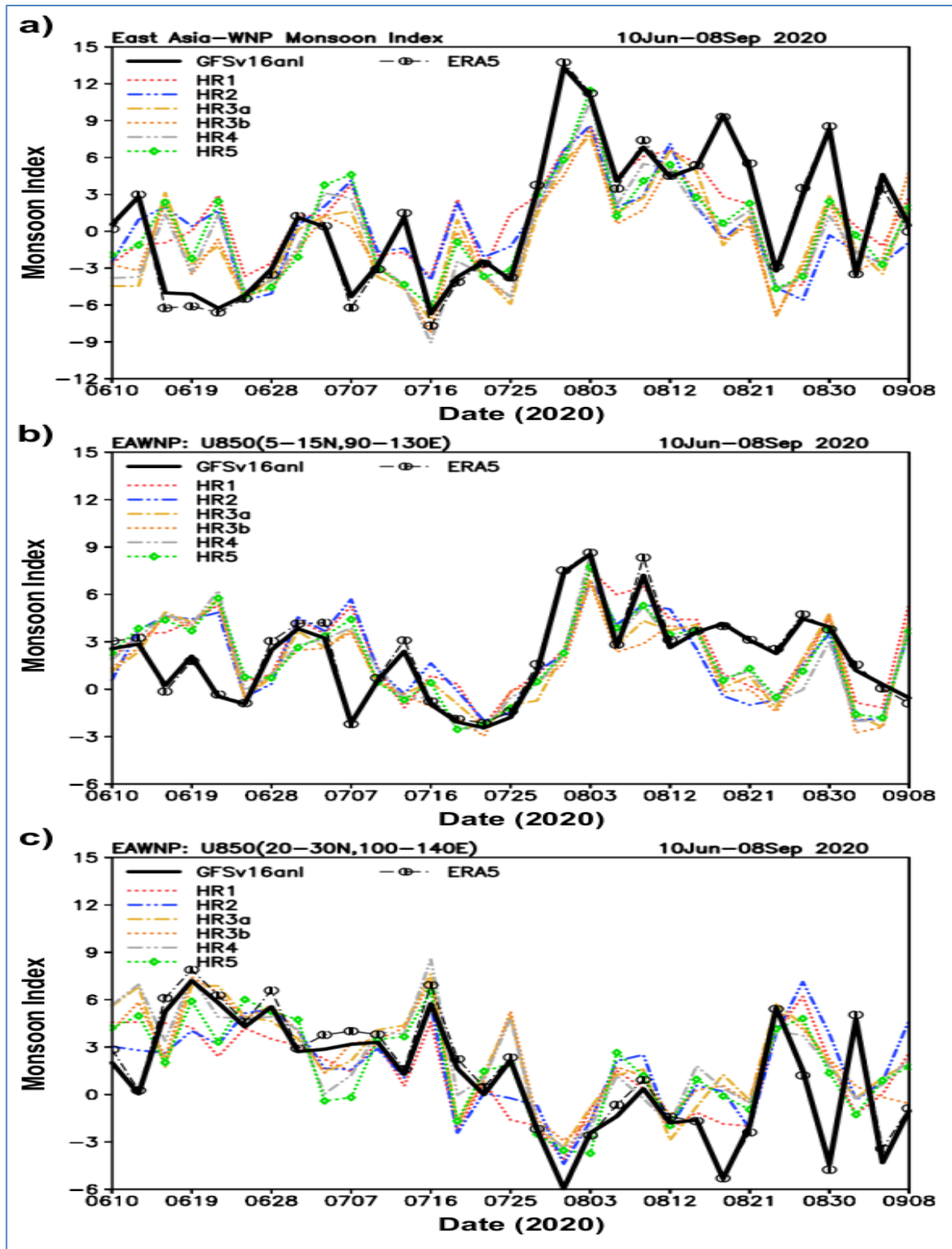
Fig. 3a compares the index calculated from the day-10 forecasts of the six high-resolution UFS configurations and the operational GFSv16 forecast with ERA5 and GFSv16 analyses during 10 June–8 September 2020. The reference analyses exhibit pronounced intraseasonal variability, with alternating positive and negative phases during the monsoon season. The forecast configurations reproduce several major features of this variability, including the negative phase in mid-July, the rapid strengthening during late July and early August, and the subsequent fluctuations during August. Nevertheless, differences remain in the timing and magnitude of individual peaks and troughs, and no single configuration consistently provides the closest agreement with the reference analyses throughout the evaluation period.

Figs. 3b and 3c present the 850-hPa zonal-wind components averaged over the southern and northern regions, respectively. The southern-region winds show substantial variability, including a marked strengthening of the low-level westerlies during late July and early August. The northern-region winds also vary considerably and alternate between positive and negative values during the evaluation period. Errors in the index therefore reflect contributions from both wind components. However, the greater spread among the forecasts over the southern region during several periods suggests that errors in the representation of the tropical low-level westerlies make an important contribution to the differences in the simulated index.

3.1.2. Webster–Yang Monsoon Index

The Webster–Yang Monsoon Index measures the vertical shear of the zonal wind between 850 and 200 hPa over the South Asian monsoon region. Larger positive values indicate stronger large-scale monsoon circulation. Fig. 4 compares the index derived from the day-10 forecasts of the six high-resolution UFS configurations and the operational GFSv16 forecast with the ERA5 and GFSv16 analyses during 10 June–8 September 2020.

The reference analyses show pronounced intraseasonal variability, including strengthening during late June, weakening in late July, a marked increase during early and mid-August, and a subsequent decline toward the end of August. All high-resolution configurations reproduce the broad temporal evolution of the index. However, differences remain in the timing and magnitude of individual peaks and troughs. The configurations generally overestimate the index during



Figs. 3(a-c). Time series for 10 June–8 September 2020 of (a) the East Asian–western North Pacific monsoon index, (b) 850-hPa zonal wind averaged over the southern domain (5°–15°N, 90°–130°E) and (c) 850-hPa zonal wind averaged over the northern domain (20°–30°N, 100°–140°E). Results from day-10 forecasts of HR1, HR2, HR3a, HR3b, HR4, HR5, and operational GFSv16 are compared with ERA5 and GFSv16 analyses. The index and zonal-wind components are expressed in m s^{-1} .

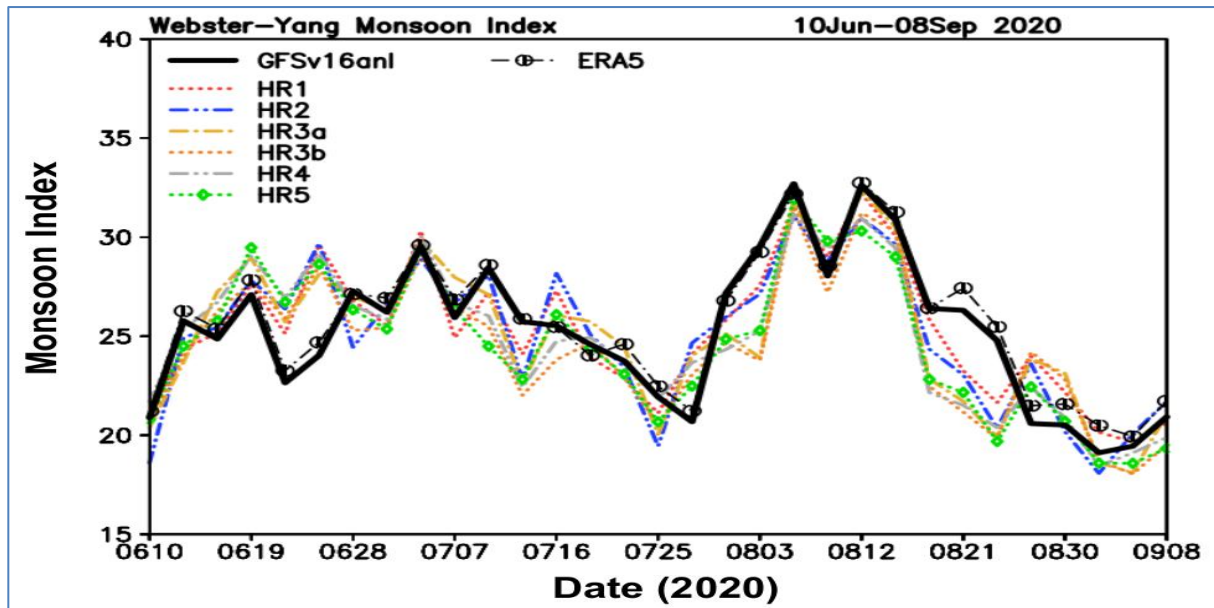


Fig. 4. Time series of the Webster–Yang Monsoon Index for 10 June–8 September 2020, calculated from the day-10 forecasts of HR1, HR2, HR3a, HR3b, HR4, HR5, and the operational GFSv16 forecast and compared with ERA5 and GFSv16 analyses. The index is expressed in ms^{-1} .

portions of late June and underestimate its magnitude during parts of the early- to mid-August strengthening period. Agreement with the reference analyses improves during several other periods. Differences among the high-resolution configurations are relatively small, and no single configuration consistently provides the best agreement throughout the evaluation period.

The Webster–Yang Monsoon Index measures the vertical shear of the zonal wind between 850 and 200 hPa over the South Asian monsoon region and is commonly used as an indicator of large-scale monsoon circulation strength. Figure 4 compares the index calculated from the high-resolution UFS configurations with ERA5 and GFSv16. The high-resolution configurations generally reproduce the observed temporal evolution of the index throughout the evaluation period. A noticeable overestimation occurs in late June, but the simulations show reasonable agreement with ERA5 during most of the remaining period. These results indicate that the high-resolution configurations capture the intraseasonal evolution of the large-scale vertical zonal-wind shear associated with the South Asian monsoon. However, differences among the configurations are relatively small, and no single configuration consistently performs best throughout the entire period.

3.1.3. South Asia Index

The South Asian Monsoon Index represents variations in the large-scale monsoon circulation over South Asia. In this study, the index is calculated from the

vertical shear of the meridional wind between 850 and 200 hPa over the region 10° – 30°N , 70° – 110°E . Larger positive values indicate a stronger meridional circulation contrast associated with the South Asian monsoon.

Fig. 5 compares the index derived from the day-10 forecasts of the six high-resolution UFS configurations and the operational GFSv16 forecast with ERA5 and GFSv16 analyses during 10 June–8 September 2020. The reference analyses exhibit considerable intraseasonal variability, including enhanced index values in mid-June and mid-August and weaker circulation during late August and early September. The high-resolution configurations reproduce the broad temporal evolution of the index, although differences remain in the magnitude and timing of individual peaks and troughs.

The operational GFSv16 forecast overestimates the index during several periods, particularly in July and early to mid-August. The high-resolution configurations generally show smaller departures from the reference analyses during these periods. HR4 and HR5 frequently show closer agreement, although no configuration performs best at every verification time. Larger departures are evident for some configurations near the end of August, including a pronounced weakening in HR2.

3.1.4. Dynamic Indian Monsoon Index

The Dynamic Indian Monsoon Index represents the horizontal contrast in the 850-hPa zonal wind between the southern Arabian Sea and the northern Indian monsoon

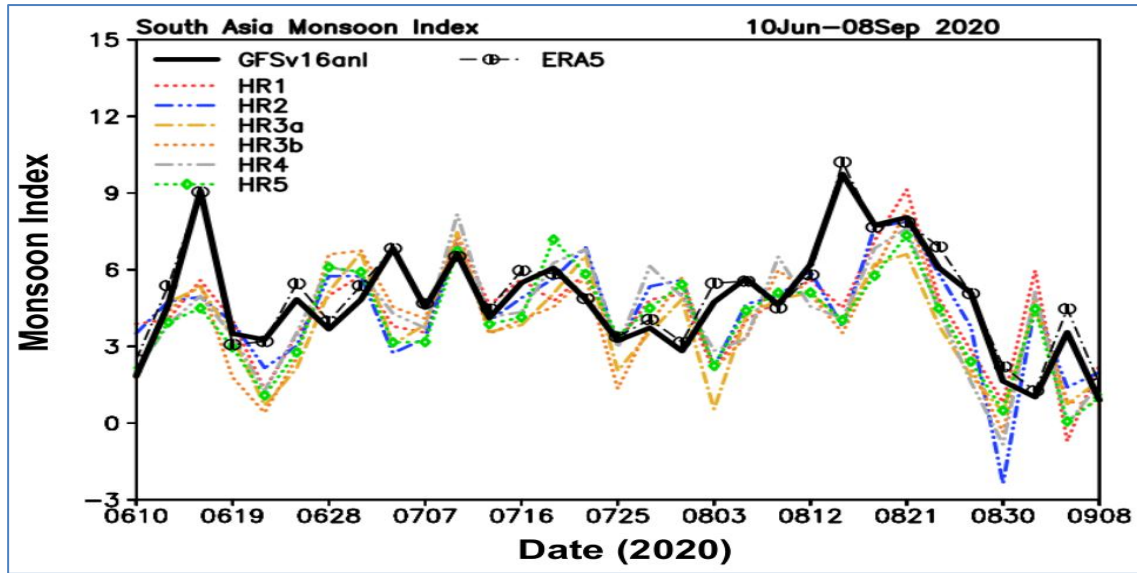


Fig. 5 Time series of the South Asian Monsoon Index for 10 June–8 September 2020, calculated from the day-10 forecasts of HR1, HR2, HR3a, HR3b, HR4, HR5, and the operational GFSv16 forecast and compared with ERA5 and GFSv16 analyses. The index is expressed in ms^{-1}

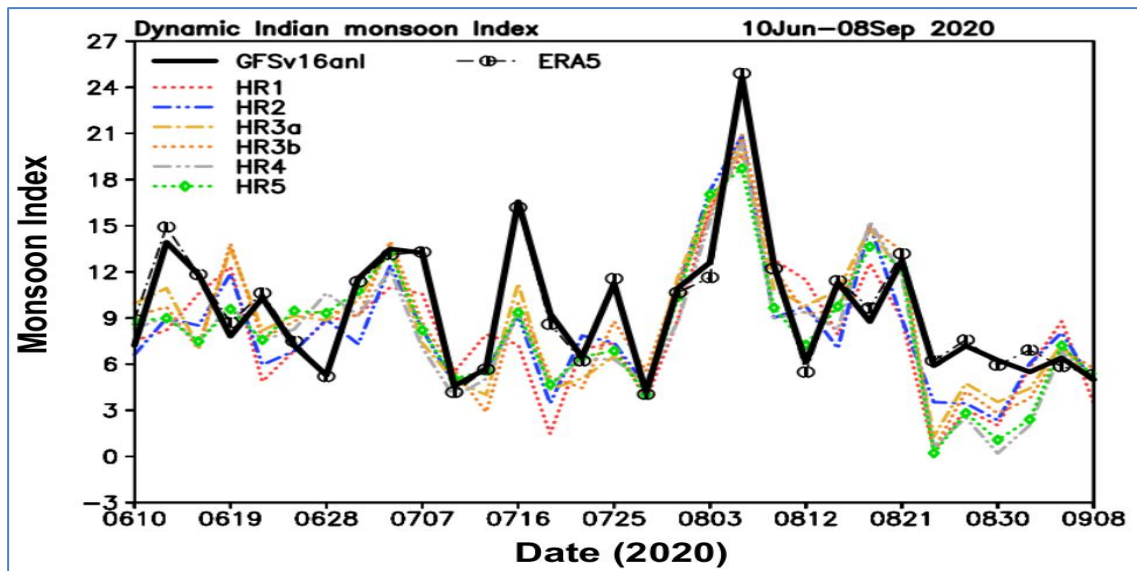


Fig. 6 Time series of the Dynamic Indian Monsoon Index for 10 June–8 September 2020, calculated from the day-10 forecasts of HR1, HR2, HR3a, HR3b, HR4, HR5, and the operational GFSv16 forecast and compared with ERA5 and GFSv16 analyses. The index is expressed in ms^{-1}

region. Larger positive values indicate a stronger low-level monsoon circulation contrast. Although this index is associated with the broader monsoon circulation, it does not directly measure the cross-equatorial flow or Somali jet, which would require analysis of the meridional wind field.

Fig. 6 compares the index calculated from the day-10 forecasts of the six high-resolution UFS configurations and the operational GFSv16 forecast with ERA5 and GFSv16

analyses during 10 June–8 September 2020. The reference analyses exhibit pronounced intraseasonal variability, with enhanced index values during mid-June, mid-July, early August, and late August, followed by weakening toward the end of the evaluation period. The forecast configurations reproduce the broad temporal evolution of the index, including the major strengthening and weakening phases. However, they generally underestimate some of the strongest peaks, particularly during mid-July and early August.

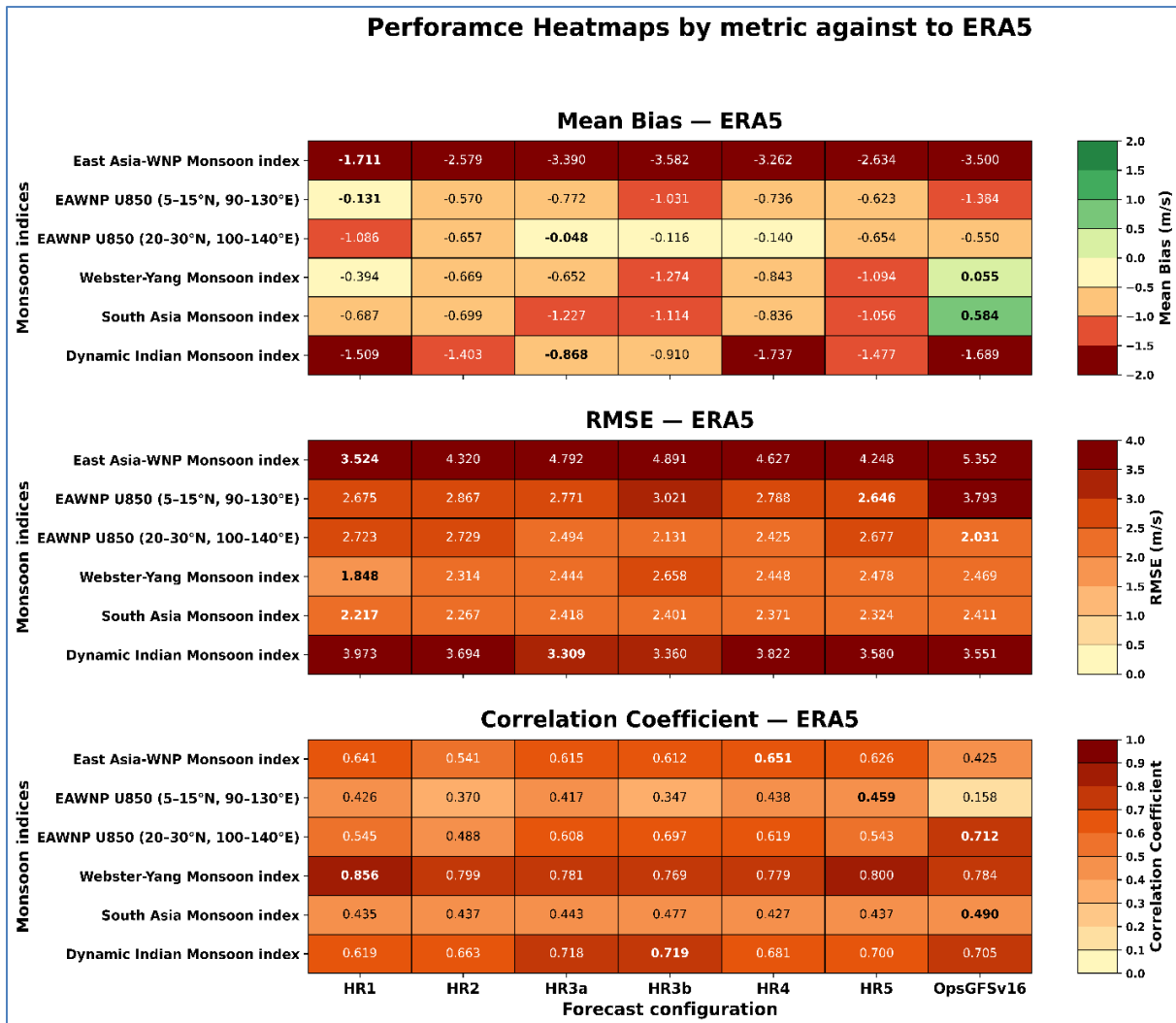


Fig. 7. Performance comparison of the high-resolution UFS configurations (HR1, HR2, HR3a, HR3b, HR4, and HR5) and the operational GFSv16 forecast against ERA5 for the dynamical monsoon indices and the two 850-hPa zonal-wind components used to calculate the East Asian–western North Pacific Monsoon Index (EAOWNPI). The three panels show mean bias (top), root-mean-square error (RMSE; middle), and temporal correlation coefficient (bottom) for the period 10 June–8 September 2020 using day-10 forecasts. Mean bias and RMSE are expressed in m s^{-1} , while the correlation coefficient is dimensionless. Bias values closer to zero, lower RMSE values, and higher correlation coefficients indicate better agreement with ERA5. Bold values identify the best-performing forecast configuration for each diagnostic and metric.

The performance of the high-resolution configurations is generally comparable to that of the operational GFSv16 forecast. Positive and negative departures occur at different times, and no single configuration consistently provides the closest agreement with the reference analyses. In contrast to some of the other monsoon indices, the Dynamic Indian Monsoon Index does not show a consistent improvement in the newer high-resolution configurations. This indicates that increased horizontal resolution and associated configuration updates do not produce uniform improvements in all aspects of the large-scale monsoon circulation.

Fig. 7 provides an integrated comparison of the dynamical performance of the six high-resolution UFS configurations and the operational GFSv16 forecast relative to ERA5 using mean bias, root-mean-square error (RMSE), and temporal correlation coefficient. The statistics show considerable variation among the forecast configurations and among the individual monsoon diagnostics, indicating that no single configuration consistently provides the best performance across all three metrics. In addition, a configuration with a relatively small mean bias does not necessarily have the lowest RMSE or highest temporal correlation, emphasizing the importance of considering the three measures together.

For the EAWNPI, all forecast configurations exhibit negative mean biases relative to ERA5. HR1 has the smallest magnitude of mean bias (-1.711 m s^{-1}) and also the lowest RMSE (3.524 m s^{-1}), whereas HR4 produces the highest temporal correlation (0.651), closely followed by HR1 (0.641). In contrast, the operational GFSv16 forecast has a relatively large negative bias (-3.5 m s^{-1}), the largest RMSE (5.352 m s^{-1}), and the lowest correlation (0.425). These results indicate that the high-resolution UFS configurations, particularly HR1 and HR4, provide a better representation of the temporal variability of the EAWNPI than operational GFSv16 during the evaluation period, although systematic negative biases remain.

The two 850-hPa zonal-wind components contributing to the EAWNPI show somewhat different behavior. For the southern EAWNPI wind component (5° – 15°N , 90° – 130°E), HR1 has the smallest mean bias (-0.131 m s^{-1}), while HR5 has both the lowest RMSE (2.646 m s^{-1}) and the highest correlation coefficient (0.459). The operational GFSv16 forecast performs less favorably for this component, with a larger negative bias (-1.384 m s^{-1}), an RMSE of 3.793 m s^{-1} , and a relatively weak correlation of 0.158. Thus, the high-resolution configurations show a clear advantage in representing variability in the tropical low-level westerlies, particularly HR5 in terms of RMSE and temporal correlation.

For the northern EAWNPI wind component, HR3a produces the smallest mean bias (-0.048 m s^{-1}), followed closely by HR3b (-0.116 m s^{-1}) and HR4 (-0.140 m s^{-1}). However, the operational GFSv16 forecast has the lowest RMSE (2.031 m s^{-1}) and the highest correlation coefficient (0.712). Among the high-resolution configurations, HR3b performs particularly well, with an RMSE of 2.131 m s^{-1} and a correlation of 0.697. The contrasting performance of the southern and northern wind components suggests that errors in the EAWNPI arise from different contributions in the two averaging regions. In particular, the improvement of the high-resolution configurations is more evident for the southern tropical wind component than for the northern component.

For the WYI, the operational GFSv16 forecast has the smallest mean bias (0.055 m s^{-1}), indicating very little systematic offset from ERA5. Nevertheless, HR1 clearly performs best in terms of RMSE and temporal variability, with the lowest RMSE (1.848 m s^{-1}) and the highest correlation coefficient (0.856). The remaining configurations have correlations ranging from 0.769 to 0.800, showing that all forecasts reproduce much of the observed temporal evolution of the large-scale vertical zonal-wind shear. Thus, although operational GFSv16 has the smallest mean bias, HR1 provides the strongest overall agreement with ERA5 when both RMSE and temporal correlation are considered.

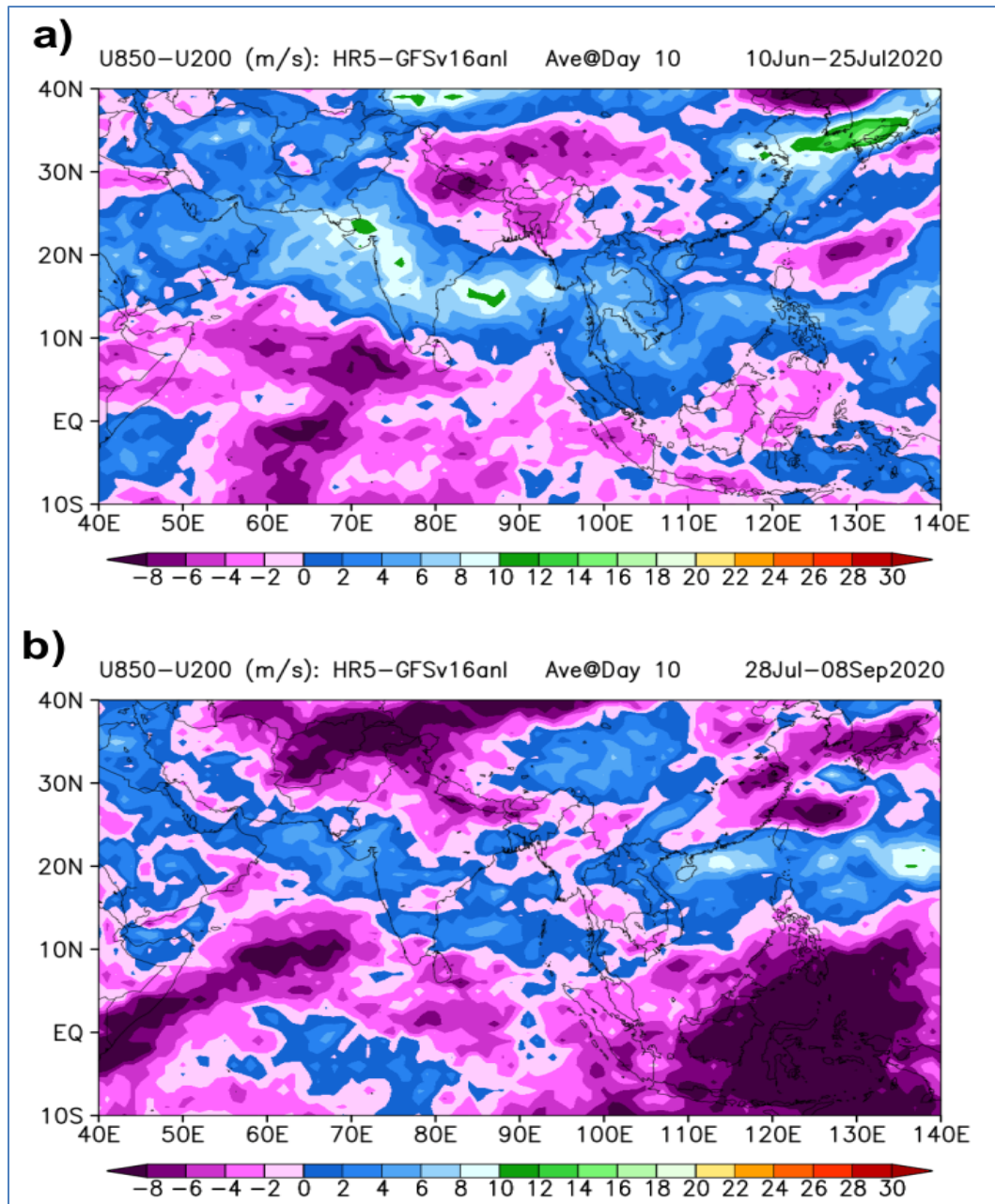
The South Asian Monsoon Index shows a different performance pattern. Operational GFSv16 has the smallest absolute mean bias (0.584 m s^{-1}) and the highest correlation coefficient (0.490). HR1, however, has the lowest RMSE (2.217 m s^{-1}), followed by HR2 (2.267 m s^{-1}). Differences in correlation among the high-resolution configurations are relatively small, ranging from 0.427 to 0.477, with HR3b providing the highest correlation among the UFS prototypes (0.477). These results indicate that improvements in the South Asian Monsoon Index are less systematic than for the EAWNPI and that operational GFSv16 remains competitive for this particular circulation diagnostic.

For the Dynamic Indian Monsoon Index, HR3a and HR3b provide the strongest overall performance. HR3a has the smallest mean bias (-0.868 m s^{-1}) and the lowest RMSE (3.309 m s^{-1}), while HR3b produces the highest temporal correlation (0.719), nearly identical to HR3a (0.718). The operational GFSv16 forecast also shows a relatively high correlation (0.705) but has a larger negative bias (-1.689 m s^{-1}) and RMSE (3.551 m s^{-1}). HR4 and HR5 do not show a systematic advantage for this index, confirming that the benefits of increased horizontal resolution and subsequent configuration changes are not uniform across all components of monsoon circulation.

Taken together, the heatmaps demonstrate that the relative performance of the UFS configurations is strongly diagnostic dependent. HR1 performs particularly well for the EAWNPI and Webster–Yang Monsoon Index, HR5 shows improved performance for the southern EAWNPI low-level wind component, HR3a and HR3b provide the strongest performance for the Dynamic Indian Monsoon Index, and operational GFSv16 remains competitive for the northern EAWNPI wind component and the South Asian Monsoon Index. HR4 provides the highest correlation for the EAWNPI but does not consistently outperform the other configurations for the remaining diagnostics. Therefore, the results do not support the selection of a single high-resolution configuration as uniformly superior. Instead, they suggest that changes in resolution and model configuration affect different aspects of the monsoon circulation in different ways, with improvements in some dynamical features accompanied by neutral or degraded performance in others relatively.

3.2. Spatial patterns during different phases of the Indian summer monsoon

To examine changes in the large-scale monsoon circulation during different phases of the monsoon season, spatial differences between the HR5 day-10 forecasts and the corresponding GFSv16 analyses were calculated for two periods: 10 June – 25 July 2020 and 28 July – 8

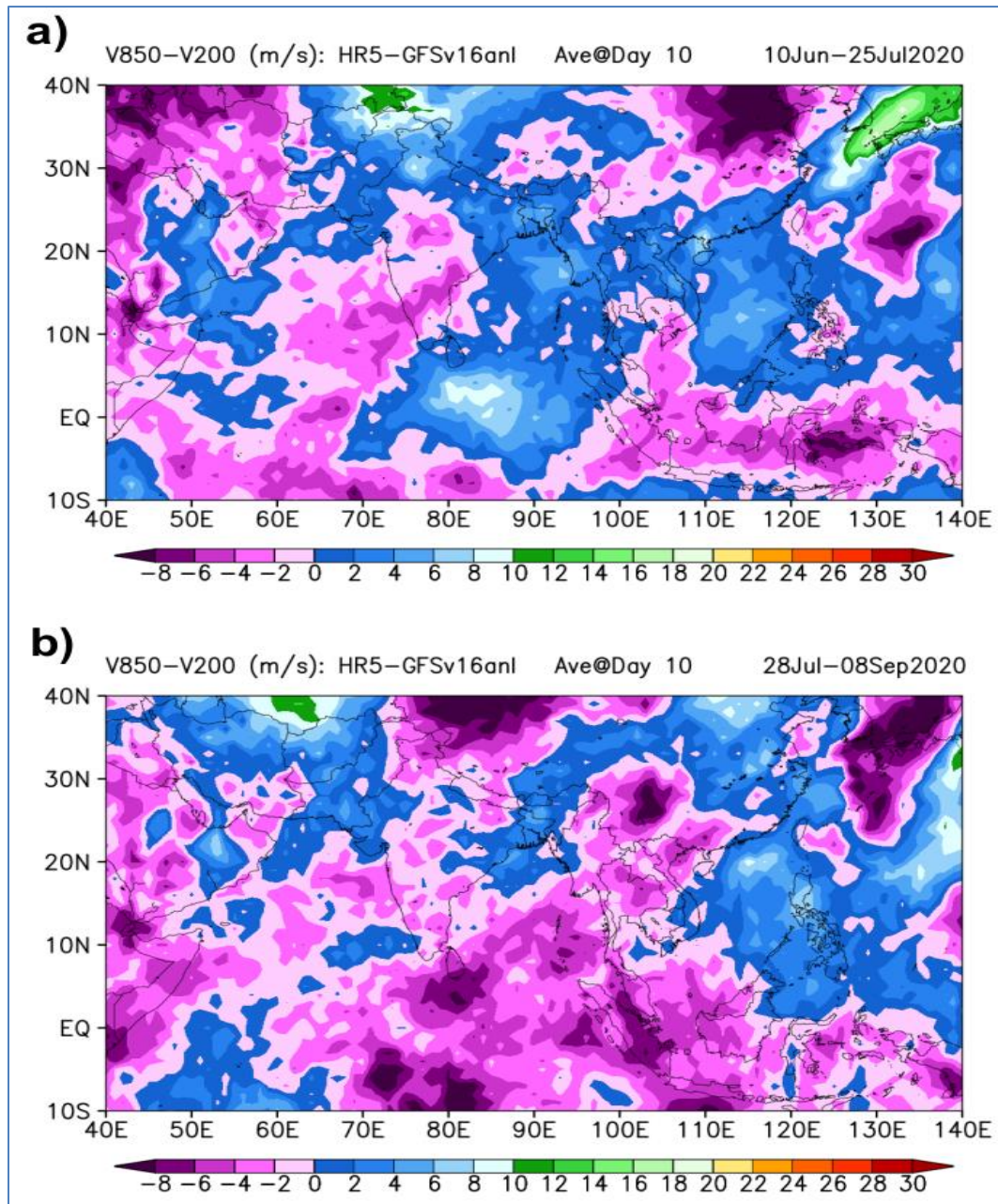


Figs. 8(a&b). Spatial differences in $U_{850}-U_{200}$ between HR5 day-10 forecasts and GFSv16 analysis, averaged over (a) 10 June–25 July 2020 and (b) 28 July–8 September 2020. Differences are calculated as HR5 minus GFSv16 analysis and are expressed in ms^{-1} .

September 2020. GFSv16 analysis was used as the operational NCEP reference for this spatial comparison, whereas ERA5 was used as the primary independent reference for the time-series evaluation in Section 3.1.

Fig. 8 presents differences in the vertical shear of the zonal wind ($U_{850}-U_{200}$). Positive values indicate that HR5 produces a more positive 850–200-hPa zonal-wind shear than the GFSv16 analysis, whereas negative values indicate a more negative shear. During 10 June–25

July, positive differences are evident over much of the Indian subcontinent and parts of Southeast Asia, while negative differences occur over portions of the Arabian Sea, the Tibetan Plateau, and the equatorial Indian Ocean (Fig. 8a). During 28 July–8 September, positive differences persist over much of India and the Bay of Bengal, whereas negative differences become more extensive over the southern Arabian Sea, the equatorial eastern Indian Ocean, and parts of the Tibetan Plateau (Fig. 8b).



Figs. 9(a&b). Spatial differences between HR5 day-10 forecasts and GFSv16 analysis in (a) $V_{850}-V_{200}$ averaged over 10 June-25 July 2020, and (b) $V_{850}-V_{200}$ averaged over 28 July-8 September 2020. Differences are calculated as HR5 minus GFSv16 analysis and are expressed in ms^{-1}

Fig. 9 shows differences in the vertical shear of the meridional wind ($V_{850}-V_{200}$). During 10 June-25 July, positive differences occur over much of India, the Bay of Bengal, and parts of the northern Indian Ocean, while negative differences are found over portions of the Arabian Sea and neighboring regions (Fig. 9a). During 28 July-8 September, negative differences become more widespread over India and the Arabian Sea, whereas positive differences remain over parts of the Bay of Bengal and the western North Pacific (Fig. 9b).

Overall, the spatial patterns indicate that differences between HR5 and the GFSv16 analysis vary substantially with region, wind component, and averaging period. The results therefore suggest that HR5 does not exhibit a uniform strengthening or weakening of the large-scale monsoon circulation; instead, the forecast differences reflect regional and temporal variations in the representation of lower- and upper - tropospheric winds.

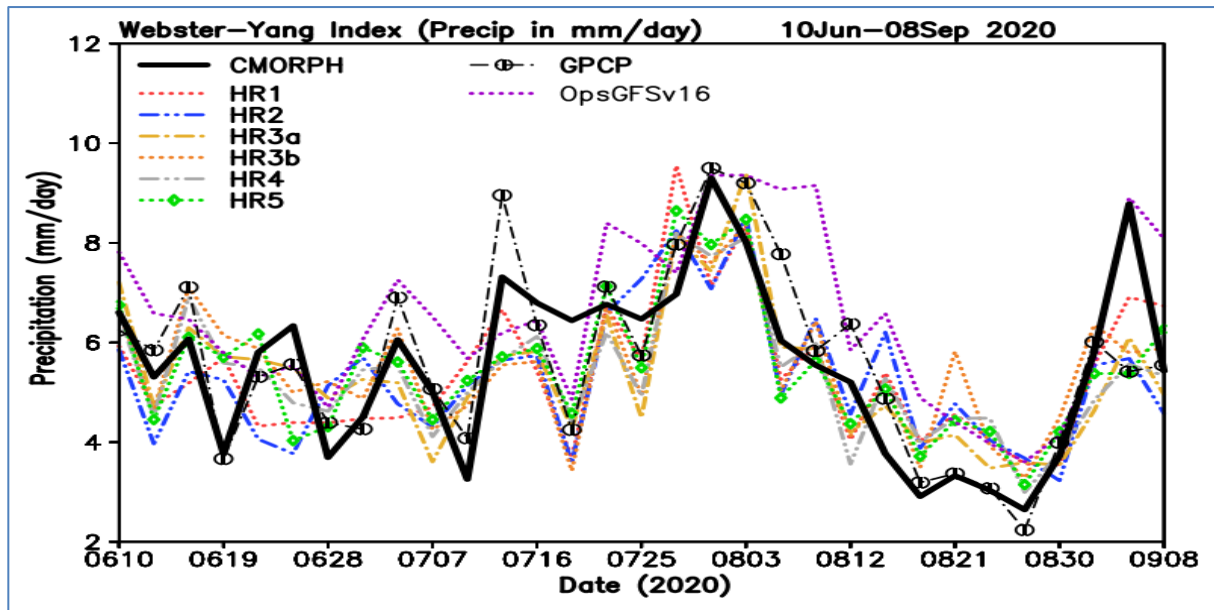


Fig. 10. Time series of precipitation averaged over the Webster–Yang monsoon rainfall region during 10 June–8 September 2020. The Webster–Yang Precipitation Index is calculated from day-10 forecasts of HR1, HR2, HR3a, HR3b, HR4, HR5, and the operational GFSv16 forecast and compared with CMORPH and GPCP. Units are mm day^{-1} .

3.3. Precipitation related to monsoon index from HRs and operational GFSv16

Precipitation-based monsoon indices were used to evaluate the ability of the forecast configurations to reproduce the intensity and intraseasonal variability of rainfall over different monsoon regions. Precipitation from the day-10 forecasts of HR1, HR2, HR3a, HR3b, HR4, HR5, and operational GFSv16 was spatially averaged over the geographical domains shown in Fig. 2. The resulting time series were compared with the corresponding CMORPH and GPCP precipitation estimates at the same valid times during 10 June–8 September 2020.

Three indices were examined: the Webster–Yang Precipitation Index (WYPI), representing rainfall over the broad Webster–Yang monsoon domain; the South Asia Precipitation Index (SAPI), representing regional rainfall across South Asia; and the Indian Continent Precipitation Index (ICPI), representing rainfall over the central Indian continental region. Together, these indices provide complementary information on broad-scale and regional variations in monsoon precipitation. Model performance was evaluated using the temporal evolution of each index and quantitative statistics, including mean bias, root-mean-square error, and correlation coefficient relative to CMORPH and GPCP.

3.3.1. Webster–Yang Precipitation Index (WYPI)

Fig. 10 shows the time series of the Webster–Yang Precipitation Index, which represents area-averaged

precipitation over the Webster–Yang monsoon rainfall region. The reference datasets, CMORPH and GPCP, show pronounced intraseasonal variability during 10 June–8 September 2020, with relatively high precipitation during mid-July and late July to early August, followed by weaker rainfall during the second half of August and a renewed increase in early September. The high-resolution UFS configurations and the operational GFSv16 forecast reproduce the broad temporal evolution of the precipitation index, including the enhanced rainfall during late July and early August and the reduced rainfall during late August. However, differences remain in the magnitude and timing of individual peaks and minima.

During several periods before 25 July, most high-resolution configurations produce precipitation values that are broadly comparable to the reference datasets, although some underestimation occurs during individual events. Around late July and early August, all configurations capture the increase in rainfall, but the simulated peak values are generally slightly weaker than those in CMORPH and GPCP. During the second half of August, when the reference datasets indicate reduced precipitation, the forecast configurations often maintain somewhat higher rainfall, indicating a tendency to overestimate precipitation during this relatively weak monsoon phase. In early September, the forecasts again underestimate the sharp increase seen in CMORPH.

Overall, the high-resolution UFS configurations reproduce the major temporal variations in the WYPI, including the enhanced rainfall during late July–early

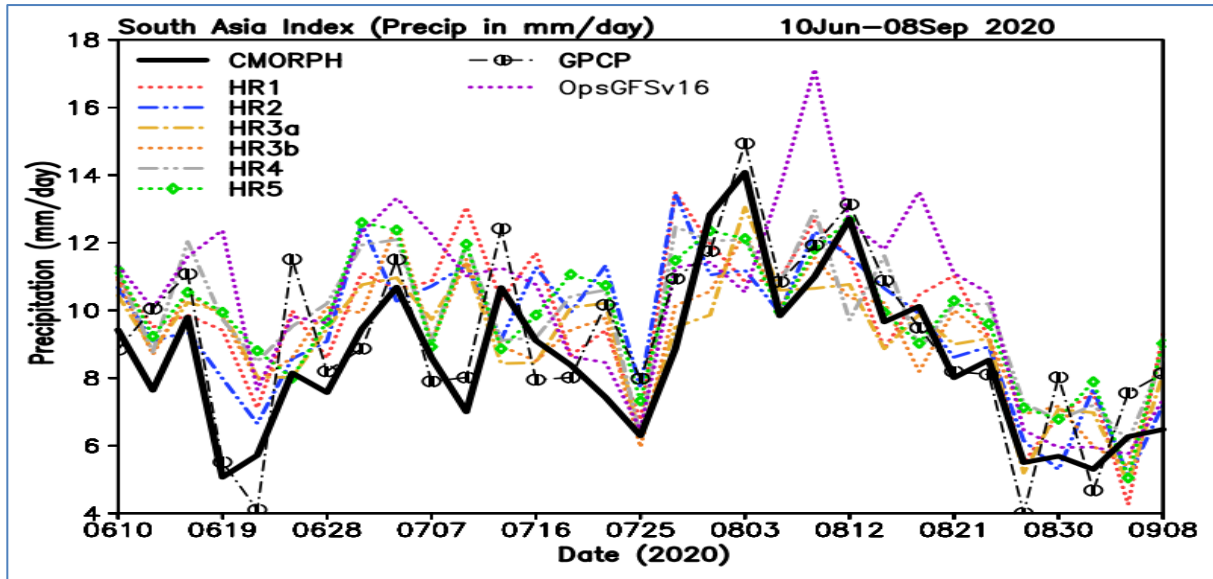


Fig. 11. Time series of the South Asia Precipitation Index during 10 June–8 September 2020, calculated from the day-10 forecasts of HR1, HR2, HR3a, HR3b, HR4, HR5, and the operational GFSv16 forecast and compared with CMORPH and GPCP. Units are mm day^{-1} .

August and the weaker rainfall period during the second half of August. However, their ability to capture the timing and magnitude of individual rainfall peaks and minima varies among the different configurations.

3.3.2. South Asia Precipitation Index

The South Asia Precipitation Index represents area-averaged rainfall over the South Asian monsoon region and describes the temporal variability of regional monsoon precipitation. Fig. 11 compares the index calculated from the day-10 forecasts of the six high-resolution UFS configurations and the operational GFSv16 forecast with CMORPH and GPCP during 10 June–8 September 2020.

CMORPH and GPCP show substantial intraseasonal variability, including relatively weak rainfall during parts of mid-June, enhanced rainfall during late June and early July, a pronounced increase during late July and early August, and a general decrease toward the end of August. The forecast configurations reproduce the broad temporal evolution of the index, although differences remain in the timing and magnitude of individual rainfall peaks and minima.

The operational GFSv16 forecast exhibits a positive precipitation bias during several periods, particularly from late June to early July and during early to mid-August. The high-resolution configurations generally remain closer to the reference datasets, although they also overestimate rainfall during portions of the period before 25 July. Agreement improves during several periods after 25 July, but noticeable differences remain during late August and

early September. No single high-resolution configuration consistently provides the closest agreement with the reference datasets at every verification date.

Overall, the high-resolution UFS configurations reproduce the major intraseasonal variations in the South Asia Precipitation Index, including the enhanced rainfall periods during late June–early July and late July–early August and the subsequent decrease toward the end of August. However, differences among the configurations remain in their ability to reproduce the timing and magnitude of individual precipitation events.

3.3.3. Indian Continent Precipitation Index (ICPI)

The Indian Continent Precipitation Index (ICPI) represents area-averaged rainfall over the central Indian continental region and provides a measure of monsoon precipitation variability over land. Fig. 12 compares the index calculated from the day-10 forecasts of the six high-resolution UFS configurations and the operational GFSv16 forecast with CMORPH and GPCP during 10 June–8 September 2020.

CMORPH and GPCP show pronounced intraseasonal variability, with alternating wet and dry periods throughout the season. Enhanced rainfall occurs during late July and several periods in August, whereas relatively weak rainfall is observed during mid-June, early July, and late August. The forecast configurations reproduce many of these temporal fluctuations, although differences remain in the timing and magnitude of individual rainfall peaks and minima.

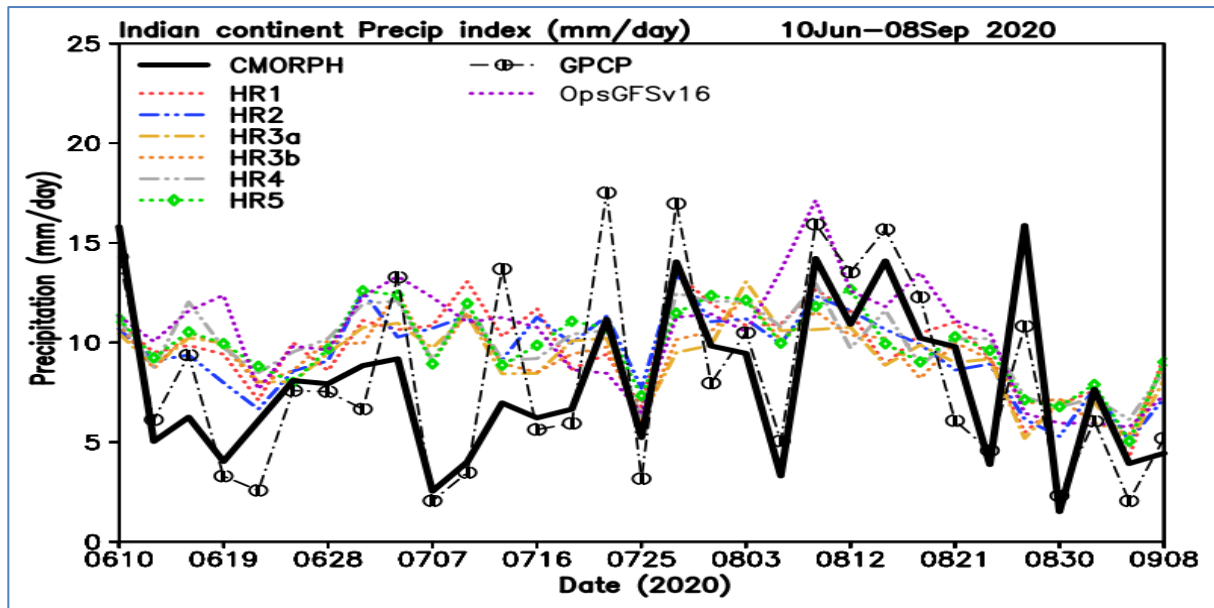


Fig. 12. Time series of the Indian Continent Precipitation Index during 10 June–8 September 2020, calculated from the day-10 forecasts of HR1, HR2, HR3a, HR3b, HR4, HR5, and the operational GFSv16 forecast and compared with CMORPH and GPCP. Units are mm day^{-1} .

Most high-resolution configurations and the operational GFSv16 forecast tend to overestimate precipitation during several periods, particularly when CMORPH indicates relatively weak rainfall. However, underestimation also occurs during some intense rainfall episodes, indicating that the forecast biases are not uniformly positive throughout the season. The spread among the forecast configurations is relatively large during July and August, suggesting differences in their representation of rainfall variability over the Indian land region. No single configuration consistently provides the closest agreement with both reference datasets at every verification time.

Overall, the forecast configurations capture the broad intraseasonal evolution of the ICPI but show greater variability in reproducing individual precipitation events over the Indian continental region. The differences in peak magnitude, timing, and forecast spread indicate that the representation of land-based monsoon rainfall remains sensitive to the individual model configuration.

A quantitative assessment was conducted to examine how effectively the different forecast configurations reproduce the observed monsoon circulation indices. Fig. 13 summarizes the mean bias, RMSE, and correlation coefficient for the Webster–Yang, South Asia, and Indian continent indices using CMORPH and GPCP as reference datasets. This comparison enables the relative strengths and limitations of each configuration to be identified in terms of systematic bias, overall error magnitude, and temporal agreement with the reference observations. For the

Webster–Yang index, the regional configurations generally exhibit small mean biases, whereas GFSv16 shows a substantially larger positive bias (1.037 against CMORPH and 0.862 against GPCP). The smallest absolute bias is obtained by HR5Ops against CMORPH (−0.017) and HR3b against GPCP (−0.135). In terms of RMSE, HR3a performs best for the Webster–Yang index against both CMORPH (1.193) and GPCP (1.212). Correlations are relatively high for this index, with GFSv16 giving the highest correlation against CMORPH (0.750), while HR3a performs best against GPCP (0.760).

For the South Asia index, all configurations show a positive mean bias, although HR3a produces the smallest bias against both CMORPH (0.639) and GPCP (0.034). HR3a also has the lowest RMSE against CMORPH (1.828), whereas HR3b gives the lowest RMSE against GPCP (2.017). Correlation values are moderate, with the strongest performance coming from HR2/HR3b against CMORPH (approximately 0.677) and HR3b against GPCP (0.615). Overall, HR3a and HR3b provide the most consistent performance for the South Asia index, particularly by reducing systematic bias and RMSE relative to the other configurations.

For the Indian continent index, biases and RMSE values are generally larger than for the Webster–Yang and South Asia indices. HR3a strongly reduces the mean bias, giving values of 0.419 against CMORPH and only 0.048 against GPCP. However, HR2 provides the lowest RMSE against both CMORPH (3.766) and GPCP (3.686), and it also yields the highest correlations, reaching 0.580 against

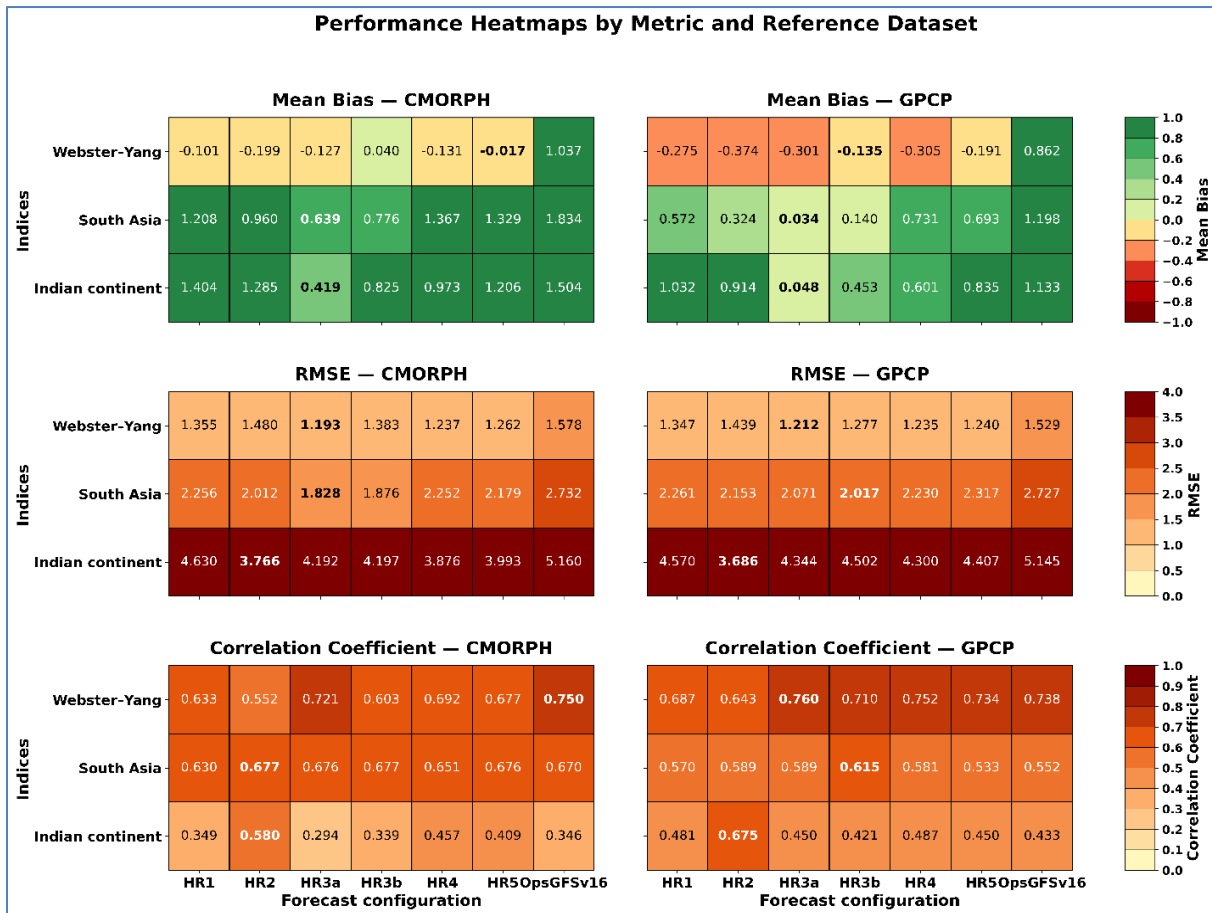


Fig. 13. Performance heatmaps of the seven forecast configurations (HR1, HR2, HR3a, HR3b, HR4, HR5Ops, and GFSv16) for the Webster–Yang, South Asia, and Indian continent indices, evaluated against CMORPH (left column) and GPCP (right column). The top, middle, and bottom panels show mean bias, root-mean-square error (RMSE), and correlation coefficient, respectively. Bold values indicate the best-performing configuration for each index and reference dataset, defined by the smallest absolute mean bias, lowest RMSE, and highest correlation coefficient

CMORPH and 0.675 against GPCP. GFSv16 generally exhibits the largest RMSE for all three indices, indicating poorer overall error characteristics despite its relatively high correlation for the Webster–Yang index.

Taken together, the results indicate that no single configuration performs best for every metric and index. Nevertheless, HR3a is particularly effective at minimizing bias and RMSE for the Webster–Yang and South Asia indices, HR3b performs well for the South Asia index against GPCP, and HR2 shows the strongest overall performance for the Indian continent index. The general agreement between the CMORPH- and GPCP-based evaluations also suggests that these relative performance characteristics are robust to the choice of reference precipitation dataset.

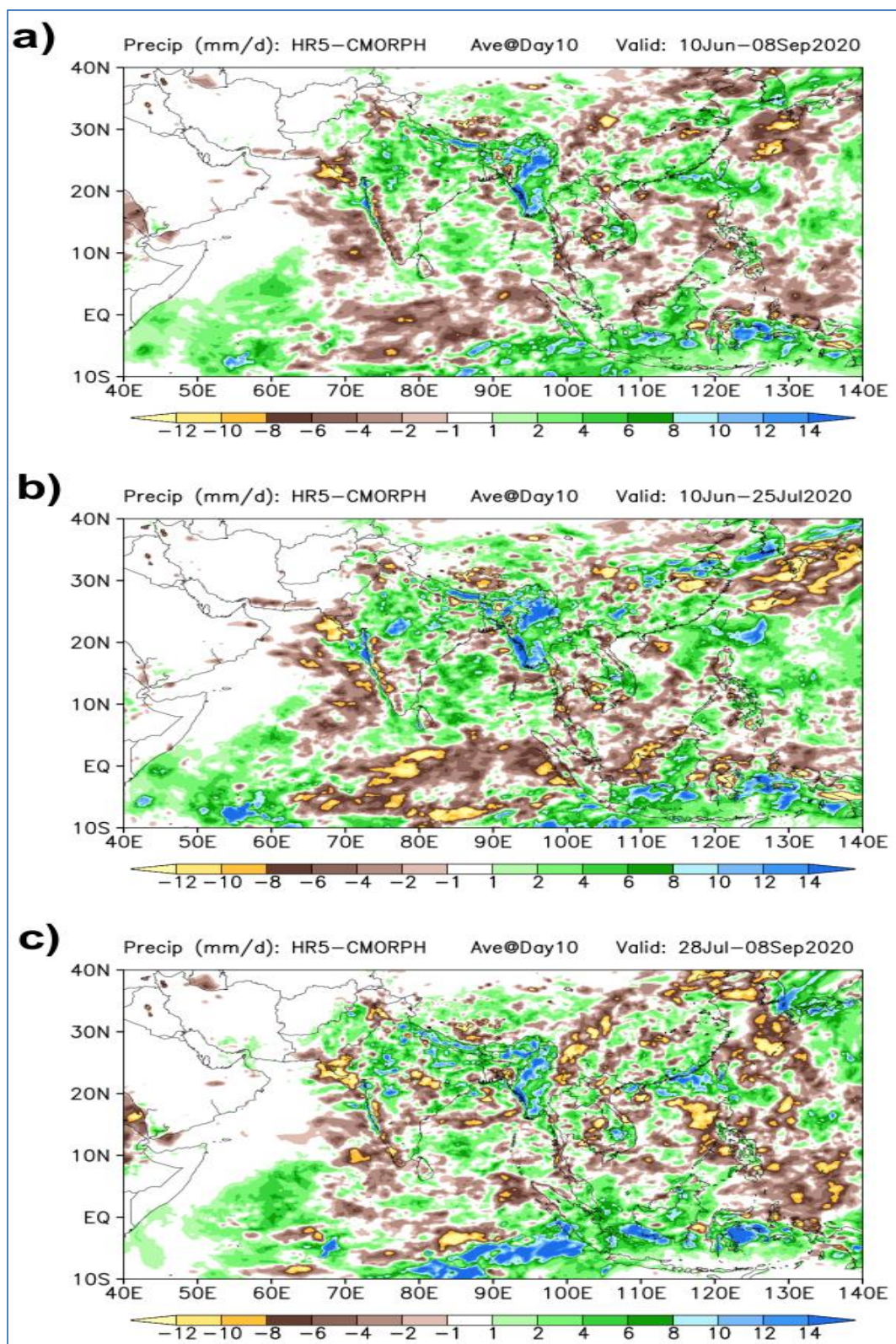
3.4. Spatial precipitation biases

To further examine the regional distribution of precipitation errors, Fig. 14 presents the difference between

the HR5 day-10 forecast precipitation and CMORPH. Positive values indicate that HR5 produces more precipitation than CMORPH, whereas negative values indicate lower precipitation in HR5.

For the complete evaluation period from 10 June to 8 September 2020 (Fig. 14a), HR5 shows positive precipitation biases over substantial portions of central, northern, and northeastern India, as well as parts of the Himalayan foothills and Bay of Bengal region. Negative biases occur over western India, portions of the Arabian Sea, the equatorial Indian Ocean, and several areas of Southeast Asia. The spatial distribution is heterogeneous, with adjacent wet and dry biases indicating regional differences in the simulated location and intensity of rainfall.

During 10 June–25 July 2020 (Fig. 14b), positive biases are prominent over central and northern India, the Himalayan foothills, and parts of eastern India. Negative



Figs. 14(a-c). Spatial differences in mean precipitation between HR5 day-10 forecasts and CMORPH for (a) 10 June–8 September 2020, (b) 10 June–25 July 2020, and (c) 28 July–8 September 2020. Differences are calculated as HR5 minus CMORPH. Positive values indicate a wet bias in HR5, and negative values indicate a dry bias. Units are mm day^{-1} .

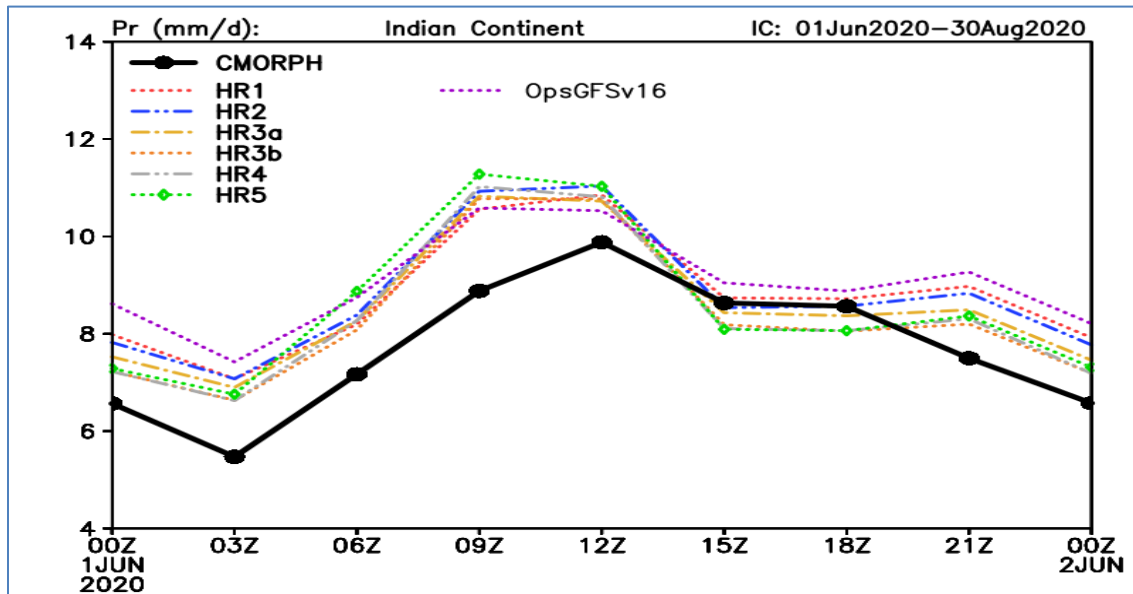


Fig. 15. Mean diurnal cycle of 3-hourly precipitation over the Indian Continent domain (75° – 85° E, 10° – 25° N), calculated from day-10 forecasts of HR1, HR2, HR3a, HR3b, HR4, HR5, and operational GFSv16 and compared with CMORPH. Time is shown in UTC, and precipitation is expressed in mm per 3 h

biases are evident over western and southern India, the Arabian Sea, and portions of the equatorial Indian Ocean. These results indicate that HR5 tends to overestimate rainfall over several continental regions while underestimating rainfall over parts of the western and southern monsoon domains.

During 28 July–8 September 2020 (Fig. 14c), the magnitude and spatial distribution of the biases change. Positive biases remain over parts of central, northern, and northeastern India, but become less spatially extensive in some regions. Negative biases are more evident over portions of eastern India, Southeast Asia, the Bay of Bengal, and the western Indian Ocean. Thus, HR5 does not exhibit a uniform wet or dry bias; instead, the sign and magnitude of the precipitation errors vary by region and averaging period.

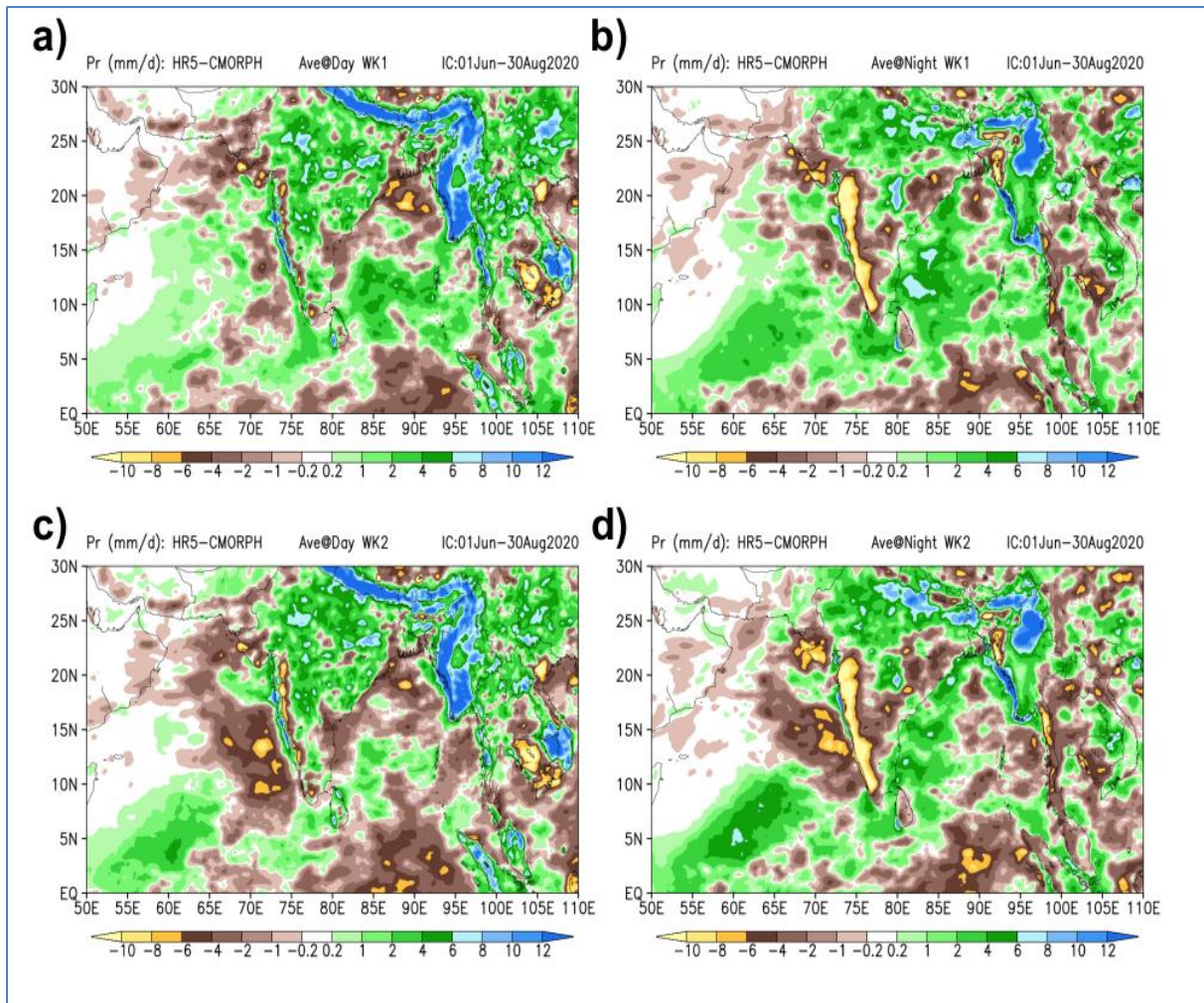
3.5. Diurnal cycle of precipitation over the Indian Continent

The diurnal cycle of monsoon precipitation provides an important measure of how well the model represents the timing and intensity of convection over land. It is influenced by daytime surface heating, boundary-layer development, moisture availability, regional circulation, and the interaction of convection with topography. Even when the daily accumulated precipitation is reasonably simulated, errors in the timing or amplitude of the diurnal cycle can indicate deficiencies in convective and land - surface processes.

Fig. 15 compares the mean 3-hourly precipitation cycle from the day-10 forecasts of the six high-resolution UFS configurations and the operational GFSv16 forecast with CMORPH over the Indian Continent domain. CMORPH shows relatively weak precipitation during the early morning hours, followed by a gradual increase after 06 UTC. The observed precipitation reaches its maximum during 12–15 UTC and then decreases through the evening and nighttime hours.

All high-resolution configurations reproduce the broad daytime increase and evening decrease in precipitation. However, the simulated rainfall begins increasing more rapidly than in CMORPH and reaches its maximum near 12 UTC, indicating a slightly earlier peak. The largest positive biases occur between 09 and 12 UTC, when all high-resolution configurations substantially overestimate the observed precipitation. These biases suggest excessive daytime convective activity over the Indian continental region.

The agreement with CMORPH improves during 15–21 UTC as the simulated precipitation decreases. Among the configurations, HR4 and HR5 are generally closest to CMORPH during the evening period. After 00 UTC, however, most configurations again overestimate precipitation, indicating that simulated convection persists too strongly during the nighttime and early morning hours. The operational GFSv16 forecast exhibits a weaker diurnal amplitude than the high-resolution configurations but produces excessive precipitation during much of the nighttime period.



Figs. 16(a-d). Spatial differences in mean precipitation between HR5 forecasts and CMORPH for (a) daytime during forecast week-1, (b) nighttime during forecast week-1, (c) daytime during forecast week-2, and (d) nighttime during forecast week-2. Differences are calculated as HR5 minus CMORPH for forecasts initialized during 1 June–30 August 2020. Positive values indicate wet biases and negative values indicate dry biases in HR5. Units are mm day^{-1} .

Overall, the high-resolution UFS configurations capture the principal phase of the observed diurnal precipitation cycle but overestimate its amplitude, particularly during the daytime maximum and after midnight. The results indicate that increased horizontal resolution improves the representation of some features of the evening rainfall evolution, especially in HR4 and HR5, but systematic biases in the timing and intensity of continental convection remain.

3.6. Spatial distribution of daytime and nighttime precipitation biases

Fig. 16 compares the spatial differences between HR5 precipitation and CMORPH during daytime and nighttime for forecast weeks 1 and 2. Positive values indicate that

HR5 produces more precipitation than CMORPH, whereas negative values indicate lower precipitation in HR5.

During week 1, the daytime precipitation differences show predominantly positive biases over central, northern, and northeastern India, including portions of the Himalayan foothills and the Bay of Bengal region (Fig. 16a). Negative biases occur over western India, along parts of the Western Ghats, and over sections of the Arabian Sea. The week-1 nighttime pattern also shows positive biases over large parts of central and northern India, while pronounced negative biases occur along the western coast and over portions of southern India (Fig. 16b). These results indicate that HR5 overestimates precipitation over several inland and northern regions but underestimates rainfall in parts of western and southern India.

During week 2, the daytime precipitation biases become more spatially variable (Fig. 16c). Positive biases remain over northern and northeastern India, whereas negative biases become more extensive over western and central India, the western coastal region, and parts of the surrounding oceans. The week-2 nighttime differences show a similar regional contrast, with positive biases over portions of northern and central India and negative biases along the Western Ghats, western India, and parts of Southeast Asia (Fig. 16d).

Overall, HR5 reproduces the broad regional contrast between daytime and nighttime precipitation but exhibits persistent wet biases over northern and northeastern India and dry biases over parts of western and southern India. The week-2 forecasts generally show more extensive and spatially heterogeneous errors than the week-1 forecasts, indicating a degradation in the regional distribution of precipitation with increasing forecast lead time. Because these panels show precipitation differences only, the associated physical causes require additional analysis of circulation and moisture transport.

4. Conclusions

Using ERA5 and GFSv16 analyses and CMORPH and GPCP precipitation products, this study evaluated six high-resolution UFS configurations (HR1, HR2, HR3a, HR3b, HR4, and HR5) during 10 June–8 September 2020. The assessment focused primarily on day-10 forecasts and included four dynamical monsoon indices, three precipitation indices, spatial differences in wind shear and rainfall, the diurnal cycle over the Indian continental domain, and week-1 and week-2 daytime and nighttime precipitation biases.

All configurations reproduced the broad intraseasonal evolution of the large-scale monsoon circulation, but performance varied by index and period. For the East Asian–western North Pacific Monsoon Index, HR4 produced the highest temporal correlation with ERA5 (0.651 compared with 0.425 for operational GFSv16), while HR1 reduced the RMSE to 3.524 m s^{-1} compared with 5.352 m s^{-1} for GFSv16. Differences among configurations were relatively small for the Webster–Yang Monsoon Index, while the Dynamic Indian Monsoon Index showed no consistent advantage of the newer configurations; HR3a had the lowest RMSE (3.309 m s^{-1}), and HR3b produced the highest correlation (0.719). These results demonstrate that no single configuration performs best across all dynamical diagnostics. The HR5 wind-shear differences were spatially heterogeneous and changed between the two analysis periods, indicating

that increased resolution and configuration updates do not produce uniform improvements in every component of the monsoon circulation.

The forecast configurations captured much of the observed intraseasonal variability in the rainfall indices, although errors persisted in the timing and magnitude of individual events. For the Indian Continent Precipitation Index, HR2 produced the lowest RMSE against both CMORPH ($3.766 \text{ mm day}^{-1}$) and GPCP ($3.686 \text{ mm day}^{-1}$), with corresponding correlations of 0.580 and 0.675. HR5 exhibited wet biases over parts of central, northern, and northeastern India and the Himalayan foothills, together with dry biases over portions of western and southern India and adjacent oceanic regions; the magnitude and spatial extent of these biases varied with the averaging period. The high-resolution configurations reproduced the broad phase of the observed diurnal cycle but produced an overly strong and slightly early daytime maximum and excessive precipitation after midnight. HR4 and HR5 showed the closest agreement with CMORPH during the early-evening decline, while the week-2 spatial errors were generally more heterogeneous than those in week 1.

Overall, the newer high-resolution UFS configurations improve selected aspects of medium-range monsoon prediction, but the improvements are strongly diagnostic dependent and no single configuration is uniformly superior. Further development should prioritize the representation of convection, cloud–radiation and land-surface processes, orographic rainfall, and regional moisture transport. The present evaluation is limited to a single monsoon season and deterministic forecasts. Evaluation across multiple monsoon seasons, a broader range of forecast lead times, and ensemble-based probabilistic verification will be necessary to assess the robustness and general applicability of the apparent improvements and to guide future UFS development.

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