University of Reading

CMIP6 skill at predicting interannual to multi-decadal summer monsoon precipitation variability

Article

Published Version

Creative Commons: Attribution 4.0 (CC-BY)

Open Access

Monerie, P.-A. ORCID: https://orcid.org/0000-0002-5304-9559, Robson, J. I. ORCID: https://orcid.org/0000-0002-3467-018X, Ndiaye, C. D., Song, C. and Turner, A. G. ORCID: https://orcid.org/0000-0002-0642-6876 (2023) CMIP6 skill at predicting interannual to multi-decadal summer monsoon precipitation variability. Environmental Research Letters, 18 (9). 094002. ISSN 1748-9326 doi: 10.1088/1748-9326/acea96 Available at https://centaur.reading.ac.uk/112717/

It is advisable to refer to the publisher's version if you intend to cite from the work. See Guidance on citing.

To link to this article DOI: http://dx.doi.org/10.1088/1748-9326/acea96

Publisher: Institute of Physics

All outputs in CentAUR are protected by Intellectual Property Rights law, including copyright law. Copyright and IPR is retained by the creators or other copyright holders. Terms and conditions for use of this material are defined in the End User Agreement.

University of Reading

www.reading.ac.uk/centaur

CentAUR

Central Archive at the University of Reading

Reading's research outputs online

ENVIRONMENTAL RESEARCH
LETTERS

LETTER • OPEN ACCESS

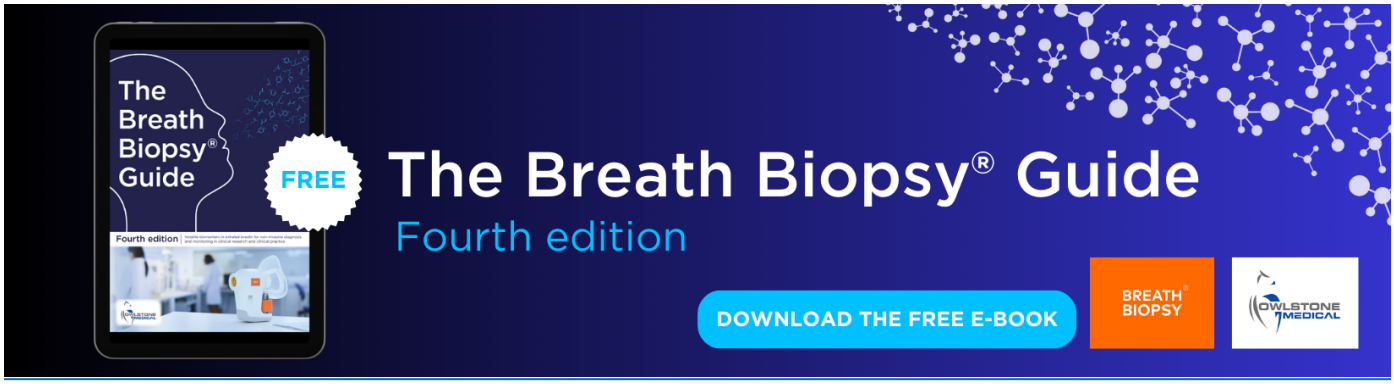
CMIP6 skill at predicting interannual to multi-decadal summer monsoon precipitation variability

To cite this article: Paul-Arthur Monerie *et al* 2023 *Environ. Res. Lett.* **18** 094002

View the article online for updates and enhancements.

You may also like

- A framework to incorporate spatiotemporal variability of rainfall extremes in summer monsoon declaration in India
Vimal Mishra, Amar Deep Tiwari and Rohini Kumar
- Speleothem records of monsoon interannual-interdecadal variability through the Holocene
Sarah E Parker, Sandy P Harrison and Pascale Braconnot
- Year-ahead predictability of South Asian Summer Monsoon precipitation
Nir Y Krakauer



This content was downloaded from IP address 134.225.31.158 on 17/01/2024 at 12:24

IOP Publishing Environ. Res. Lett. 18 (2023) 094002 https://doi.org/10.1088/1748-9326/acea96

ENVIRONMENTAL RESEARCH
LETTERS

CrossMark

OPEN ACCESS

RECEIVED
20 April 2023

REVISED
30 June 2023

ACCEPTED FOR PUBLICATION
25 July 2023

PUBLISHED
7 August 2023

Original content from this work may be used under the terms of the Creative Commons Attribution 4.0 licence.

Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

LETTER

CMIP6 skill at predicting interannual to multi-decadal summer monsoon precipitation variability

Paul-Arthur Monerie[1,*], **Jon I Robson**[1], **Cassien D Ndiaye**[2,3], **Cenyao Song**[4] and **Andrew G Turner**[1,5]

[1] National Centre for Atmospheric Science, Reading, United Kingdom
[2] LPAO-SF/Cheikh Anta Diop University, Dakar, Senegal
[3] LOCEAN/IPSL/Sorbonne University, Paris, France
[4] Previously at Department of Meteorology, University of Reading, Reading, United Kingdom
[5] Department of Meteorology, University of Reading, Reading, United Kingdom
[*] Author to whom any correspondence should be addressed.

E-mail: p.monerie@reading.ac.uk

Keywords: summer monsoon precipitation, prediction systems, skill, interannual variability, multi-decadal variability

Supplementary material for this article is available online

Abstract

Monsoons affect the economy, agriculture, and human health of two thirds of the world's population. Therefore, predicting variations in monsoon precipitation is societally important. We explore the ability of climate models from the sixth phase of the Climate Model Intercomparison Project to predict summer monsoon precipitation variability by using hindcasts from the Decadal Climate Prediction Project (Component A). The multi-model ensemble-mean shows significant skill at predicting summer monsoon precipitation from one year to 6–9 years ahead. However, this skill is dependent on the model, monsoon domain, and lead-time. In general, the skill of the multi-model ensemble-mean prediction is low in year 1 but increases for longer-lead times and is largely consistent with externally forced changes. The best captured region is northern Africa for the 2–5 and 6–9 year forecast lead times. In contrast, there is no significant skill using the ensemble-mean over East and South Asia and, furthermore, there is significant spread in skill among models for these domains. By sub-sampling the ensemble we show that the difference in skill between models is tied to the simulation of the externally forced response over East and South Asia, with models with a more skilful forced response capable of better predictions. A further contribution is from skilful prediction of Pacific Ocean temperatures for the South Asian summer monsoon at longer lead-times. Therefore, these results indicate that predictions of the East and South Asian monsoons could be significantly improved.

1. Introduction

Two thirds of the world's population lives in areas where there is a monsoon in summer (Wang and Ding 2006). Monsoon precipitation variability has effects on economies, agriculture, and human health, among other sectors. Therefore, predicting the future evolution of monsoon precipitation is important, for adaptation strategies (e.g., infrastructure planning).

Individual predictions systems have shown skill at predicting monsoon precipitation on a large range of time scales (Dunstone *et al* 2020, Monerie *et al* 2021). Regionally, some skill has been found over East and southern Africa (Beraki *et al* 2013, Monerie *et al* 2018, Walker *et al* 2019), South America (Jones *et al* 2012), Australia (King *et al* 2020), India (Johnson *et al* 2017, Chevuturi *et al* 2021) and southern China (Lu *et al* 2017) at a seasonal time scale. On longer time scales, prediction systems have exhibited substantial skill at predicting decadal variations in Sahel precipitation (Gaetani and Mohino 2013, Martin and Thorncroft 2014, Mohino *et al* 2016, Otero *et al* 2016, Sheen *et al* 2017, Ndiaye *et al* 2022).

There are multiple sources of skill for predicting summer monsoon precipitation. The role of sea surface temperatures (SSTs), among other slowly varying lower boundary conditions, in predicting monsoon precipitation variations, was theorized by Charney

© 2023 The Author(s). Published by IOP Publishing Ltd

and Shukla (1981). On seasonal time scales, it was shown that the El Niño Southern Oscillation is key for providing skill at predicting precipitation over the tropics (Shukla and Paolino 1983, Wang *et al* 2018, Sohn *et al* 2019, Dunstone *et al* 2020). On decadal time scales, the North Atlantic and Indian Ocean SSTs also yield a certain amount of predictability for monsoon precipitation (Mohino *et al* 2016, Wang *et al* 2018), due to the high prediction skill of prediction systems for Atlantic and Indian Ocean SST (Guemas *et al* 2013, García-Serrano *et al* 2015) and to the effects of these oceanic basins on monsoon precipitation.

Anthropogenic forcing is a source of prediction skill for global mean surface air temperature (Boer *et al* 2016) and SST (e.g., Guemas *et al* 2013) and has known effects on summer monsoon precipitation worldwide (Marvel *et al* 2020, Monerie *et al* 2022).

Previous studies have quantified skill at predicting monsoon precipitation on multi-year time scales with a small number of climate models and ensemble members (e.g., Bellucci *et al* 2015). However, prediction skill values increases with ensemble size (Smith *et al* 2019) and we therefore use the large ensemble of the Decadal Climate Prediction Project (DCPP; Boer *et al* 2016), reducing unpredictable noise, and providing a better estimate of prediction skill. The large ensemble facilitates understanding of the causes of differences between prediction systems at predicting monsoon precipitation, including structural differences between prediction systems. No robust evaluation across a range of models, monsoon domains and timescales has been provided so far. We thus provide, for the first time, a quantification of the ability of sixth phase of the Climate Model Intercomparison Project (CMIP6) prediction systems at predicting interannual to decadal summer monsoon precipitation variability in a global monsoon framework. We expect skill at predicting summer monsoon precipitation to be model dependent (as shown by Delgado-Torres *et al* (2022) for the surface air temperature), area-dependent and lead-time dependent.

We address the following questions:

- Are CMIP6 initialized prediction systems skilful at predicting summer monsoon precipitation on interannual-to-decadal time scales?
- How model dependent is the skill at predicting summer monsoon precipitation?
- Can we identify the sources of skill?

The paper is organized as follows: section 2 describes the simulations and the methodologies used. In section 3 we quantify skill at prediction monsoon precipitation for the multi model mean and for each individual prediction system. Sources of skill are shown in section 4. We discuss results in sections 5 and 6 concludes the main findings of the study.

2. Methods and data

2.1. Data

We use hindcasts of nine climate models from DCPP Component A (Boer *et al* 2016) (DCPPA hereafter). These climate predictions are initialized from observationally constrained datasets every year from 1960 to 2019 and 5–10 ensemble members are used depending on the climate model (table 1). We assume 5–10 ensemble members to be large enough to allow considerably increased prediction skill of monsoon precipitation (Jain *et al* 2019, Monerie *et al* 2021). DCPPA simulations are initialized in November each year and last for 5–10 years after initialization and are forced with historical external forcing.

We assess the impact of initialization by comparing DCPPA simulations to the uninitialized CMIP6 historical simulations (Eyring *et al* 2016; table S1), using the same climate models. These historical simulations begin in 1850 and last for ∼150 years (1850–2014) and use the same external forcings as the DCPPA simulations. Prior to analysis, observations and simulations are first interpolated onto a common 1° horizontal grid.

We assess skill at predicting precipitation using the data of the Climate Research Unit (CRU; Harris *et al* 2014), available from 1901 to present. Skill at predicting surface air temperature is quantified using the NCEP reanalysis (Kanamitsu *et al* 2002), which is given on a 2.5° × 2.5° horizontal resolution and from 1948 to present.

2.2. Method

2.2.1. Assessing skill

Prediction skill is estimated using the anomaly correlation coefficient (ACC) metric, computed between observed and simulated time series. We assess skill at three lead times. The 1 year lead time allows determination of skill at predicting interannual variability in summer monsoon precipitation and is months 14–17 (8–11) for the southern (northern) hemisphere in DJFM (JJAS). Years 2–5 and years 6–9 are 4 years averaged between years 2–5 and 6–9, respectively, and documents predictability of the summer monsoon precipitation on longer time scales. Prediction skill is assessed over the period 1960–2020.

We estimate the significance of the ACC by randomly resampling time series of the ensemble means. We use a 5 year block bootstrap to conserve low-frequency variability in precipitation and temperature using 5000 permutations in a Monte Carlo framework. The ACC values are judged significant at the $p < 0.05$ level if the correlations are stronger than 97.5% of the randomly obtained correlation values, using a two-sided test.

We acknowledge that ACC scores are sensitive to the existence of linear trends (*e.g.*, in precipitation, figure S1). However, we note that removing a

Table 1. List of DCPPA prediction systems and number of simulations used in the study.

Models	Institutions	No. of ensemble members	Length of the integrations (years)	Horizontal resolution (lat × lon)	References
CanESM5	Canadian Center for Climate Modeling and Analysis, Canada	10	10	64 × 128	Swart *et al* (2019)
CMCC-CM2-SR5	Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici. Italy	6	10	192 × 288	Cherchi *et al* (2019)
EcEarth3	EC-Earth-Consortium	10	10	256 × 512	Wyser *et al* (2020)
HadGEM3-GC31-MM	Met Office Hadley Centre, United Kingdom	10	10	324 × 432	Kuhlbrodt *et al* (2018)
IPSL-CM6A-LR	Institut Pierre Simon Laplace, France	10	10	144 × 143	Boucher *et al* (2020)
MIROC6	Japanese modeling community, Japan	10	10	128 × 256	Tatebe *et al* (2019)
MPI-ESM1-2-HR	Deutsches Klimarechenzentrum, Germany	5	10	192 × 384	Mauritsen *et al* (2019)
MRI-ESM2-0	Meteorological Research Institute, Japan	10	5	160 × 320	Yukimoto *et al* (2019)
NorCPM1	NorESM Climate modeling Consortium	10	10	96 × 144	Bethke *et al* (2021)

linear trend can artificially improve skill (figure S2). Therefore, we document the skill at predicting the total summer monsoon variability (internal variability + variability induced by the externally forced response).

2.2.2. Drift correction

DCPPA simulations are initialized from observationally constrained datasets, but then drift away to reach their own model's climatology. The drift can result in fast and large changes in temperature and precipitation (Hermanson *et al* 2018). Hence, we remove the lead-time-dependent drift following the World Climate Research Programme recommendations (ICPO 2011) (see drift correction in the supplementary material) prior to displaying simulated time series. Note that removing the drift does not impact skill as defined by the ACC.

2.2.3. Persistence

The *n*-year persistence is computed based on the observed values in the *n* years prior to the start date. We computed a 1 year and a 4 year persistence.

2.2.4. Defining ensembles

We define ensembles to explore the spread in model skill and to understand sources of prediction skill for summer monsoon precipitation.

2.2.4.1. Ensemble mean (ENSM and HIST)

We assess the ability of DCPPA simulations to predict monsoon precipitation by defining the ensemble mean across models and ensemble members, hereafter called ENSM, as:

$$\bar{P}(j) = \frac{1}{m}\sum_{i=1}^{m} P_i^j,$$

with P precipitation of all m ensemble members i and for each start date j, and $\bar{P}$ precipitation averaged across all ensemble members and start date. m is the total number of ensemble members across all models.

HIST is defined in the same way as ENSM but using the uninitialized simulations. Uninitialized ensemble members simulate internal climate variability, but ensemble members would not be expected to be in-phase and the ensemble mean is an estimate of the forced response to external drivers (e.g., Deser *et al* 2012). Therefore, the comparison of ENSM and HIST allows for an exploration of the importance of initialization for the prediction skill.

2.2.4.2. Best model (BEST)

The prediction system that performs best is selected, according to the ACC values, with the BEST ensemble consisting of only one individual model, for each monsoon domain and each lead-time.

2.2.4.3. A subset of models (SUBSET and WORST SUBSET)

The SUBSET approach follows the ENSM approach, computing the ensemble mean with only the three prediction systems that have the highest ACC values over a given monsoon domain and for a given lead time. The composition of the SUBSET ensemble is, thus, monsoon domain and lead time dependent.

The WORST SUBSET is defined in the same way as SUBSET but selecting the three prediction models that have the lowest ACC values. We expect a comparison of SUBSET against WORST SUBSET and ENSM to provide information on sources of prediction skill. Finally, the effect of initialization is here estimated by comparing SUBSET with HIST SUBSET, which is composed of the same models as SUBSET but using historical uninitialized simulations only.

2.3. Monsoon domains

Monsoon domains are defined where the difference between May to September (MJJAS) and November to March (NDJFM) precipitation exceeds 2.5 $mm.d^{-1}$ (Wang *et al* 2011) in observations (GPCC; Schneider *et al* 2014). We only consider precipitation that falls within the tropical latitudes [30° S–30° N] and over land. Monsoon domains are shown in figure 1 and are named NAM (Northern America), NAF (Northern Africa), SAS (South Asia), EAS (East Asia), SAM (Southern America), SAF (Southern Africa) and AUS (Australia), following the literature (e.g., Kitoh *et al* 2013). We assess skill at predicting summer monsoon precipitation, in JJAS for the NAM, NAF, SAS and EAS monsoon domains and in DJFM for the SAM, SAF and AUS monsoon domains. In addition, we averaged monsoon precipitation of all domains in the northern (NHM) and southern (SHM) Hemispheres.

2.4. The Interdecadal Pacific Oscillation (IPO)

We define the IPO as the difference between the central-eastern Pacific [150° E–150° W; 10° S–10° N] and the tropical central-eastern Pacific [170° W–90° W; 25° N–45° N] after Huang *et al* (2020), using surface air temperature. According to Huang *et al* (2020), this index gives similar results that the tripole index of Henley *et al* (2015).

3. DCPPA prediction skill

3.1. Quantifying DCPPA ensemble-mean prediction skill

We assess prediction skill of ENSM for summer monsoon precipitation at each grid point, and when averaged over each monsoon domain.

We find significant skill in predicting summer monsoon precipitation in ENSM, but the skill appears to increase with lead time. Figure 1(a) shows that skill at predicting precipitation at the 1 year forecast lead time is relatively low over much of the globe, although there are regions with statistically significant prediction skill. For example, over the tropics, prediction skill is significant over northern South America, Argentina, and the western Sahel. Nevertheless, relative to the 1 year predictions, we find an increase in skill for the 2–5 and 6–9 forecast lead times. This increase in skill stands out over the Sahel, western India and Southeast Asia, and northern South America (figures 1(b) and (c)).

Figure 2 shows the skill at predicting summer monsoon precipitation when averaged over all monsoon domains. At the 1 year forecast lead time, ENSM is skilful at predicting NAM and AUS precipitation, as well as the hemisphere-wide quantities (NHM and SHM) (figure 2(a)). However, there is no significant skill over the NAF, SAS, EAS, SAM and SAF monsoon domains. For the 2–5 and 6–9 year forecast lead times, skill remains statistically significant for NHM, SHM, and NAM precipitation (figures 2(b) and (c)) and increases substantially for NAF and SAM precipitation. In contrast, ENSM does not show significant skill for the SAS, EAS and SAF monsoon domains for any lead-time. Results show higher skill for ENSM than for the CMIP5 decadal prediction systems (Bellucci *et al* 2015).

We assess the sources of model skill at predicting summer monsoon precipitation variability compared with persistence forecasts and with uninitialized simulations. Figure 2 shows that ENSM prediction skill generally exceeds persistence, implying that the skill does not only depend on the inertia of the climate system. We note, however, that persistence is more skilful than ENSM for the 1 year and 2–5 year forecast lead times for NAF summer monsoon precipitation (figures 2(a) and (b)). The effect of initialization (defined as the difference between initialized and uninitialized hindcasts) only emerges for a limited number of monsoon domains, especially at the longer lead times (e.g., 6–9 years), indicating that changes in external forcing are an important source of prediction skill on these time scales.

3.2. Understanding the range of prediction skill

So far, we have only explored the multi-model mean skill. But modelling systems will likely exhibit different levels of skill. Figure 2 also shows the range of skill for each model in the DCPPA ensemble and there is a significant diversity of model skill for all lead times (purple vertical lines). There is a consensus for some monsoon domains and lead-times, with all models exhibiting positive skill (*e.g.*, NAM summer monsoon precipitation for the 1 year forecast lead-time and NAF summer monsoon precipitation for the 2–5 and 6–9 forecast lead-times). However, there is more diversity in prediction skill for the SAS and EAS domains, with individual models performing much better or lesser than ENSM (figures 2(b) and (c)), as also shown with seasonal hindcasts (Mishra *et al* 2018,

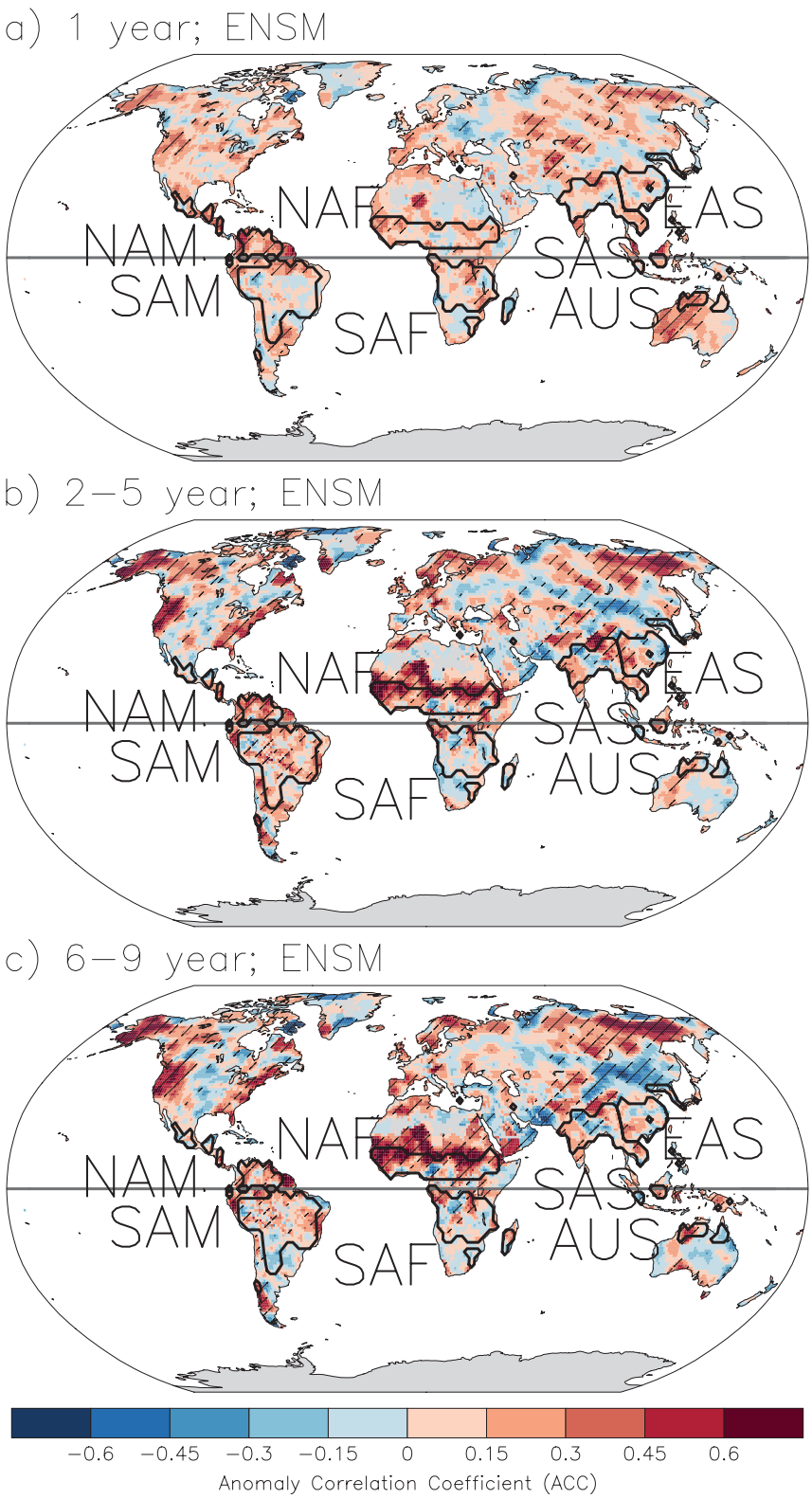


Figure 1. Anomaly correlation coefficient skill score for predictions of precipitation in ENSM at the (a) 1, (b) 2–5 and (c) 6–9 year forecast lead times, relative to CRU. ACC values are shown for JJAS (DJFM) in the northern (southern) hemisphere. Stippling indicates that ACC is significantly different to zero according to a Monte-Carlo procedure with 5000 permutations and a 95% confidence level. Black contours show the monsoon domains.

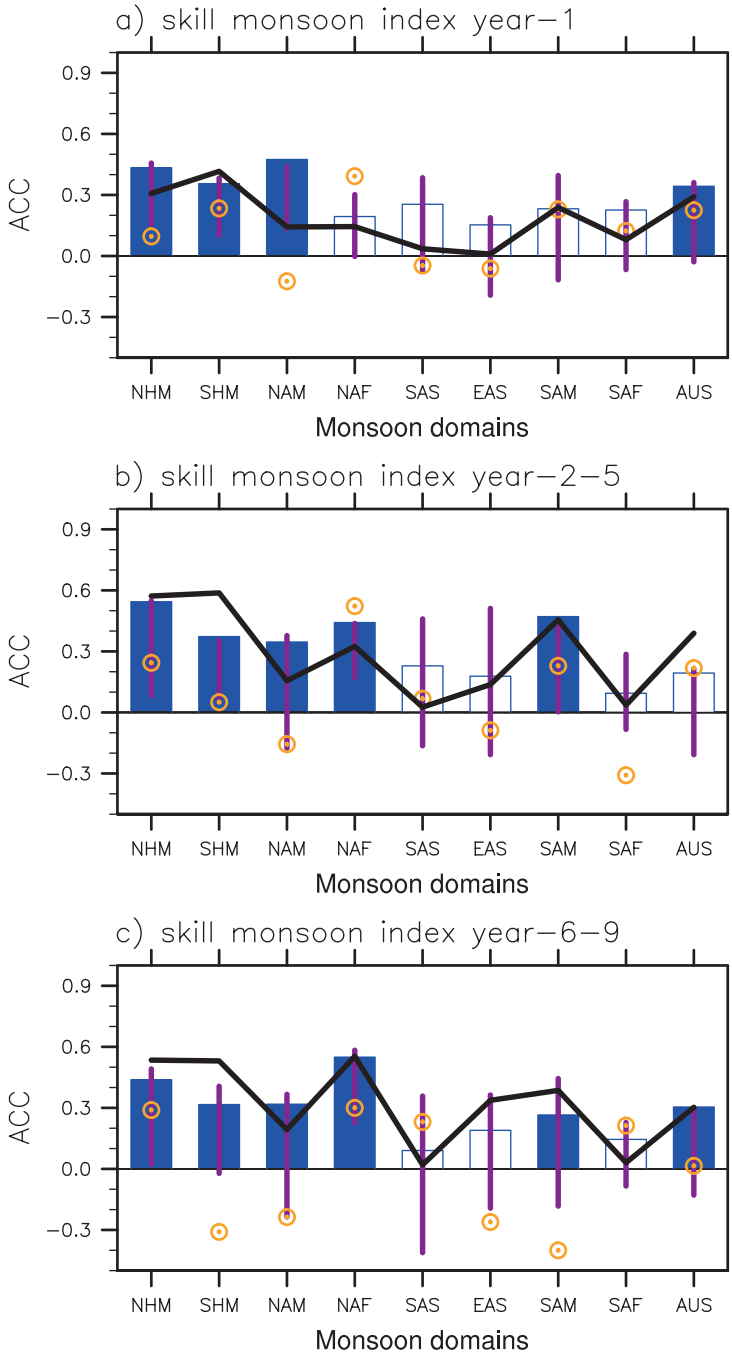


Figure 2. Anomaly correlation coefficient skill score for predictions of summer monsoon precipitation averaged over each monsoon domain and for the northern hemisphere (NHM) and the southern hemisphere (SHM). Results are given for ENSM (bars), uninitialized simulations (black line), and persistence (orange circles), and for the (a) 1 year, (b) 2–5 year, and (c) 6–9 year forecast lead times. The magenta vertical line shows the range in DCPPA prediction skill, defined between the lowest and highest skill and from each prediction system. A solid blue bar indicates that ACC is significantly different to zero according to a Monte-Carlo procedure with 5000 permutations and a 95% confidence level.

Jain *et al* 2019). Skill scores for each model and monsoon domain are shown in figures S3 and S4.

4. Sources of prediction skill

We explore the source of skill by selecting models according to their prediction skill. As expected, the BEST and SUBSET ensembles generally show improved skill relative to ENSM for all forecast lead time (figure 3).

ACC value is around tripled in SUBSET (ACC = 0.61) compared to ENSM (ACC = 0.18) for EAS summer monsoon precipitation and the 2–5 year forecast lead time (figure 3(b) and table S2). ACC values is approximately quadrupled in SUBSET (ACC = 0.40) relative to ENSM (ACC = 0.09) for SAS summer monsoon precipitation and for the 6–9 year forecast lead time (figure 3(c) and table S3). This is a consequence of the large diversity in prediction skill over South and East Asia, with prediction systems

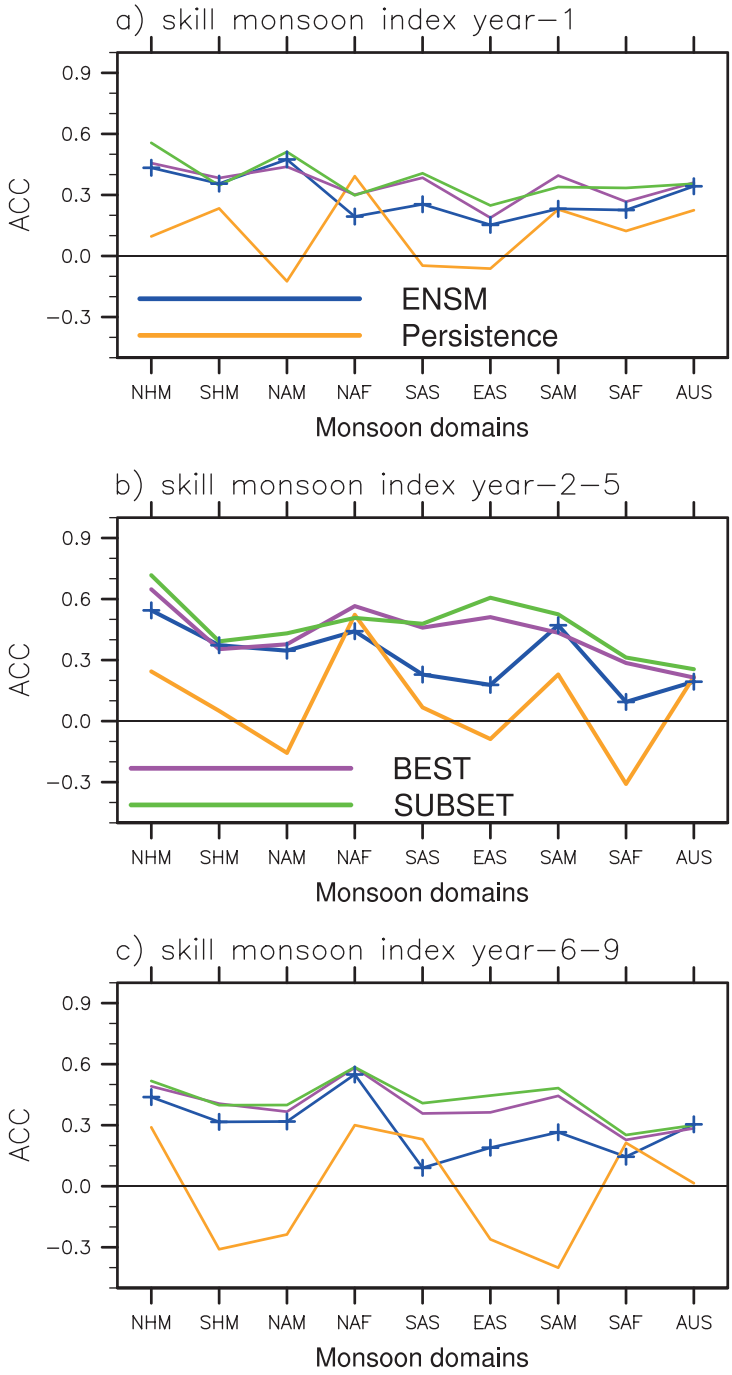


Figure 3. Anomaly correlation coefficient skill score for predictions of summer monsoon precipitation averaged over the northern hemisphere (NHM), the southern hemisphere (SHM) and each monsoon domain. Results are given for ENSM (dark blue), persistence (orange), BEST (magenta), and SUBSET (light green). Results are given for the (a) 1 year, (b) 2–5 year, and (c) 6–9 year forecast lead times.

exhibiting either high or low skill. Thus, skilful predictions can be obtained in the regions that ENSM is not skilful. We used another observational dataset (GPCC) and show that results are robust across observations (not shown).

4.1. Source of prediction skill for EAS summer monsoon precipitation

We focus on prediction of EAS summer monsoon precipitation for the 2–5 year forecast lead time, for which the SUBSET-ENSM difference in skill is the largest. The improved skill in SUBSET, relative to ENSM, is largely due to the multi-decadal variation in EAS summer monsoon precipitation. After applying a 7 year running mean to the 2–5 year forecasts we find the ACC is 0.70 in SUBSET but only 0.14 in ENSM. This is further confirmed using a 21 year running mean to only capture the slow variation of the EAS summer monsoon precipitation (figure S5). In contrast, the difference in skill between SUBSET (ACC = 0.18) and ENSM (ACC = 0.07) is low when considering higher frequency variability (defined as

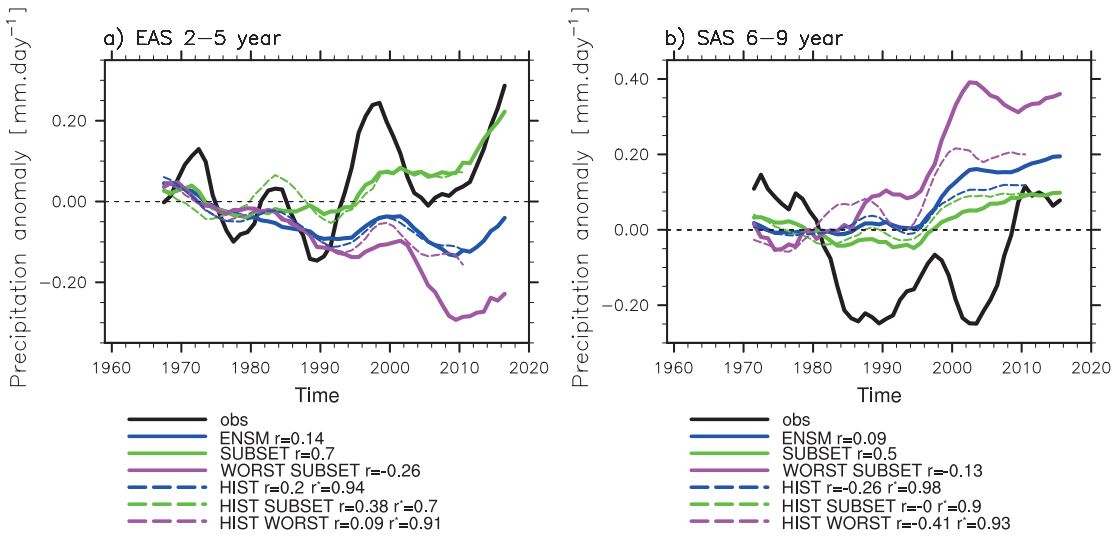


Figure 4. Precipitation anomalies in (a) EAS and (b) SAS summer monsoons, for the 2–5 and 6–9 year forecast lead times, respectively. Observations (CRU) are shown in black, ENSM in blue, SUBSET in green, WORST SUBSET in magenta, and HIST with discontinuous black line. Anomalies are computed relative to the 1961–1981 period. The high frequency variability is removed using a 7 year running average after computing the 2–5 and 6–9 averages. The *r* number indicates the ACC value, computed between each ensemble and observations, the r^* number indicates the correlation coefficient between initialized and uninitialized simulations.

the residual relative to the 7 year running mean). Figure 4(a) shows the smoothed time series in EAS summer monsoon precipitation. Although there is significant skill in SUBSET, both ENSM and SUBSET ensemble underestimate the observed variability. The difference between SUBSET and ENSM ensembles is that there is a long-lasting drying trend in ENSM while SUBSET simulates a small decrease in precipitation from 1960 to the 1980s and an increase in precipitation afterwards, hence better following the observation (figure 4(a)). In contrast, the WORST SUBSET shows a strong drying trend. Therefore, the difference in trends appears to be key to understand the differences in monsoon precipitation skill.

There is a large effect of the externally forced response on the multi-annual variation in EAS summer monsoon precipitation, as evidenced by the high correlation coefficient between the uninitialized and initialized simulations ($r^* = 0.94$ between ENSM and HIST; figure 4(a)).

Hence, we hypothesise that the range in skill of the DCPPA ensemble to be due to the differences in the response to external forcing. This is assessed by comparing maps of SUBSET-WORST SUBSET difference in skill (figure 5(a)) to the HIST SUBSET-HIST WORST SUBSET difference in skill (figure 5(b)). As the skill of uninitialized simulations is due to the response to the external forcing, the strong similarity between figures 5(a) and (b) confirms a strong role of the simulation of the externally forced response on the spread in prediction skill over EAS. These results have a strong societal importance because the increase in skill is the highest over eastern China, a heavily populated region where precipitation variability is high (figure 5(a)).

4.2. Sources of prediction skill for SAS summer monsoon precipitation

We focus on prediction of SAS summer monsoon precipitation for the 6–9 year forecast lead time, for which the SUBSET-ENSM difference in skill is the greatest. As for EAS summer monsoon precipitation, the externally forced response has strong effects on the long-term variation in simulated SAS summer monsoon, as shown by the high correlation coefficient between uninitialized and initialized simulations ($r^* = 0.98$ between ENSM and HIST; figure 4(b)). The spread in SAS summer monsoon prediction skill is also associated with the ability of prediction systems to simulate the multi-decadal variation in SAS summer monsoon precipitation. This is evidenced by the absence of pre-1990 drying in WORST SUBSET, while SUBSET shows a multi-decadal variation in SAS summer monsoon precipitation, in better agreement with the observations (figure 4(b)).

An effect of the response to external forcing on the spread of South Asian summer monsoon prediction skill is confirmed by the similarity between patterns of difference in prediction skill (SUBSET-WORST SUBSET; figure 5(c), and HIST SUBSET-HIST WORST SUBSET; figure 5(d)). However, the response to externally forced response does not fully explain the SUBSET-WORST SUBSET difference in skill. We thus also expect other drivers of South Asian summer monsoon precipitation variability to contribute to the spread in SAS summer monsoon precipitation skill.

The multi-decadal variability in South Asian precipitation has been linked to the interdecadal variability of the Pacific Ocean (IPO) (Zhang *et al* 2018,

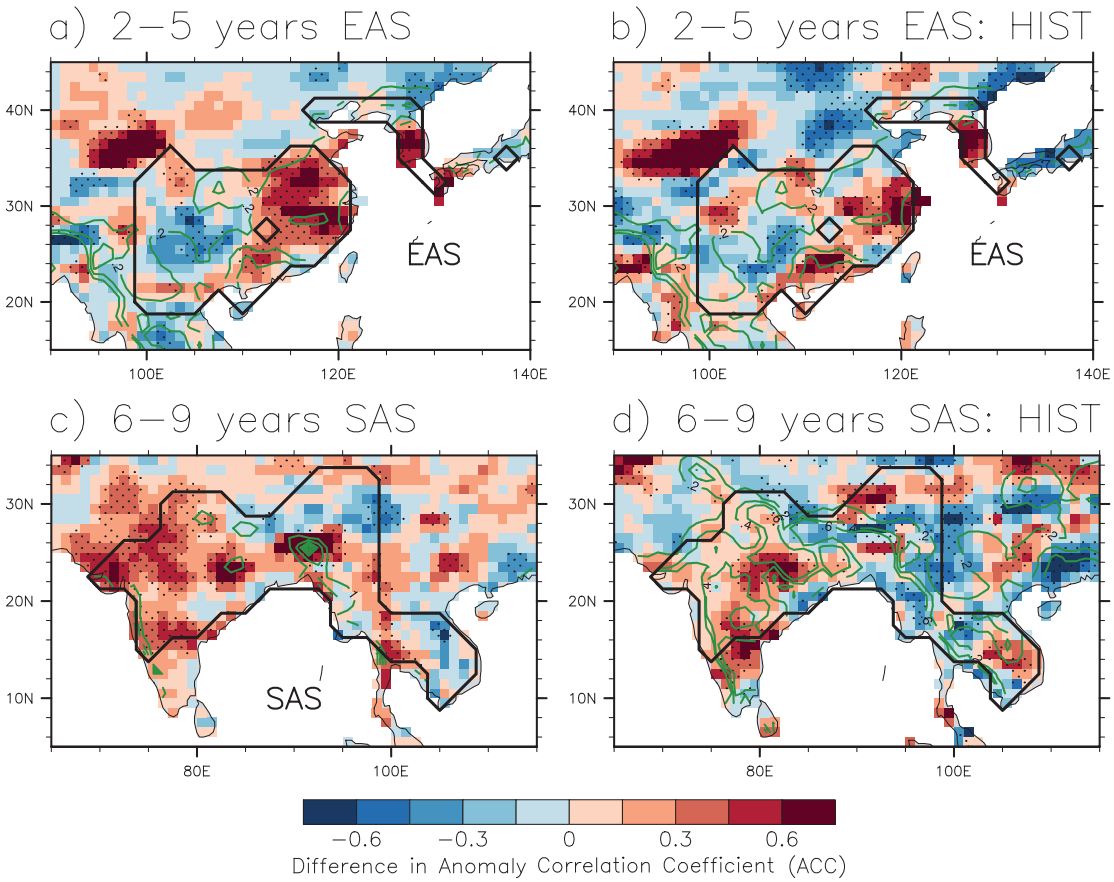


Figure 5. SUBSET minus WORST SUBSET difference in anomaly correlation coefficient skill score for predictions of precipitation over (a) East Asia for the 2–5 year forecast lead time, (c) South Asia for the 6–9 year forecast lead time. Skill at predicting precipitation is computed in comparison to CRU. Green contours indicate the precipitation variance, in $mm^2.d^{-2}$, (b) and (d), as in (a) and (c) but for the HIST SUBSET-HIST WORST SUBSET difference in anomaly correlation coefficient skill score for precipitation. Stippling indicates that the difference in ACC is significantly different to zero according to a Monte-Carlo procedure, resampling both BEST and ENSM and computing difference in ACC values. We use 5000 permutations and a 95% confidence level. The same number of ensemble members are used for the ensembles of initialized and uninitialized simulations (19 ensemble members for HIST SUBSET and 26 ensemble members for WORST SUBSET for EAS summer monsoon precipitation; 30 ensemble members for HIST SUBSET and 15 ensemble members for WORST SUBSET and for the SAS summer monsoon precipitation.).

Huang *et al* 2020). We show a strong relationship between skill at predicting the IPO and that of the SAS summer monsoon precipitation at the 6–9 year forecast lead time (figure 6(b); $r = 0.88$). The spread at predicting the IPO thus also contribute to the spread at prediction the SAS summer monsoon precipitation. We performed the same analysis with the uninitialized simulations and show that the result of figure 6(b) is due to initialization ($r = 0.01$ with the uninitialized simulations), and thus to the simulation of internal climate variability and to the correction of an incorrect forced response.

5. Discussion

Although we show improved skill over EAS and SAS summer monsoon precipitation in SUBSET, which we attribute to the impact of external forcing and to the simulation of the IPO, the exact mechanisms that explain the higher skill are unclear. For example, we explored mechanisms focusing on known drivers of the monsoon circulation, such as the large-scale gradients in surface air temperature and of surface air temperature over the oceans. However, differences in skill at predicting surface air temperature between the SUBSET and ENSM ensembles are low (figures S6 and S7). Further work could focus on understanding differences in atmospheric circulation, and regional changes between SUBSET and ENSM. We also acknowledge that different estimations of the internal components of the IPO could lead to different conclusions and future work could be devoted to understanding what leads to better prediction skill of the IPO and its role for predicting summer monsoon precipitation at multi-annual forecast lead times. In addition, the results are expected to be sensitive to the estimate of the IPO (e.g., Parker *et al* 2007, Henley *et al* 2015) and to the use of different observations/reanalysis. However, we show that skill at predicting South Asian summer

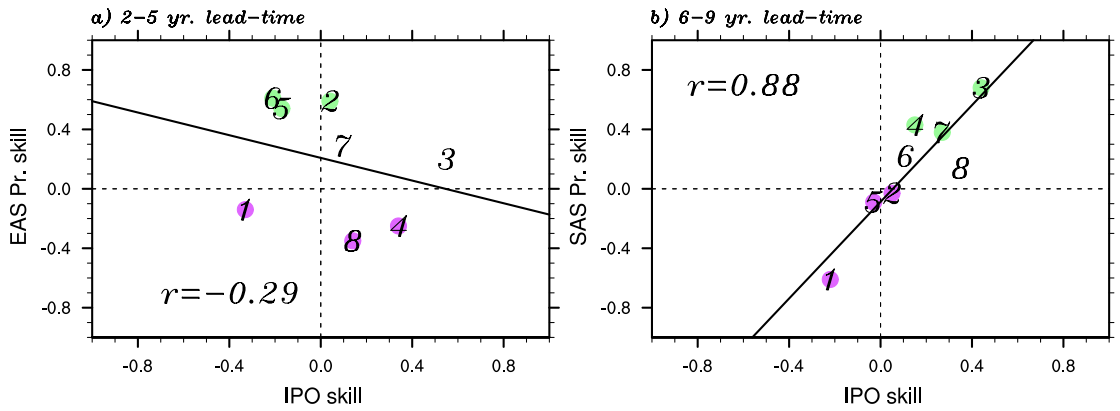


Figure 6. Anomaly correlation coefficient skill score for predictions of IPO index and (a) EAS and (b) SAS summer monsoon precipitation for each prediction system (1-CMCC-CM2-SR5; 2-HadGEM3-GC31-MM; 3-IPSL-CM6A-LR; 4-MIROC6; 5-MPI-ESM1-2-HR; 6-CanESM5; 7-EcEarth3; 8-NorCPM1) and the 2–5 and 6–9 year forecast lead times, respectively. A 7 year running mean was applied to both precipitation and IPO time series before to compute anomaly correlation coefficients. SUBSET (WORST SUBSET) models are shown with a green (magenta) circle.

monsoon precipitation is sensitive to the skill at predicting the Pacific Ocean SSTs for the 6–9 year forecast lead-time.

We explored further the role of the IPO indices on summer monsoon prediction skill, correcting IPO indices and effects on summer monsoon precipitation, using observations. We show that an improved prediction skill for the IPO leads to a better prediction skill for the SAS summer monsoon precipitation (figure S8 and text in the supplementary material). Better predicting the IPO can allow improved prediction skill over South Asia. In addition to the IPO, we found a moderate relationship between skill at predicting North Atlantic temperature and SAS summer monsoon precipitation ($r = 0.35$) for the 6–9 year forecast lead-time. In contrast, prediction skill of the IPO has no effects on prediction skill for EAS summer monsoon precipitation (figure 6(a); $r = -0.18$) and we found no relationship between prediction of the North Atlantic, Indian Ocean, and equatorial Pacific Ocean temperature on prediction skill of EAS summer monsoon precipitation skill (not shown) for the 2–5 year forecast lead-time.

We acknowledge here that we do not suggest the full skill of the prediction systems to arise only due to the externally forced response. Instead, we suggest that differences in skill in initialized predictions are partly due to differences in the simulation of the externally forced response. These differences in skill could be due to model biases. However, we found no relationships between biases in seasonal mean precipitation (or variability) and prediction skill, when using monsoon domain averages (not shown). Yet, further work might identify the importance of model biases for prediction skill. A focus could be given to the biases in simulation of the mean state tropical SSTs (e.g., Turner *et al* 2005). We also highlight that an increased number of models could allow increasing robustness of the results.

6. Conclusions

We quantify the ability of CMIP6 initialized decadal prediction systems (Boer *et al* 2016) to predict summer monsoon precipitation in a global monsoon framework and focus on three forecast lead times (1 year, 2–5 years, and 6–9 years). Overall, skill is low for the forecast 1 year lead time but increases for the 2–5 and 6–9 year horizons. Furthermore, the skill is model dependent, monsoon-domain dependent and lead-time dependent.

We explore sources of skill for predicting summer monsoon precipitation. In particular, the impact of initialization is rather small when focusing on the 2–5 and 6–9 forecast lead times. Therefore, the results highlight the importance of the externally forced response for providing skill at predicting summer monsoon precipitation. By selecting models, based on their prediction skill, we suggest that differences in simulating the externally forced response between models explains a large proportion of the diversity skill of the CMIP6 model ensemble, over South and East Asia.

Nevertheless, differences in skill at predicting the IPO also contributes to differences in skill between models for predictions of the South Asian summer monsoon precipitation at the 6–9 year forecast lead time. We show that initialization and improved prediction of the Pacific SSTs is important for prediction of South Asian summer monsoon precipitation, but it is unclear if this is due to improved prediction of internal variability, a correction of an incorrect forced response or mean state. Besides, we acknowledge that

skill at predicting the IPO can be a manifestation of an effect of the externally forced response on temperature over the Pacific Ocean. Therefore, improving our understanding of the differences between how models simulate the effects of external forcing and of IPO on South and East Asian summer monsoon precipitation could be an important avenue for improving prediction skill on a multi-annual time scale. The mechanism (e.g., anomalies in atmospheric circulation, in temperature gradients) that explains model skill diversity remains unclear. Further work is needed, focusing on, for instance, the atmosphere dynamics or model biases.

We do not argue here that selecting models based on their prediction skill should be used for predicting the future evolution of the East and South Asian summer monsoon precipitation up to ten years ahead. A reason for that is that prediction skill depends on the period used as reference (figure S9) and the ensembles might thus not provide the best prediction for the coming decade.

Data availability statement

DOIs/URLs for the historical simulations are https://doi.org/10.22033/ESGF/CMIP6.3610, https://doi.org/10.22033/ESGF/CMIP6.3825, https://doi.org/10.22033/ESGF/CMIP6.4700, https://doi.org/10.22033/ESGF/CMIP6.6112, https://doi.org/10.22033/ESGF/CMIP6.5195, https://doi.org/10.22033/ESGF/CMIP6.5603, https://doi.org/10.22033/ESGF/CMIP6.6594, https://doi.org/10.22033/ESGF/CMIP6.6842, https://doi.org/10.22033/ESGF/CMIP6.10894, respectively for CanESM5, CMCC-CM2-SR5, EcEARTH3, HadGEM3-GC31-MM, IPSL-CM6A-LR, MIROC6, MPI-ESM1-2-HR, MRI-ESM2-0 and NorCPM1. DOIs/URL for the hindcasts are https://doi.org/10.22033/ESGF/CMIP6.3557, www.wdc-climate.de/ui/entry?acronym=C6_4368435, https://doi.org/10.22033/ESGF/CMIP6.4553, https://doi.org/10.22033/ESGF/CMIP6.5892, https://doi.org/10.22033/ESGF/CMIP6.5137, https://doi.org/10.22033/ESGF/CMIP6.890, https://doi.org/10.22033/ESGF/CMIP6.768, https://doi.org/10.22033/ESGF/CMIP6.630 and https://doi.org/10.22033/ESGF/CMIP6.10865, respectively for CanESM5, CMCC-CM2-SR5, EcEARTH3, HadGEM3-GC31-MM, IPSL-CM6A-LR, MIROC6, MPI-ESM1-2-HR, MRI-ESM2-0 and NorCPM1. NCEP temperature data are provided by the NOAA/OAR/ESRL PSL, Boulder, Colorado, USA, from their website at https://downloads.psl.noaa.gov/Datasets/ncep.reanalysis/Monthlies/pressure/. CRU Precipitation is provided by the Climate Research Unit, from the website at https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.03/cruts.1905011326.v4.03/pre/.

The data that support the findings of this study are openly available at the following URL/DOI: https://esgf-index1.ceda.ac.uk/search/cmip6-ceda/.

Acknowledgments

J R was funded by NERC via the ACSIS (NE/N018001/1) and CANARI (NE/W004984/1) programs, and the WISHBONE (NE/T013516/1) project. C D N was supported by PDI/MSC (Programme Doctoral International: Modélisation des Systèmes Complexes), the scholarship of SCAC (Service de Coopération et d'Action Culturelle), the ERASUMUS+ programme through action KA107, and the Laboratoire Mixte International ECLAIRS2 (IRD), the UCM XVII call for cooperation and sustainable development. A G T was funded via the National Centre for Atmospheric Science through the NERC National Capability International Programme Award (NE/X006263/1).

We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modelling groups for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals. We also thank the two anonymous reviewers for their comments and suggestions.

ORCID iDs

Paul-Arthur Monerie https://orcid.org/0000-0002-5304-9559
Jon I Robson https://orcid.org/0000-0002-3467-018X
Cassien D Ndiaye https://orcid.org/0000-0002-7091-1438
Andrew G Turner https://orcid.org/0000-0002-0642-6876

References

Bellucci A *et al* 2015 An assessment of a multi-model ensemble of decadal climate predictions *Clim. Dyn.* **44** 2787–806
Beraki A F, DeWitt D G, Landman W A and Olivier C 2013 Dynamical seasonal climate prediction using an ocean–atmosphere coupled climate model developed in partnership between South Africa and the IRI *J. Clim.* **27** 1719–41
Bethke I *et al* 2021 NorCPM1 and its contribution to CMIP6 DCPP *Geosci. Model Dev.* **14** 7073–116
Boer G J *et al* 2016 The Decadal Climate Prediction Project (DCPP) contribution to CMIP6 *Geosci. Model Dev.* **9** 3751–77
Boucher O *et al* 2020 Presentation and evaluation of the IPSL-CM6A-LR climate model *J. Adv. Model. Earth Syst.* **12** e2019MS002010
Charney J G and Shukla J 1981 Predictability of monsoons *Monsoon Dynamics* ed J Lighthill and R P Pearce (Cambridge University Press)
Cherchi A *et al* 2019 Global mean climate and main patterns of variability in the CMCC-CM2 coupled model *J. Adv. Model. Earth Syst.* **11** 185–209

Chevuturi A, Turner A G, Johnson S, Weisheimer A, Shonk J K P, Stockdale T N and Senan R 2021 Forecast skill of the Indian monsoon and its onset in the ECMWF seasonal forecasting system 5 (SEAS5) *Clim. Dyn.* **56** 2941–57

Delgado-Torres C *et al* 2022 Multi-model forecast quality assessment of CMIP6 decadal predictions *J. Clim.* **35** 4363–82

Deser C, Phillips A, Bourdette V and Teng H 2012 Uncertainty in climate change projections: the role of internal variability *Clim. Dyn.* **38** 527–46

Dunstone N *et al* 2020 Skilful interannual climate prediction from two large initialised model ensembles *Environ. Res. Lett.* **15** 094083

Eyring V, Bony S, Meehl G A, Senior C A, Stevens B, Stouffer R J and Taylor K E 2016 Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization *Geosci. Model Dev.* **9** 1937–58

Gaetani M and Mohino E 2013 Decadal prediction of the Sahelian precipitation in CMIP5 simulations *J. Clim.* **26** 7708–19

García-Serrano J, Guemas V and Doblas-Reyes F J 2015 Added-value from initialization in predictions of Atlantic multi-decadal variability *Clim. Dyn.* **44** 2539–55

Guemas V *et al* 2013 The Indian Ocean: the region of highest skill worldwide in decadal climate prediction* *J. Clim.* **26** 726–39

Harris I, Jones P D, Osborn T J and Lister D H 2014 Updated high-resolution grids of monthly climatic observations—the CRU TS3.10 dataset *Int. J. Climatol.* **34** 623–42

Henley B J, Gergis J, Karoly D J, Power S, Kennedy J and Folland C K 2015 A tripole index for the interdecadal Pacific oscillation *Clim. Dyn.* **45** 3077–90

Hermanson L *et al* 2018 Different types of drifts in two seasonal forecast systems and their dependence on ENSO *Clim. Dyn.* **51** 1411–26

Huang X *et al* 2020 The recent decline and recovery of Indian summer monsoon rainfall: relative roles of external forcing and internal variability *J. Clim.* **33** 5035–60

ICPO 2011 Data and bias correction for decadal climate predictions *International CLIVAR Project Office Publication Series, 150:5* (available at: www.wcrp-climate.org/decadal/references/DCPP_Bias_Correction.pdf)

Jain S, Scaife A A and Mitra A K 2019 Skill of Indian summer monsoon rainfall prediction in multiple seasonal prediction systems *Clim. Dyn.* **52** 5291–301

Johnson S J, Turner A, Woolnough S, Martin G and MacLachlan C 2017 An assessment of Indian monsoon seasonal forecasts and mechanisms underlying monsoon interannual variability in the met office GloSea5-GC2 system *Clim. Dyn.* **48** 1447–65

Jones C, Carvalho L M V and Liebmann B 2012 Forecast skill of the South American monsoon system *J. Clim.* **25** 1883–9

Kanamitsu M *et al* 2002 NCEP–DOE AMIP-II reanalysis (R-2) *Bull. Am. Meteorol. Soc.* **83** 1631–43

King A D, Hudson D, Lim E-P, Marshall A G, Hendon H H, Lane T P and Alves O 2020 Sub-seasonal to seasonal prediction of rainfall extremes in Australia *Q. J. R. Meteorol. Soc.* **146** 2228–49

Kitoh A, Endo H, Krishna Kumar K, Cavalcanti I F A, Goswami P and Zhou T 2013 Monsoons in a changing world: a regional perspective in a global context *J. Geophys. Res.* **118** 3053–65

Kuhlbrodt T *et al* 2018 The low-resolution version of HadGEM3 GC3.1: development and evaluation for global climate *J. Adv. Model. Earth Syst.* **10** 2865–88

Lu B, Scaife A A, Dunstone N, Smith D, Ren H-L, Liu Y and Eade R 2017 Skillful seasonal predictions of winter precipitation over southern China *Environ. Res. Lett.* **12** 074021

Martin E R and Thorncroft C 2014 Sahel rainfall in multimodel CMIP5 decadal hindcasts *Geophys. Res. Lett.* **41** 2169–75

Marvel K, Biasutti M and Bonfils C 2020 Fingerprints of external forcings on Sahel rainfall: aerosols, greenhouse gases, and model-observation discrepancies *Environ. Res. Lett.* **15** 084023

Mauritsen T *et al* 2019 Developments in the MPI-M Earth System Model version 1.2 (MPI-ESM1.2) and its response to increasing CO_2 *J. Adv. Model. Earth Syst.* **11** 998–1038

Mishra S K, Sahany S, Salunke P, Kang I-S and Jain S 2018 Fidelity of CMIP5 multi-model mean in assessing Indian monsoon simulations *npj Clim. Atmos. Sci.* **1** 39

Mohino E, Keenlyside N and Pohlmann H 2016 Decadal prediction of Sahel rainfall: where does the skill (or lack thereof) come from? *Clim. Dyn.* **47** 3593–612

Monerie P-A, Robson J I, Dunstone N J and Turner A G 2021 Skilful seasonal predictions of global monsoon summer precipitation with DePreSys3 *Environ. Res. Lett.* **16** 104035

Monerie P-A, Robson J, Dong B, Dieppois B, Pohl B and Dunstone N 2018 Predicting the seasonal evolution of southern African summer precipitation in the DePreSys3 prediction system *Clim. Dyn.* **52** 6491–510

Monerie P-A, Wilcox L J and Turner A G 2022 Effects of anthropogenic aerosol and greenhouse gas emissions on Northern Hemisphere monsoon precipitation: mechanisms and uncertainty *J. Clim.* **35** 1–66

Ndiaye C D, Mohino E, Mignot J and Sall S M 2022 On the detection of externally-forced decadal modulations of the Sahel rainfall over the whole 20th century in the CMIP6 ensemble *J. Clim.* **35** 1–51

Otero N, Mohino E and Gaetani M 2016 Decadal prediction of Sahel rainfall using dynamics-based indices *Clim. Dyn.* **47** 3415–31

Parker D, Folland C, Scaife A, Knight J, Colman A, Baines P and Dong B 2007 Decadal to multidecadal variability and the climate change background *J. Geophys. Res.* **112** D18115

Schneider U, Becker A, Finger P, Meyer-Christoffer A, Ziese M and Rudolf B 2014 GPCC's new land surface precipitation climatology based on quality-controlled in situ data and its role in quantifying the global water cycle *Theor. Appl. Climatol.* **115** 15–40

Sheen K, Smith D, Dunstone N, Eade R, Rowell D and Vellinga M 2017 Skilful prediction of Sahel summer rainfall on inter-annual and multi-year timescales *Nat. Commun.* **8** 14966

Shukla J and Paolino D A 1983 The Southern oscillation and long-range forecasting of the summer monsoon rainfall over India *Mon. Weather Rev.* **111** 1830–7

Smith D M *et al* 2019 Robust skill of decadal climate predictions *npj Clim. Atmos. Sci.* **2** 13

Sohn S-J, Tam C-Y and Kug J-S 2019 How does ENSO diversity limit the skill of tropical Pacific precipitation forecasts in dynamical seasonal predictions? *Clim. Dyn.* **53** 5815–31

Swart N C *et al* 2019 The Canadian Earth System Model Version 5 (CanESM5.0.3) *Geosci. Model Dev.* **12** 4823–73

Tatebe H *et al* 2019 Description and basic evaluation of simulated mean state, internal variability, and climate sensitivity in MIROC6 *Geosci. Model Dev.* **12** 2727–65

Turner A G, Inness P M and Slingo J M 2005 The role of the basic state in the ENSO–monsoon relationship and implications for predictability *Q. J. R. Meteorol. Soc.* **131** 781–804

Walker D P, Birch C E, Marsham J H, Scaife A A, Graham R J and Segele Z T 2019 Skill of dynamical and GHACOF consensus seasonal forecasts of East African rainfall *Clim. Dyn.* **53** 4911–35

Wang B and Ding Q 2006 Changes in global monsoon precipitation over the past 56 years *Geophys. Res. Lett.* **33** L06711

Wang B, Kim H-J, Kikuchi K and Kitoh A 2011 Diagnostic metrics for evaluation of annual and diurnal cycles *Clim. Dyn.* **37** 941–55

Wang B, Li J, Cane M A, Liu J, Webster P J, Xiang B, Kim H-M, Cao J and Ha K-J 2018 Toward predicting changes in the land monsoon rainfall a decade in advance *J. Clim.* **31** 2699–714

Wyser K, van Noije T, Yang S, von Hardenberg J, O'Donnell D and Döscher R 2020 On the increased climate sensitivity in the EC-Earth model from CMIP5 to CMIP6 *Geosci. Model Dev.* **13** 3465–74

Yukimoto S *et al* 2019 The Meteorological Research Institute Earth System Model Version 2.0, MRI-ESM2.0: description and basic evaluation of the physical component *J. Meteorol. Soc. Japan.* II **97** 931–65

Zhang Z, Sun X and Yang X-Q 2018 Understanding the interdecadal variability of East Asian summer monsoon precipitation: joint influence of three oceanic signals *J. Clim.* **31** 5485–506