

An assessment of Indian monsoon seasonal forecasts and mechanisms underlying monsoon interannual variability in the Met Office GloSea5-GC2 system

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An assessment of Indian monsoon seasonal forecasts and mechanisms underlying monsoon interannual variability in the Met Office GloSea5-GC2 system

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1 **Abstract** We assess Indian summer monsoon seasonal 26 forecasts in GloSea5-GC2, the Met Office fully coupled 27 subseasonal to seasonal ensemble forecasting system. 28 Using several metrics, GloSea5-GC2 shows similar skill 29 to other state-of-the-art forecast systems. The predic- 30 tion skill of the large-scale South Asian monsoon cir- 31 culation is higher than that of Indian monsoon rain- 32 fall. Using multiple linear regression analysis we eval- 33 uate relationships between Indian monsoon rainfall and 34 five possible drivers of monsoon interannual variability. 35 Over the time period studied (1992-2011), the El Niño- 36 Southern Oscillation (ENSO) and the Indian Ocean 37 dipole (IOD) are the most important of these drivers 38 in both observations and GloSea5-GC2. Our analysis 39 indicates that ENSO and its teleconnection with the 40 Indian rainfall are well represented in GloSea5-GC2. 41 However, the relationship between the IOD and Indian 42 rainfall anomalies is too weak in GloSea5-GC2, which 43 may be limiting the prediction skill of the local mon- 44soon circulation and Indian rainfall. We show that this 45 weak relationship likely results from a coupled mean 46 state bias that limits the impact of anomalous wind 47 forcing on SST variability, resulting in erroneous IOD 48 sst anomalies. Known difficulties in representing con- 49 vective precipitation over India may also play a role. 50

51 Since Indian rainfall responds weakly to the IOD, it 52 responds more consistently to ENSO than in observa- 53 tions. Our assessment identifies specific coupled biases 54 that are likely limiting GloSea5-GC2 prediction skill, 55 providing targets for model improvement.

Keywords Indian monsoon, seasonal forecasting, 56 Indian Ocean dipole

1 Introduction

57 Analysis of intraseasonal and interannual modes of Indian summer monsoon rainfall variability suggests that 58 there is a significant seasonally persisting component 59 of Indian monsoon rainfall anomalies forced by slowly 60 varying boundary conditions (Charney and Shukla, 1981; 61 Krishnamurthy and Shukla, 2000, 2007). For variabil- 62 ity in boundary conditions to be a useful source of sea- 63 sonal predictability, anomalies must be large and persis- 64 tent, they must interact with monsoon rainfall through 65 a consistent physical mechanism and the response of 66 monsoon rainfall must be large enough to distinguish 67 from the intrinsic variability of the atmosphere (Kang 68 and Shukla, 2006). Studies have investigated the pre- 69 dictability gained from many sources, including modes 70 of sea surface temperature (SST) variability, variabil- 71 ity of soil moisture and interannual variability of snow 72 cover (e.g. Palmer and Anderson, 1994; Goddard et al, 73 2001).

74 For the Indian summer monsoon, the most signif- 75 icant and well known source of predictability is the 76 El Niño-Southern Oscillation (ENSO, e.g. Shukla and 77 Paolino, 1983). A developing El Niño event warms SSTs 78 in the east Pacific, shifting the Walker circulation such 79 that anomalous subsidence occurs over the Maritime

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58 Continent and Indian Ocean, reducing monsoon rain-₁₁₁
 59 fall. A developing La Niña event has the opposite effect₁₁₂
 60 (e.g. Webster and Yang, 1992; Ju and Slingo, 1995).₁₁₃
 61 Recent work suggests that the zonal location of the₁₁₄
 62 warm SSTs alters the strength of the relationship by₁₁₅
 63 altering the location of the anomalous subsidence. Cen-₁₁₆
 64 tral Pacific El Niño events are consequently more likely₁₁₇
 65 to strongly suppress monsoon rainfall than east Pacific₁₁₈
 66 El Niño events (Krishna Kumar et al, 2006).₁₁₉

67 Another important known source of predictability₁₂₀
 68 is the the Indian Ocean dipole (IOD, also known as₁₂₁
 69 the Indian Ocean Zonal mode). The IOD is a coupled₁₂₂
 70 mode of SST variability in the equatorial Indian ocean₁₂₃
 71 analogous to ENSO in many ways. In a positive IOD₁₂₄
 72 event, anomalous easterlies develop in spring off the₁₂₅
 73 coast of Sumatra which increase upwelling, shoal the₁₂₆
 74 thermocline and create cool SST anomalies that ex-₁₂₇
 75 tend into the eastern equatorial Indian Ocean (EEIO).₁₂₈
 76 These are often accompanied by warm SST anom-₁₂₉
 77 lies in the western equatorial Indian Ocean (WEIO).₁₃₀
 78 This changes the zonal equatorial SST gradient, and₁₃₁
 79 consequently reinforces equatorial zonal easterly wind₁₃₂
 80 anomalies. An IOD event continues to develop through₁₃₃
 81 July and August and peaks in the autumn (Saji et al,₁₃₄
 82 1999; Webster et al, 1999; Annamalai et al, 2003). Us-₁₃₅
 83 ing an atmospheric GCM (AGCM), Ashok et al (2001)₁₃₆
 84 demonstrated that a positive IOD event drives anom-₁₃₇
 85 arious low-level atmospheric convergence in the WEIO₁₃₈
 86 and divergence in the EEIO that strengthens the South₁₃₉
 87 Asian monsoon circulation, increasing rainfall over In-₁₄₀
 88 dia.₁₄₁

89 Kucharski et al (2007, 2008) identify a component₁₄₂
 90 of Indian monsoon interannual variability that is forced₁₄₃
 91 by the Atlantic Niño, an ENSO-like mode of SST vari-₁₄₄
 92 ability in the southeastern tropical Atlantic. Atlantic₁₄₅
 93 Niño SST anomalies extend from the Angola coast to₁₄₆
 94 the Gulf of Guinea in spring and summer (Chang et al,₁₄₇
 95 2006). Using AGCM experiments, Kucharski et al (2007,₁₄₈
 96 2008) demonstrate that cool SSTs (Atlantic Niña) drive₁₄₉
 97 a stationary wave response that creates a low-level cy-₁₅₀
 98 clone over India, bringing increased moisture to India₁₅₁
 99 and increasing seasonal monsoon precipitation.₁₅₂

100 Many studies have explored the role of snow over₁₅₃
 101 Asia in driving monsoon rainfall interannual variabil-₁₅₄
 102 ity (see references in Fasullo, 2004). Sensitivity experi-₁₅₅
 103 ments in atmospheric GCMs (Turner and Slingo, 2011)₁₅₆
 104 and the ECMWF seasonal forecast system 4 (Senan
 105 et al, 2015), demonstrate a mechanism linking snow₁₅₇
 106 over the Himalayas and Tibetan Plateau (HimTP) with
 107 the timing and intensity of the Indian monsoon. They₁₅₈
 108 show that increased snow cover over the HimTP in
 109 spring and summer reduces surface sensible and long-₁₅₉
 110 wave heating as proposed by Blanford (1884), which₁₆₀

delays the onset of the monsoon and significantly re-
 111 duces monsoon rainfall in June. As HimTP snow cover
 112 decreases rapidly through the spring and early summer,
 113 interannual snow variability has little impact on rainfall
 114 variability later in the monsoon season.

115 Despite these many sources of predictability, Indian
 116 monsoon rainfall prediction skill is modest in state-of-
 117 the-art coupled seasonal prediction systems (Kim et al,
 118 2012; Rajeevan et al, 2012; Nanjundiah et al, 2013).
 119 The DEMETER sample of six seasonal forecast sys-
 120 tems had a multimodel mean interannual correlation
 121 skill of 0.28 ($p > 0.1$) over 1960-2001. The more recent
 122 ENSEMBLES sample, which uses updated versions of
 123 the DEMETER systems, improved to 0.45 ($p < 0.05$)
 124 over the slightly longer time period of 1960-2005. Mean
 125 state biases in boundary conditions, poor representa-
 126 tion of coupled teleconnections with monsoon rainfall,
 127 large ensemble spread and the lack of seasonal pre-
 128 dictability of intraseasonal variability are some of the
 129 challenges that face monsoon seasonal prediction (Sper-
 130 ber et al, 2000; Krishnamurthy and Shukla, 2007; Kim
 131 et al, 2012; Rajeevan et al, 2012; Sperber et al, 2013).

132 Here, we assess Indian summer monsoon seasonal
 133 forecasts in GloSea5-GC2, the Met Office fully cou-
 134 pled subseasonal to seasonal ensemble forecasting sys-
 135 tem. We assess the representation of the tropical mean
 136 state, the prediction skill of monsoon rainfall (all In-
 137 dia rainfall, AIR) and representation of relationships
 138 between monsoon rainfall and ENSO, the IOD, the At-
 139 lantic Niño and HimTP snow cover. In this publica-
 140 tion we focus on the interannual variability of monsoon
 141 rainfall; a future publication will focus on intraseasonal
 142 variability (Jayakumar et al, 2016).

143 In Section 2 we describe the forecast system, the
 144 integrations analysed and our analysis techniques. In Sec-
 145 tion 3 we describe the global properties of the forecast
 146 system, including mean state biases and maps of en-
 147 semble signal-to-noise ratios. In Section 4 we assess the
 148 interannual prediction skill of Indian summer monsoon
 149 rainfall. In Section 5 we use multiple regression analy-
 150 sis to assess the representation of relationships between
 151 AIR and sources of predictability. Where the regression
 152 analysis indicates these relationships are poorly repre-
 153 sented, we explore the mechanisms behind these rela-
 154 tionships in more detail, to determine the source of the
 155 errors. We conclude in Section 6.

2 Methodology

2.1 GloSea5-GC2

156 Full details of the GloSea5-GC2 configuration are de-
 157 scribed in Williams et al (2015), so we limit our descrip-

tion here to a brief introduction of the component models. GloSea5-GC2 uses the MetUM global atmosphere 6.0 (GA6.0) configuration at N216 resolution ($0.833^\circ \times 0.556^\circ$) with 85 vertical levels (Walters et al, 2015). It includes a stochastic physics scheme, Stochastic Kinetic Energy backscatter v2 (SKEB2, Bowler et al, 2009), to represent unresolved stochasticity. SKEB2 introduces small grid-level perturbations throughout the integrations to create ensemble spread. The global land (GL6.0) configuration of JULES (Best et al, 2011; Walters et al, 2015) with four vertical soil levels is “tightly coupled” to the MetUM: integrated on the MetUM grid as part of the same executable. The MetUM is coupled on a three-hourly time scale to ocean and sea ice models using the OASIS3 coupler (Valcke, 2013). The global ocean 5.0 (GO5.0) configuration of the Nucleus for European Modelling of the Ocean (NEMO) model is integrated on the ORCA 0.25° tripolar grid with 75 vertical levels. The level thickness is a double tanh function of depth such that the level spacing increases from 1 m near the surface to 200 m at 6000 m (Megann et al, 2014). The global sea ice 6.0 configuration of the Los Alamos sea ice model (CICE) is tightly coupled to NEMO on the NEMO grid (Rae et al, 2015; Megann et al, 2014) and integrated with five sea-ice thickness categories.

2.2 Hindcast set

The hindcast set we assess here is composed differently than the ensemble used for operational seasonal forecasts and from the hindcasts used to bias correct the operational forecast. For comparison, we describe the operational forecast system before describing the dataset we use here.

In the operational forecast system, two seasonal forecast ensemble members are initialised every day and integrated for 210 days. Three weeks of ensemble members are combined to create the operational seasonal forecast, a total of 42 ensemble members in each forecast. These are bias corrected using a 14 year (1996–2009), three ensemble member hindcast set initialised on the 1, 9, 17 and 25th of each month. The four nearest weeks of hindcasts, a total of 12 ensemble members, are weighted, combined, and then used to bias correct the forecasts. The GloSea5-GC2 operational forecast system is fully described in MacLachlan et al (2015).

The hindcast set in this study contains 20 years of hindcasts, spanning 1992 to 2011, which are initialised on three start dates, 25 April, 1 May and 9 May. They are integrated for 140 days, ending on 11, 17 and 25 September. To assess seasonal monsoon rainfall, we validate JJA values, leaving a forecast lead time of approximately one month. For years 1992 through 1995, 2010 and 2011 eight ensemble members are initialised on each start date, resulting in 24 members for each hindcast year. For 1996 through 2009, five ensemble members are initialised on each start date, resulting in 15 members for each hindcast year.

The MetUM and JULES are initialised from daily ERA-Interim reanalysis (gridded to $0.75 \times 0.75^\circ$, Dee et al, 2011). JULES soil moisture is initialised from a JULES re-analysis climatological seasonal cycle of soil moisture calculated (1989 to 2011). NEMO and CICE are initialised from the GloSea5 Ocean and Sea ice analysis using the GloSea5 global ocean 3.0 system (hereafter referred to as the GloSea5-GO3 analysis), which is driven by ERA-Interim reanalysis and incorporated using the NEMOVAR data assimilation scheme (Blockley et al, 2014). NEMOVAR is based on NEMO and CICE using the same resolution and similar parametrisations as the forecast model configurations (Mogensen et al, 2009).

A climatological seasonal cycle of solar forcing is prescribed. Climate forcings such as CO_2 are set to observed values until the year 2005, and subsequently follow the Intergovernmental Panel on Climate Change RCP4.5 scenarios. Other aerosols are updated every five days and use a climatological seasonal cycle derived from previous versions of the MetUM. Ozone concentrations are updated every 30 days and are set to the observational climatology of the Stratosphere-troposphere Processes And their Role in Climate (SPARC, Cionni et al, 2011) dataset (1994 to 2005). Further details are described in MacLachlan et al (2015) and Williams et al (2015).

2.3 Analysis techniques

2.3.1 Multiple linear regression analysis

To assess relationships between Indian rainfall and slowly varying boundary conditions, we perform multiple linear regression analysis. We use the “regress” function in IDL8.2 (modified version of “regres” in Bevington, 1969), which uses all independent variables to minimise the overall residual and give the best fit. We assess goodness of fit using the coefficient of determination, or R^2 , value. In the case of a perfect fit, $R^2 = 1$; in the case of no relationship, $R^2 = 0$. In addition to the regression coefficients (the slopes of the regression lines) we analyse the standard error of the regression fit. The standard error is the sampling error in the regression coefficient assuming the data is normally distributed about the fit.

261 *2.3.2 Forward selection of parameters*

262 To diagnose the relative importance of independent vari-
 263 ables in our multiple regression analysis, we use for-
 264 ward selection (Wilks, 2006). First, a single linear re-
 265 gression is calculated between the dependent variable
 266 and each independent variable in turn. The indepen-
 267 dent variable with the highest R^2 is noted. Then a two-
 268 parameter regression is calculated using this indepen-
 269 dent variable and each of the remaining independent
 270 variables in turn. The regression with the highest R^2
 271 is kept and so on, until all independent variables have
 272 been included in the fit. The change in the R^2 value
 273 as each independent variable is added to the regression
 274 indicates the importance of each of the independent
 275 variables to the final regression.

276 *2.3.3 Samples of ensemble members*

277 To validate GloSea5-GC2 against observations, it is cru-
 278 cial that we do not solely analyse the ensemble mean.
 279 Observations contain chaotic noise as well as variability
 280 forced by slowly varying components of the climate sys-
 281 tem (e.g. Palmer and Anderson, 1994; Goddard et al,
 282 2001). Ensemble averaging reduces noise, reducing the
 283 total atmospheric variability and increasing the relative
 284 contribution of forced variability to the total variabil-
 285 ity. To accurately compare GloSea5-GC2 variability to
 286 observed variability and to reduce the risk of mistak-
 287 ing noise in observations for forced variability, we must
 288 compare individual ensemble members from the hind-
 289 cast set to observations. To accomplish this we repeat
 290 our statistical calculations, such as the regression analy-
 291 sis in Section 5, on many samples of ensemble members
 292 and compare a distribution of the resulting values, such
 293 as regression coefficients, to a single observed value.

294 In this article, most metrics require a twenty year
 295 JJA time series from the hindcast set. We create many
 296 JJA time series for our statistical calculations by com-
 297 bining different ensemble members from different years.
 298 Ensemble members with the same start date are ini-
 299 tialised identically, so any combination ensemble mem-
 300 bers with the same start date can be used.

301 The first step is to create five time series for each of
 302 the start dates by randomly sampling ensemble mem-
 303 bers with the same start date from each hindcast year
 304 without replacement. In years with five members for
 305 each start date, each of the five ensemble members is
 306 used in one of these time series. In years with eight en-
 307 semble members for each start date, five of the eight
 308 members are used in these five time series. There are
 309 three start dates in the hindcast set, so this process
 310 results in 15 time series. We then repeat this process

311 N times. We raised N until raising it further did not
 312 change the results, to $N = 2000$, creating 3×10^4 JJA
 313 time series which we refer to as “hindcast samples.”
 314 In these samples, every ensemble member in the years
 315 with five ensemble members for each start date is used
 316 an equal number of times. In the years with eight en-
 317 semble members for each start date, each individual
 318 member is used fewer times and it is also possible that
 319 some members are used more than others. Given the
 320 large value of N we would not expect this to affect our
 321 results.

322 *2.4 Observational and reanalysis datasets*

To assess precipitation we use the Global Precipitation Climatology Project (GPCP) Version 2.2 Monthly Precipitation Analysis (Adler et al, 2003). GPCP is a 2.5° gridded merged analysis that incorporates precipitation estimates from low-orbit satellite microwave data, geostationary satellite infrared data and surface rain gauge observations. GloSea5-GC2 data are bilinearly interpolated to the GPCP grid for comparison.

We assess winds using the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-Interim atmospheric reanalysis product gridded to $0.70 \times 0.70^\circ$ (Dee et al, 2011). Fields were interpolated to the MetUM grid and compared on equivalent pressure levels. We assess snow using snow water equivalent (snow mass) from ERA-Interim/Land, a global land surface reanalysis dataset driven by ERA-Interim (Balsamo et al, 2015), which is also interpolated to the MetUM grid for comparison.

SST is assessed using the GloSea5-GO3 analysis used to initialise the NEMO ocean model, as described in Section 2.2, interpolated to the MetUM grid. The ocean temperature profile is assessed using the EN4.1.1 analyses ($1^\circ \times 1^\circ$, Good et al, 2013). This analysis includes ocean temperature and salinity profiles from many sources, including the Global Temperature and Salinity Profile Program and the Argo dataset, which are quality controlled before creating the analysis. An updated version of the Gouretski and Reseghetti (2010) bias correction is then applied. Profiles are compared on their native levels.

All fields are compared over 1992 to 2011. In the rest of this paper, when a combination of observations and reanalysis are used to validate the model they will be collectively referred to as “observations.”

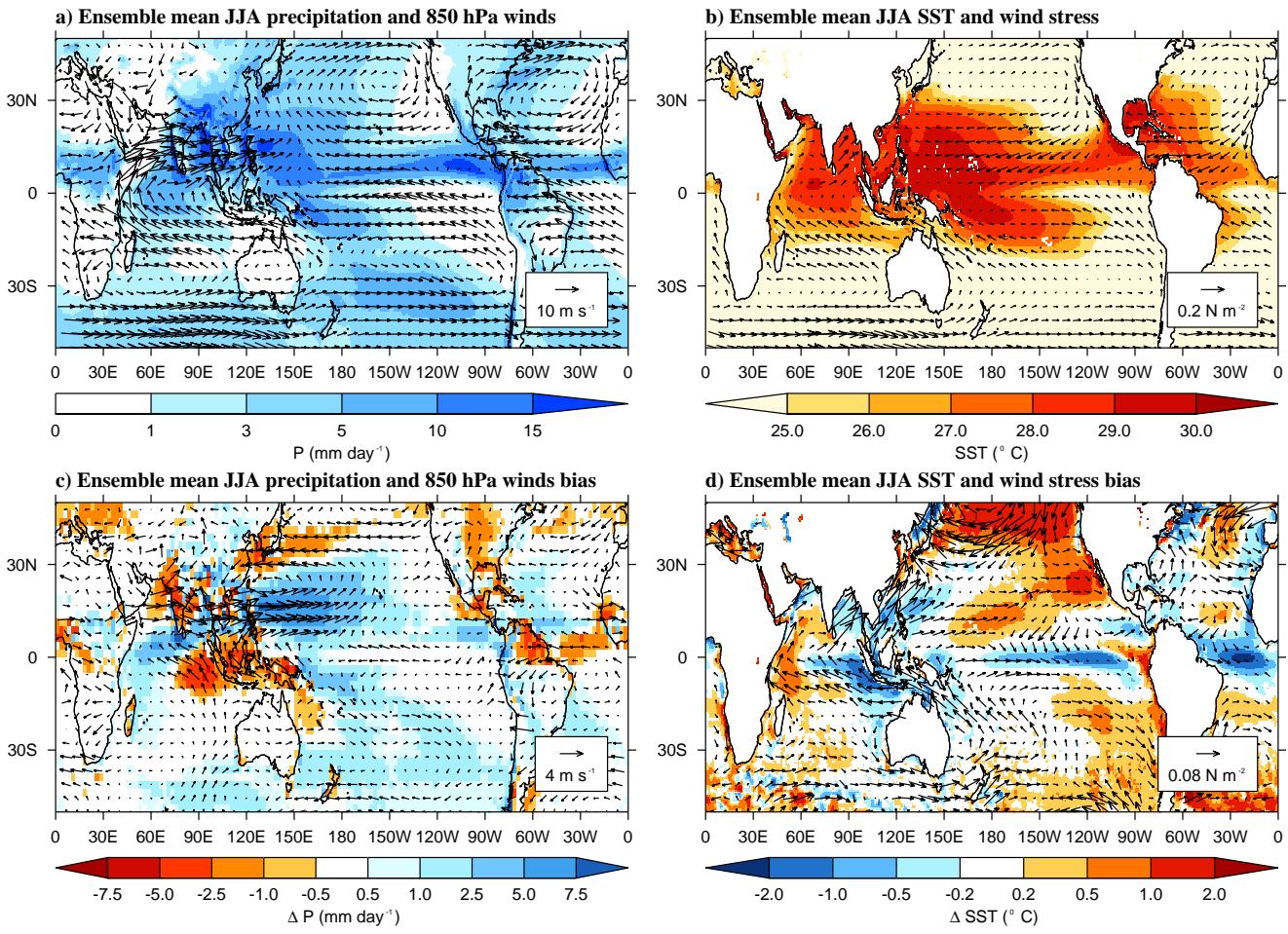


Fig. 1 Ensemble mean JJA (a) precipitation and 850 hPa winds in GloSea5-GC2, (b) SST and surface wind stress in GloSea5-GC2, (c) precipitation and 850 hPa winds bias with respect to GPCP and ERA-Interim, (d) SST and surface wind stress bias with respect to GloSea5-GO3 analysis and ERA-Interim.

3 Forecast system global performance

3.1 Ensemble mean bias

The GloSea5-GC2 ensemble mean JJA precipitation and 850 hPa winds are shown in Figure 1a alongside their bias with respect to GPCP and ERA-Interim in Figure 1c. Precipitation biases in the Indo-Pacific are similar to those seen in the CMIP5 models (Sperber et al., 2013) and state-of-the-art seasonal forecast systems (Rajeevan et al., 2012; Kim et al., 2012), with excess precipitation over the WEIO and western north Pacific and a deficit of precipitation over India, the Maritime Continent and the EEIO. The deficit of precipitation over India (AIR deficit of 0.72 mm day^{-1}) is largely due to a climatologically late onset of the monsoon in GloSea5-GC2, which reduces the precipitation over and around India in May and June. Precipitation is similar to the observed climatology in July and August (not shown). Monsoon westerlies, which

extend from the Arabian Peninsula across the Indian and Indochina peninsulas, are overly strong in GloSea5-GC2, in contrast to the CMIP5 multi-model mean weak bias (Sperber et al., 2013). This is likely associated with the overly strong precipitation and convergence in the western north Pacific in GloSea5-GC2 and a smaller Arabian Sea cold bias than is generally seen in the CMIP5 models (Levine et al., 2013). The well documented Arabian Sea cold SST bias in coupled GCMs tends to weaken the monsoon circulation and monsoon precipitation, but initialisation in May prevents the growth of a large bias (Levine and Turner, 2012; Levine et al., 2013, personal communication R. Levine). The excess precipitation bias in the western north Pacific seen in GloSea5-GC2 is also associated with the cyclonic wind bias over the western north Pacific and east Asia (Bush et al., 2015).

GloSea5-GC2 JJA SST and wind stress are shown alongside their biases in Figure 1b and Figure 1d. The eastern side of each ocean basin shows an equatorial

395 cold bias. Equatorial cold biases are common in coupled models (e.g. Li and Xie, 2012, 2014) and seasonal forecast systems (Kim et al, 2012; Vanniere et al, 2013), especially in the Pacific. GloSea5-GC2 also has a cold SST bias associated with the western north Pacific excess precipitation bias and a warm bias in the western Indian Ocean opposite the cold bias in the EEIO. Large wind stress biases are associated with many of the cold SST biases in the warm pool region, including the EEIO, Bay of Bengal, South China Sea and western north Pacific. We address how these Indian Ocean biases may be impacting the monsoon rainfall forecast skill in Section 5.2.2.

408 3.2 Ensemble spread

409 To quantify the ensemble spread in the forecast system, we calculate the signal-to-noise ratio (S/N) of JJA anomalies, defined as the ratio of the variance of the ensemble mean anomaly time series to the average variance of the ensemble member anomalies in each year (Rowell et al, 1995; Kang and Shukla, 2006). If $S/N > 1$ then the interannual variability in the ensemble mean is greater than the average ensemble spread. In Figure 2 we show S/N maps for JJA precipitation and zonal vertical wind shear (850-200 hPa), which is a diagnostic of the large-scale monsoon circulation related to the strength of the monsoon diabatic heating (Gill, 1980; Webster and Yang, 1992). In both metrics, there is lower S/N in the Indian Ocean than in the other ocean basins. JJA precipitation $S/N > 1$ is confined to the equatorial Pacific and Maritime Continent, indicating that the precipitation anomalies most directly forced by ENSO SST anomalies have the highest S/N .

427 S/N can also be expressed as a theoretical limit on the correlation skill, using the expression $R_{\text{limit}} = \sqrt{\frac{S/N}{S/N+1}}$ (Kang and Shukla, 2006). A $R_{\text{limit}} = 0.5$ contour is shown on both panels of Figure 2. The precipitation R_{limit} exceeds 0.5 over most of the equatorial oceans and the circulation R_{limit} exceed 0.5 throughout the tropics. This indicates that the S/N of GloSea5-GC2 is high enough to permit precipitation and circulation correlation skill greater than 0.5 over much of the tropics.

437 3.3 Anomaly correlations

438 To assess the global forecast skill, in Figure 3 we show the grid point anomaly correlations of GPCP JJA precipitation and the ERA-Interim vertical wind shear with their GloSea5-GC2 ensemble mean equivalents. In both fields, significant skill (0.44, $p < 0.05$) is restricted to

439 the tropics, consistent with other state-of-the-art seasonal forecasting systems (Kim et al, 2012). Precipitation prediction skill is lower than circulation prediction skill. In both circulation and precipitation, the lowest skill in the tropics is located in the Indian Ocean, suggesting difficulties in seasonal prediction of the South Asian monsoon system. In the next section we examine the prediction skill of Indian monsoon precipitation and the South Asian monsoon circulation in detail.

4 Indian summer monsoon forecast skill

453 JJA AIR is a commonly used measure of seasonal monsoon rainfall (e.g. Rajeevan et al, 2012; Nanjundiah et al, 2013) and is reported in seasonal forecasts issued by the Indian Meteorological Department¹. The inter-annual variation of AIR does not necessarily reflect the regional detail of the interannual variation of Indian rainfall (e.g. Ihara et al, 2007), but AIR is convenient for conducting a first-order assessment of monsoon seasonal prediction skill. JJA AIR anomalies in GPCP and GloSea5-GC2 are shown in Figure 4. The box plots represent the minimum, median, maximum and interquartile range of the ensemble, while the diamond represents the ensemble mean. In some years, such as 2008, the forecast is very good, with tight ensemble spread. In other years, such as 1997, all of the ensemble members predict the incorrect sign of the precipitation anomaly. Overall, the ensemble spread is large compared to the size of the anomalies, consistent with the S/N map in Figure 2a. It is rare that all ensemble members predict anomalies of the same sign.

454 JJA anomalies of the Webster-Yang dynamical index, an index representing the strength of the large-scale monsoon circulation using the vertical zonal wind shear over a large domain (difference between 850 hPa and 200 hPa over 40° to 110°E, 0° to 20°N; Webster and Yang, 1992), are also shown in Figure 4. There is not a one-to-one relationship between correctly predicting Indian precipitation anomalies and correctly predicting the large scale circulation anomalies. In some years, such as 1997, the circulation anomaly is well predicted while the precipitation anomaly is poorly predicted. In other years, such as 1996, the precipitation is well predicted and the circulation is poorly predicted. In GloSea5-GC2, the monsoon circulation and precipitation over India are strongly related, with the ensemble mean correlating at 0.67 ($p < 0.01$). However, in the observations, they are quite unrelated, with a correlation of 0.18 ($p > 0.1$). This indicates precipitation over India is too directly forced by the large scale circulation

¹ http://www.imd.gov.in/pages/monsoon_main.php

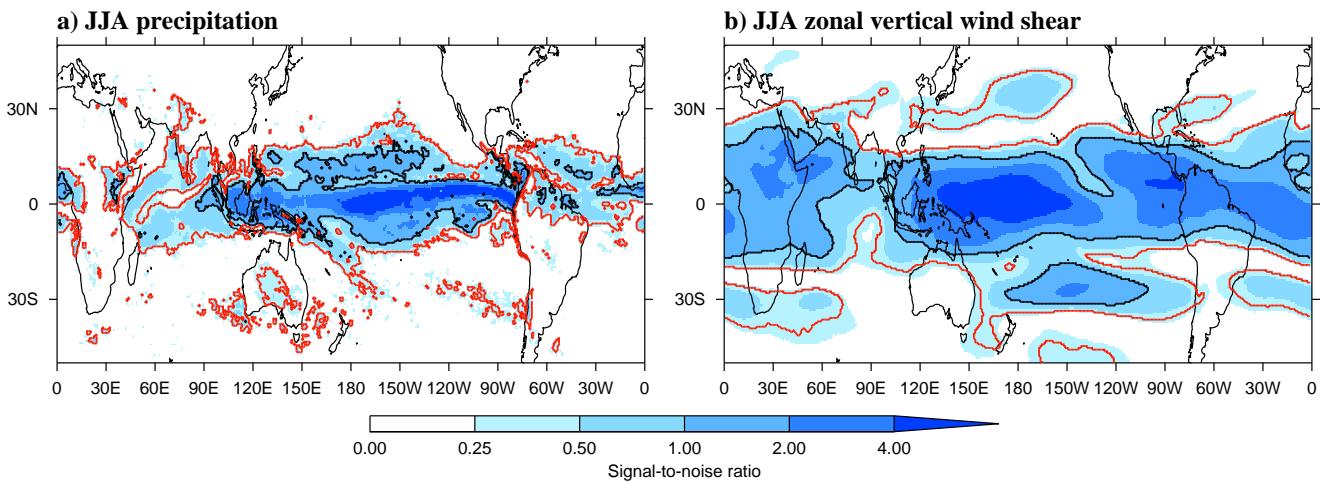


Fig. 2 Maps of GloSea5-GC2 JJA signal-to-noise ratio (see Section 3.2) for (a) precipitation and (b) zonal vertical wind shear (850 hPa - 200 hPa). A signal-to-noise ratio greater than one is indicated by the dark solid contour. A theoretical correlation limit (R_{limit}) of 0.5 is indicated by the red contour.

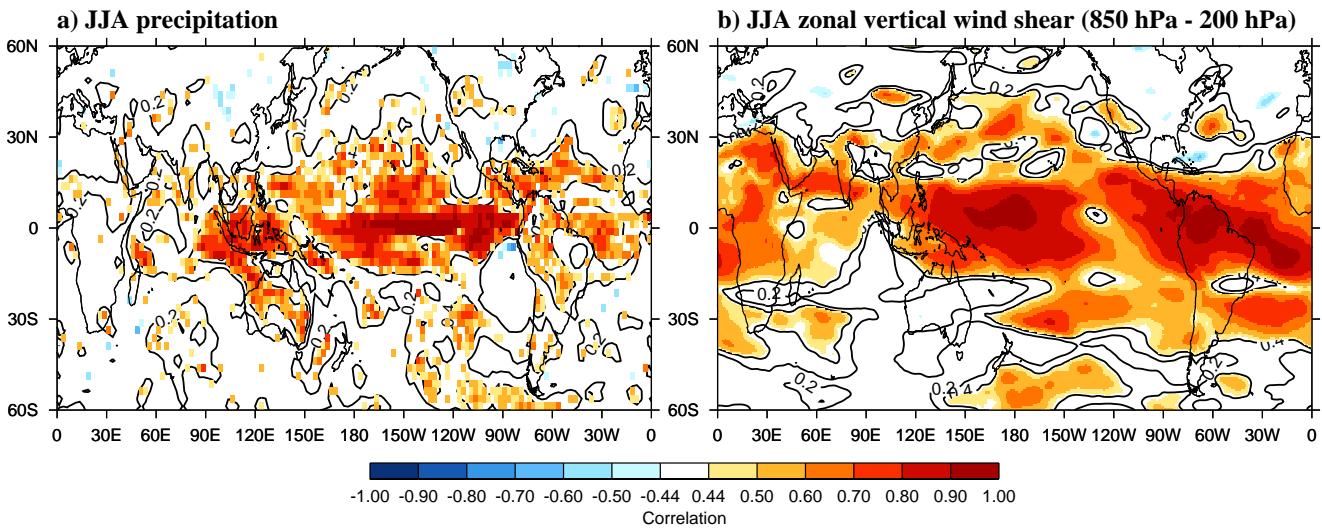


Fig. 3 Grid-point anomaly correlations of GPCP JJA precipitation and ERA-Interim JJA vertical wind shear with their GloSea5-GC2 ensemble mean equivalents. Significant skill ($0.44, p < 0.05$) is shaded, while lower skill is contoured at 0.2 and 0.4.

492 in GloSea5-GC2. Ensemble spread in the Webster-Yang₅₀₇
 493 index is still large compared to the magnitude of the₅₀₈
 494 mean anomaly, but less so than in JJA AIR, consistent₅₀₉
 495 with the S/N maps in Figure 2. ₅₁₀

511
 496 A simple measure of forecast skill is the correlation₅₁₂
 497 of observed and ensemble mean anomaly time series,₅₁₃
 498 such as those shown in Figure 4. We have listed these₅₁₄
 499 correlations in Table 1. The correlation of the GPCP₅₁₅
 500 and GloSea5-GC2 ensemble mean JJA AIR anomaly₅₁₆
 501 time series is 0.41 ($p < 0.1$). This indicates a mod-₅₁₇
 502 est level of skill, consistent with other forecast systems₅₁₈
 503 (Rajeevan et al., 2012). The Wang-Fan dynamical index₅₁₉
 504 represents the strength of the local Indian monsoon cir-₅₂₀
 505 culation in the northern Indian Ocean and over India₅₂₁
 506 itself using horizontal shear in the 850 hPa zonal winds₅₂₁

(difference between 40° to 80° E, 5° to 15° N and 70° to
 90° E, 20° to 30° N Wang and Fan, 1999). The Wang-
 Fan index shows a very similar correlation value (0.36,
 $p > 0.1$) to AIR, suggesting modest skill in predicting
 the local Indian monsoon circulation is related to the
 modest skill in predicting AIR.

The Webster-Yang dynamical index has a higher
 correlation of 0.66 ($p < 0.01$). This indicates that the
 large scale South Asian monsoon circulation is better
 predicted than the local Indian monsoon circulation
 and rainfall over India, consistent with the global cor-
 relation maps (Figure 3). However, this skill in predicting
 the Webster-Yang index is lower than that seen over a
 longer time period (1982-2009) with similar lead times
 and numbers of ensemble members in CfSv4 (0.74, $p <$

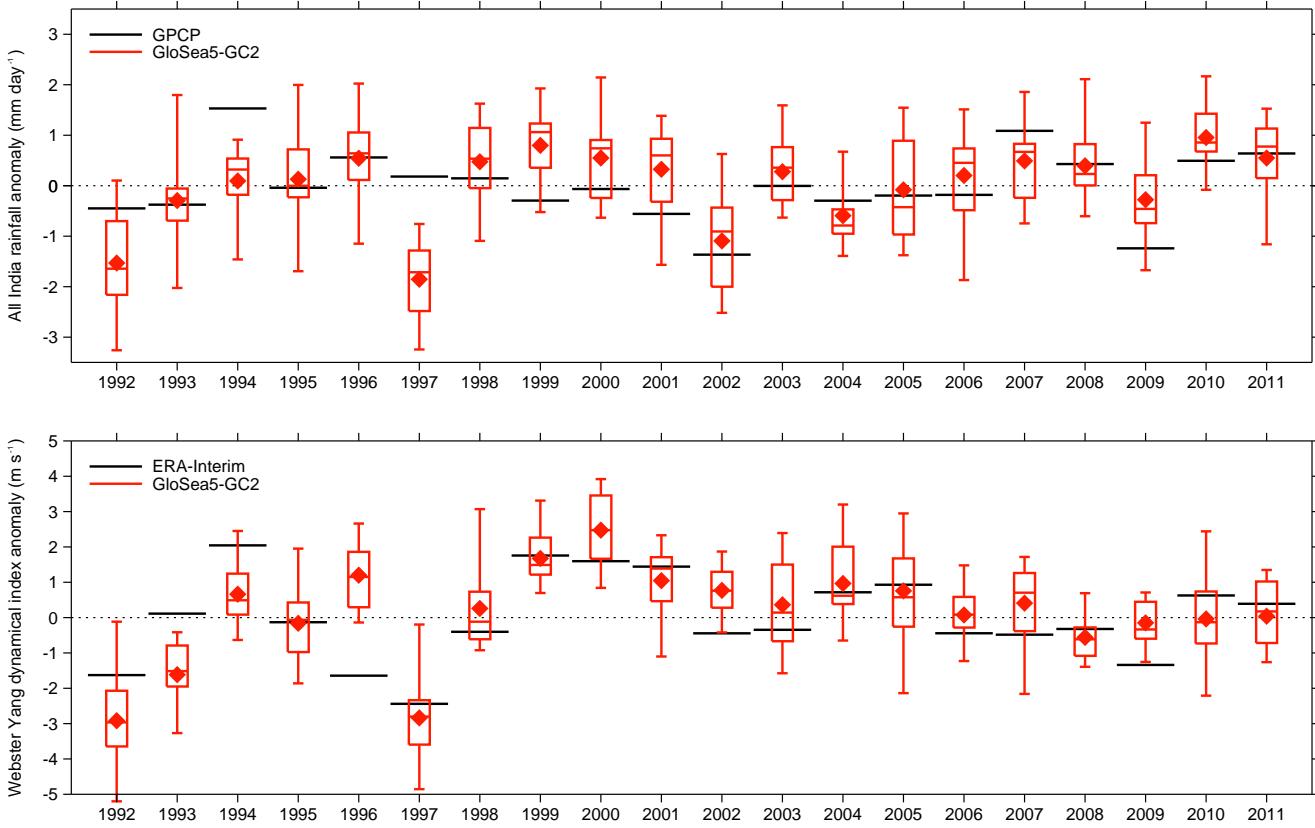


Fig. 4 JJA AIR (top) and Webster-Yang dynamical index (bottom) anomalies in GloSea5-GC2 (red), GPCP (top, black) and ERA-Interim (bottom, black). Box plots represent minimum, median, maximum and interquartile ranges of the ensemble, and the red diamond represents the ensemble mean. The Webster-Yang dynamical index subtracts the 850 hPa winds from the 200 hPa winds over 40° to 110°E and 0° to 20°N (Webster and Yang, 1992).

Table 1 Evaluating the GloSea5-GC2 skill in representing JJA monsoon precipitation and circulation index anomalies (indices defined in the text). Column 1 lists the correlation of observed JJA anomalies with GloSea5-GC2 ensemble mean anomalies. Columns 2 and 3 compare the observed interannual standard deviation (σ) to the hindcast sample median σ in mm day⁻¹ (see Figure 5).

	Correlation of ensemble mean	Observations interannual σ	Hindcast sample median σ
AIR	0.41	0.69	1.06
Wang-Fan index	0.36	0.66	0.89
Webster-Yang index	0.66	1.21	1.62

522 0.01) and ECMWF System 4 (0.78, $p < 0.01$, Kim et al.,⁵³⁶ 2012).⁵³⁷

524 To evaluate the interannual variance, we calculate⁵³⁸ standard deviations (σ) of the JJA time series of AIR,⁵³⁹ Wang-Fan dynamical index and Webster-Yang dynam-⁵⁴⁰ 526 ical index. Ensemble averaging enhances the com-⁵²⁷ ponent of interannual variability forced by slowly vary-⁵⁴¹ 528 ing components of the climate system relative to at-⁵⁴² 529 mospheric noise, likely artificially lowering the inter-⁵⁴³ 530 annual variance relative to observations. Accordingly, we⁵⁴⁴ 531 do not compare the ensemble mean σ to the observa-⁵⁴⁵ 532 tions. Instead we create distributions of σ for each index⁵⁴⁶ 533 (Figure 5) using the hindcast samples described in Sec-⁵⁴⁷ 534 tion 2.3.3 and compare the median to the observed σ .⁵⁴⁸

535 in Table 1. We find that in all indices, the variance in GloSea5-GC2 is too high, with the observed σ well separated from the hindcast sample distribution. This is consistent with the high ensemble spread seen in Figures 2 and 4.

5 Relationship between AIR and drivers of monsoon interannual variability

Slowly evolving boundary conditions such as SST, snow and soil moisture provide sources of tropical rainfall seasonal prediction skill (Charney and Shukla, 1981). In this section, we assess the representation of relationships between AIR and slowly evolving boundary con-

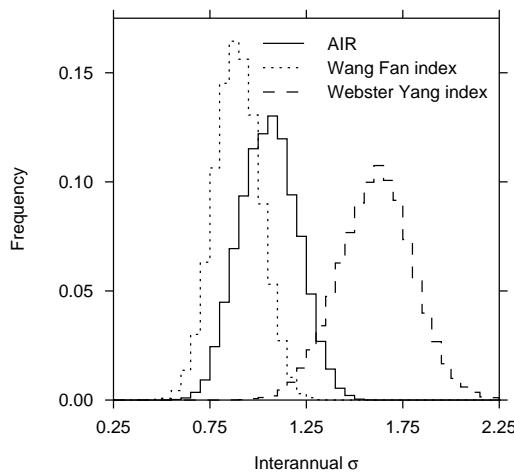


Fig. 5 Histograms of the standard deviation (σ) of JJA anomalies of monsoon precipitation and circulation indices in the hindcast sample time series. Medians of these distributions are compared to observed σ in Table 1. The hindcast samples are described in Section 2.3.3.

ditions in GloSea5-GC2. We perform a multiple linear regression analysis of AIR in observations and GloSea5-GC2 using indices representing modes of variability such as ENSO and the IOD as independent variables. We use the regression coefficients as a diagnostic of the relationships and explore sources of error in relationships that are poorly represented. Correcting these errors has potential to improve forecast skill, making them important targets for model development.

5.1 Indices

We use five indices of slowly varying boundary conditions in our analysis. Four indices represent three modes of SST variability: ENSO, the IOD and the Atlantic Niño. The final index represents interannual variability in snow mass over the HimTP. Each index has published proposed physical mechanisms that link their interannual variability to interannual variability in AIR (see review in Section 1). Table 2 defines the indices used. JJA anomalies are calculated relative to the time period covered by the hindcast set, 1992 to 2011, and are not standardised.

In Figure 6, regions used to calculate SST indices (Table 2) are overlaid on a JJA interannual correlation map of GloSea5-GO3 analysis SST and GloSea5-GC2 ensemble mean SST. GloSea5-GC2 has much higher prediction skill for SST than it does for precipitation or the circulation (Figure 3). There are significant correlation values across the globe, but the highest values are in the tropics. We use the Niño-3.4 index to represent the overall amplitude of ENSO and a trans-Niño index (TNI), calculated by subtracting the Niño-4 index

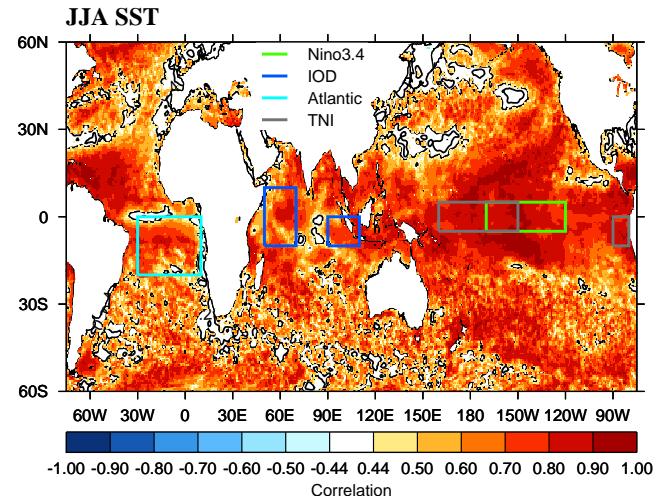


Fig. 6 Interannual correlation map of GloSea5-GO3 analysis and GloSea5-GC2 ensemble mean JJA SST. Grid points where the correlation is significant ($0.44, p > 0.05$) are shaded, while lower values are contoured. Most correlations are significant. The regions used as indices to represent modes of SST variability are outlined on this figure and listed in Table 2. Note that the Niño-4 region used to calculate the TNI index overlaps with the Niño-3.4 region from 120°W to 150°W .

from the Niño-1.2 index, to represent the zonal position of the heating. TNI has a positive value in an east Pacific El Niño, and a negative value in a central Pacific El Niño (Trenberth and Stepaniak, 2001). The IOD is represented by the IOD index (Saji et al, 1999), and the Atlantic Niño is represented by averaging SST anomalies over the region used in Kucharski et al (2007, 2008) (note this is the negative of the index used in Kucharski et al, 2007, 2008). The correlations of the GloSea5-GO3 analysis and the GloSea5-GC2 ensemble mean SST indices are listed in Table 2. All four correlation values are high and significant ($p < 0.01$) and the ENSO indices (Niño-3.4 and the TNI) have the highest values. The GloSea5-GC2 skill in predicting these indices should generate AIR prediction skill if the mechanism linking them is well represented.

Following Turner and Slingo (2011), who showed that snow cover over HimTP is the most relevant to AIR interannual variability, we adopt their HimTP index (Table 2). Figure 7 shows this region, as well as the JJA climatological snow mass over the HimTP in GloSea5-GC2 (Figure 7a), the JJA bias against ERA-Interim/Land (Figure 7b) and the JJA interannual correlation map with ERA-Interim/Land (Figure 7c). In ERA-Interim/Land, not much snow is present in JJA; the climatological HimTP JJA snow depth is only 2.56 cm of snow water equivalent (SWE). However, GloSea5-GC2 is missing 37% of the ERA-Interim/Land snow mass; a bias of -0.96 cm SWE. The correlation map

Table 2 Definition of JJA indices used as independent variables in the regression analysis, including the quantity and averaging domain. Also listed are the interannual standard deviations (σ) of the JJA indices in GloSea5-GO3 analysis and ERA-Interim/Land, and the interannual correlation of the indices with the GloSea5-GC2 ensemble mean indices.

Index	Quantity	Domain	Reanalysis σ	Correlation
Niño-3.4	SST	120° – 170°W, 5°S – 5°N	0.68 (°C)	0.87
IOD	SST	difference between 50° – 70°E, 10°S – 10°N and 90° – 110°E, 10°S – 0°	0.49 (°C)	0.71
ATL	SST	30°W – 10°E, 20°S – 0°	0.40 (°C)	0.79
TNI	SST	difference between 80° – 90°W, 10°S – 0° and 160°E – 150°W, 5°S – 5°N	1.30 (°C)	0.91
HimTP	Snow water equivalent (SWE)	67.5° – 100°E, 27.5° – 40°N	0.07 (cm SWE)	0.46

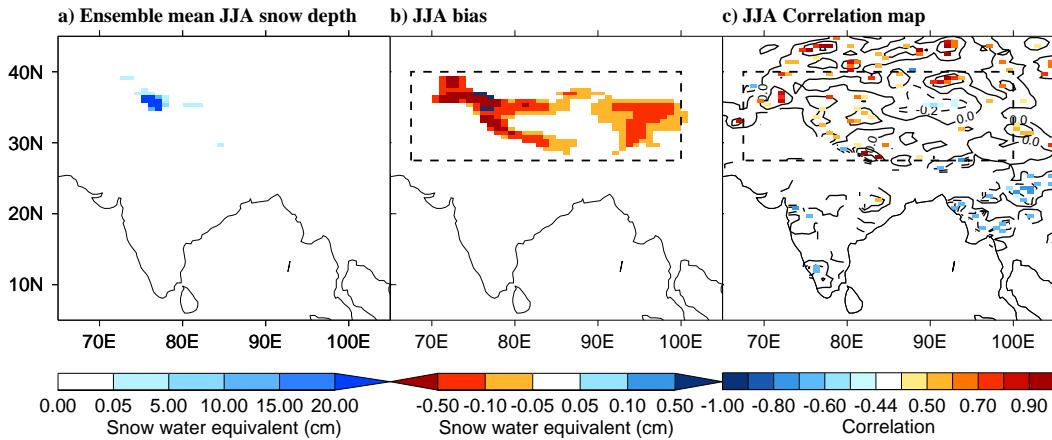


Fig. 7 a) Climatological JJA snow depth in GloSea5-GC2. b) JJA bias against ERA-Interim/Land. Also shown, as the dashed line, is the region used to calculate the HimTP index (Table 2). c) JJA interannual correlation map of ERA-Interim/Land and GloSea5-GC2 ensemble mean SWE. Grid points where the correlation is significant ($0.44, p > 0.05$) are shaded, while lower values are contoured at 0.0, 0.2 and 0.4. Most correlations are in this domain insignificant.

608 shows that the interannual prediction skill of GloSea5-
 609 GC2 snow mass in the region is low, though it tends to
 610 be higher in the locations with the most snow. The in-
 611 terannual correlation of the HimTP index is 0.46 ($p < 612 0.05$, Table 2), indicating modest skill. Consequently,
 613 even if the mechanism linking HimTP snow to AIR is
 614 well represented in GloSea5-GC2, HimTP snow may
 615 contribute little to the overall prediction skill of AIR. 635

616 5.2 Regression

617 To assess the relationship between AIR and the indices
 618 listed in Table 2, we perform a five parameter multiple
 619 regression analysis with each index included as an inde-
 620 pendent variable. We first perform this analysis on the
 621 observed and ensemble mean indices. However, ensem-
 622 ble averaging enhances the component of interannual
 623 variability forced by slowly varying boundary condi-
 624 tions relative to atmospheric noise, so comparing the
 625 relationships in the ensemble mean to the relationships
 626 in observations is unfair. To make a fair comparison,
 627 we perform our regression analysis on the many indi-
 628 636
 637
 638
 639

635 individual 20 year JJA series selected from our ensemble
 636 members, as described in Section 2.3.3. We use the re-
 637 gression coefficients for each index, the standard error
 638 for each coefficient (a measure of uncertainty in the re-
 639 gression coefficient), and the final R^2 value for the fit in
 640 our analysis (see Section 2.3.1 for a detailed description
 641 of each of these statistics). Performing the regression
 642 analysis on the hindcast samples creates a distribution
 643 of each statistic, which illustrates the ensemble spread,
 644 to compare to the single value from the observations.
 645 The median of each distribution is listed in Table 3 with
 646 the statistics from the observed and ensemble mean re-
 647 gressions. We also show the hindcast sample distribu-
 648 tions for the regression coefficients and the R^2 value in
 649 Figure 8.

650 The ensemble mean R^2 (Table 3) is much higher
 651 than the observed R^2 , demonstrating that ensemble av-
 652 eraging enhances the forced component of the variabil-
 653 ity relative to the noise. In the rest of our analysis,
 654 we only compare the statistics from the hindcast sam-
 655 ples to the observations. The hindcast sample median
 656 R^2 is lower than that of the observations, indicating
 657 there could be predictability from these indices that is
 658 659

651 unexploited in the GloSea5-GC2 system. However, the 652 observed R^2 value falls well within the R^2 distribution 653 in Figure 8, suggesting the R^2 values of the observations 654 and GloSea5-GC2 are consistent within the ensemble 655 spread in GloSea5-GC2. We will now examine 656 the regression coefficient from each index in turn, as 657 a diagnostic of the relationship between AIR and that 658 index.

659 5.2.1 ENSO

660 As expected, the observations show a negative regression 661 between Niño-3.4 and AIR in Figure 8, indicating 662 that a positive Niño-3.4 anomaly, i.e. El Niño conditions, 663 reduces AIR. The GloSea5-GC2 hindcast sample peak 664 matches the observed value well, indicating the relationship 665 between AIR and Niño-3.4 is well represented. Regression 666 maps of SST and precipitation on the Niño-3.4 index 667 confirm that the ENSO teleconnections in observations and 668 GloSea5-GC2 hindcasts are spatially very similar (not shown). This is likely the main 669 source of the prediction skill in the Webster-Yang 670 large-scale dynamical index (Figure 4).

671 The observations show a weak negative relationship between TNI and AIR, suggesting that an East Pa-cific El Niño decreases AIR more than a central Pa-cific El Niño, which disagrees with Krishna Kumar et al (2006). However, the regression is weak, with a 1σ variation in TNI resulting in a reduction in AIR of 0.14 mm day^{-1} (using Tables 2 and 3). There are also only three El Niño years in our hindcast set (JJA Niño-3.4 anomaly $> 0.5^\circ\text{C}$), and one of them is the very large east Pacific El Niño event of 1997, which likely dominates the relationship. Consequently, it is not surprising that the relationship between TNI and AIR is weak over this time period. The hindcast set replicates this weak relationship, with the peak of the distribution aligning with the observed value. This analysis indicates that the relationship between ENSO and AIR is well represented in GloSea5-GC2.

689 5.2.2 Indian Ocean dipole

690 As expected, the observations show a large positive regression 691 between the IOD index and AIR, indicating a positive 692 IOD increases AIR. The hindcast samples also show a 693 positive regression, but at a much smaller value, and the 694 value derived from observations falls in the extreme tail of 695 the hindcast sample distribution. This suggests the 696 relationship between the IOD and AIR is too weak in 697 GloSea5-GC2.

698 To confirm this interpretation and diagnose any related 699 errors in GloSea5-GC2, we calculate a multiple

700 regression with the same independent variables at each 701 grid point in JJA maps of SST, land precipitation and 702 850 hPa zonal and meridional winds. In Figure 9, the 703 IOD index regression coefficient is shown for the 704 observations, analogous to the dashed line on the IOD 705 panel of Figure 8, and for the hindcast sample median, 706 analogous to the median of the distribution in the IOD 707 panel of Figure 8. In the observations, the expected 708 IOD SST anomalies are clear, with warm anomalies in 709 the WEIO and cool anomalies in the EEIO, especially 710 off the coast of Sumatra and Java (Saji et al, 1999; 711 Webster et al, 1999). The SST anomalies are associated 712 with wind anomalies, including a strengthening of 713 equatorial easterly winds and strengthening of the west- 714 erlies across the Arabian Sea, India and Indochina. This 715 brings increased moisture transport to India, increasing 716 monsoon precipitation (Ashok et al, 2001). In GloSea5- 717 GC2, the EEIO anomalies are too cold and extend to 718 70°E , too far west. The WEIO SST anomalies are not 719 warm enough, reducing the anomalous zonal SST gradient. 720 The circulation anomalies and Indian precipitation 721 anomaly are also weak.

722 Using wind stress correction experiments in HiGEM, 723 an older version of the coupled MetUM (Shaffrey et al, 724 2009), Marathayil (2013) demonstrated that similar 725 errors in IOD SST anomalies were due to a coupled mean 726 state bias in the Indian Ocean. Stronger than observed 727 mean state easterlies in the EEIO, which are related 728 to errors in convective precipitation in the WEIO, lead 729 to cooler than observed EEIO SSTs and increased up- 730 welling, shoaling the thermocline in the east. The erroneously 731 cool EEIO SSTs and erroneously warm WEIO SSTs 732 reinforce the erroneously strong easterlies. This 733 is consistent with the GloSea5-GC2 precipitation, SST 734 and winds biases shown in Figure 1. We show the 735 ensemble mean IO vertical temperature profile averaged 736 from 3°S to 3°N in GloSea5-GC2 compared to EN4 737 analysis in Figure 10. The 20°C isotherm is highlighted 738 as a proxy for thermocline depth. The thermocline is 739 slightly too deep in the WEIO, and much too shallow 740 in the EEIO in GloSea5-GC2, also consistent with the 741 HiGEM bias (Marathayil, 2013).

742 This coupled mean state bias results in errors in the 743 representation of the IOD. The shallower thermocline 744 makes the EEIO SSTs more susceptible to wind anomalies 745 during IOD initiation, leading to erroneously cool 746 SST anomalies. The erroneous SST anomalies cause 747 errors in the anomalous circulation and Indian precipitation, 748 which could be further exacerbated by known 749 errors in the representation of convective precipitation 750 over the WEIO and India (Figure 1 and e.g. Bush et al, 751 2015). Marathayil (2013) demonstrated that mean state 752 wind stress corrections in the EIO decrease these mean

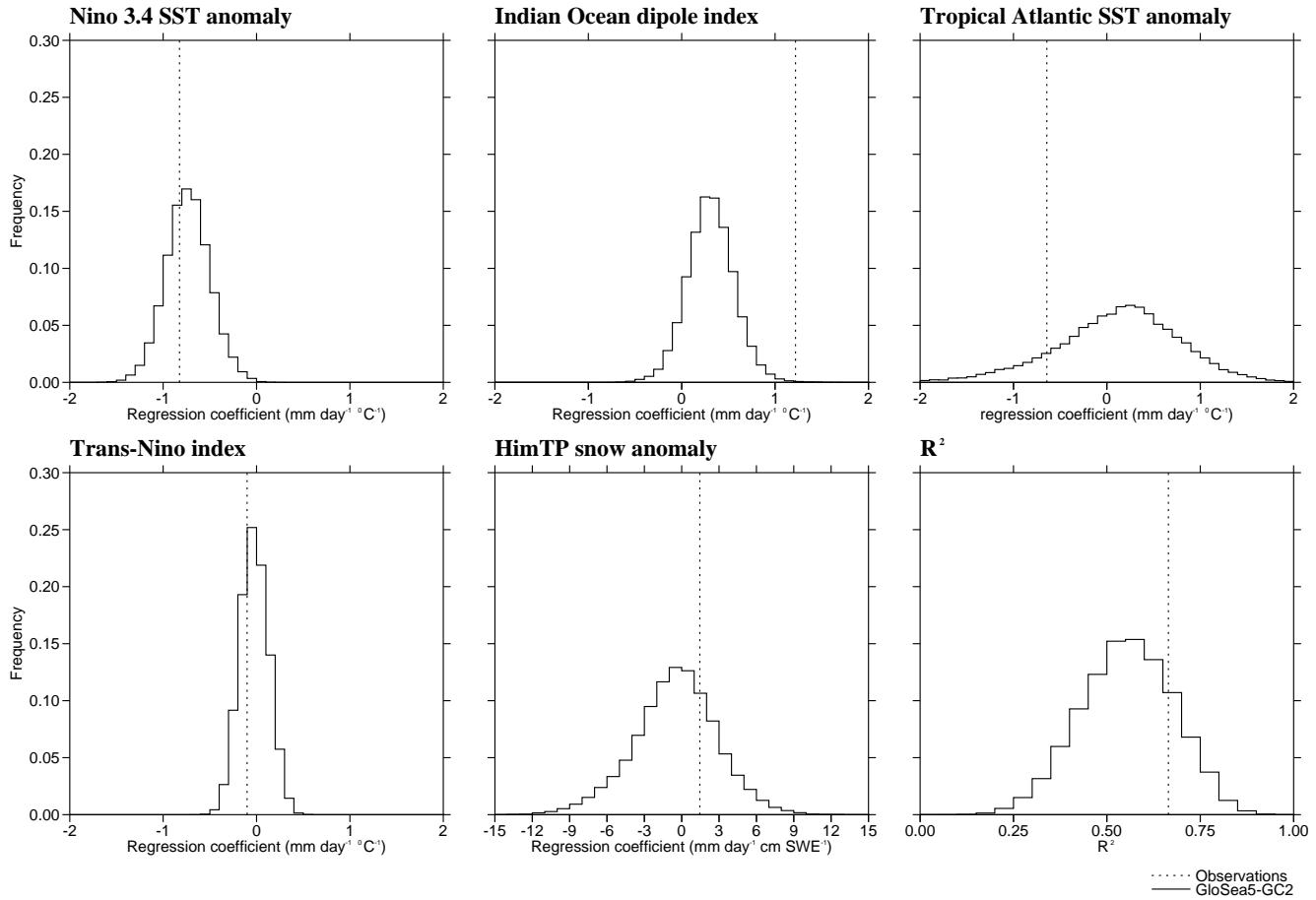


Fig. 8 Regression coefficients and R^2 from the five parameter JJA AIR multiple regression analysis. The dashed lines are the regression coefficients from observations, and the distributions in the solid lines show the results from many JJA series selected from the ensemble members in the GloSea5-GC2 hindcast set (Section 2.3.3).

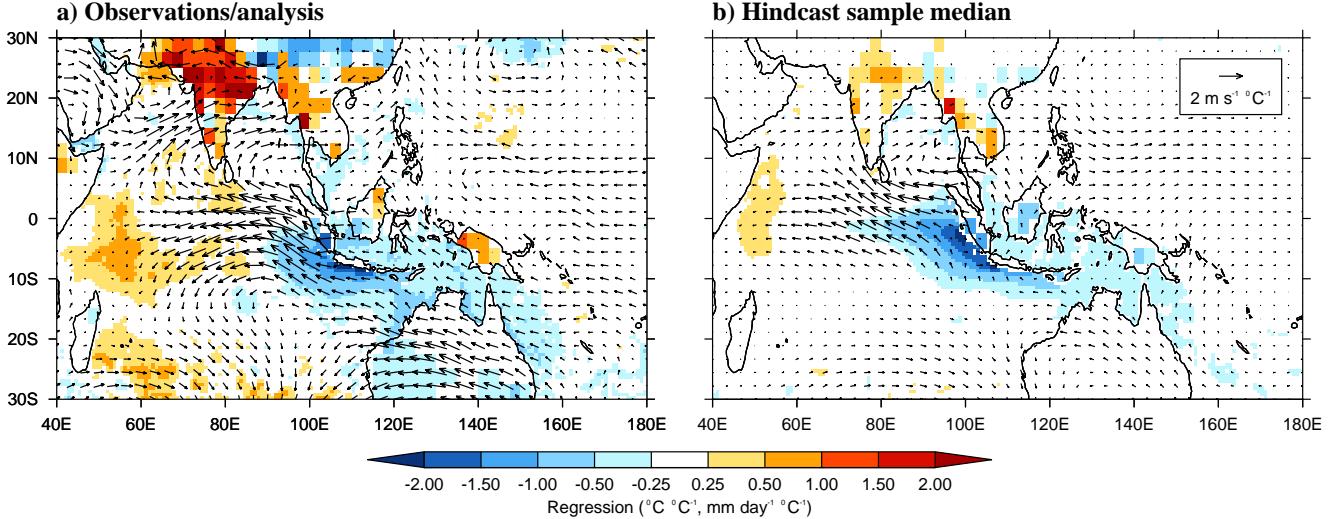


Fig. 9 Maps of the IOD regression coefficient from the five parameter regression analysis computed at each grid point of JJA SST, land precipitation and 850 hPa winds in (a) GloSea5-GO3 analysis, GPCP and ERA-Interim and (b) GloSea5-GC2. For GloSea5-GC2, the regression is calculated for each hindcast sample and the median is taken at each grid point. The map in (a) is equivalent to the dotted line in the IOD panel of Figure 8 at each grid point and the map in (b) is equivalent to the median of the distribution in the IOD panel of Figure 8 at each grid point.

Table 3 The regression coefficient and standard error for each independent variable in the multiple regression analysis of JJA indices with JJA AIR. The R^2 value for the regression is also listed. The statistics from the multiple regression analysis of the observations, statistics from the multiple regression analysis of the ensemble mean and the median of the hindcast sample statistics (median regression coefficient and median standard error) are all shown. The final line shows only the HimTP regression coefficient and standard error from a multiple regression analysis of June indices with June AIR. The units of regression coefficients and standard errors for SST indices are $\text{mm day}^{-1} \text{ }^{\circ}\text{C}^{-1}$. The units of regression coefficients and standard errors for the HimTP snow indices are $\text{mm day}^{-1} \text{ cm SWE}^{-1}$.

	Obs and Analysis	Ensemble mean	Ensemble median
Niño-3.4	-0.82 ± 0.21	-0.68 ± 0.13	-0.74 ± 0.24
IOD	1.22 ± 0.26	0.31 ± 0.18	0.31 ± 0.28
Atlantic	-0.64 ± 0.33	0.41 ± 0.38	0.15 ± 0.61
TNI	-0.10 ± 0.09	-0.02 ± 0.08	-0.03 ± 0.16
HimTP Snow	1.45 ± 1.62	-1.06 ± 2.13	-0.35 ± 3.15
R^2	0.66	0.79	0.56
June HimTP Snow	-1.54 ± 1.21	-2.14 ± 2.63	-2.18 ± 4.70

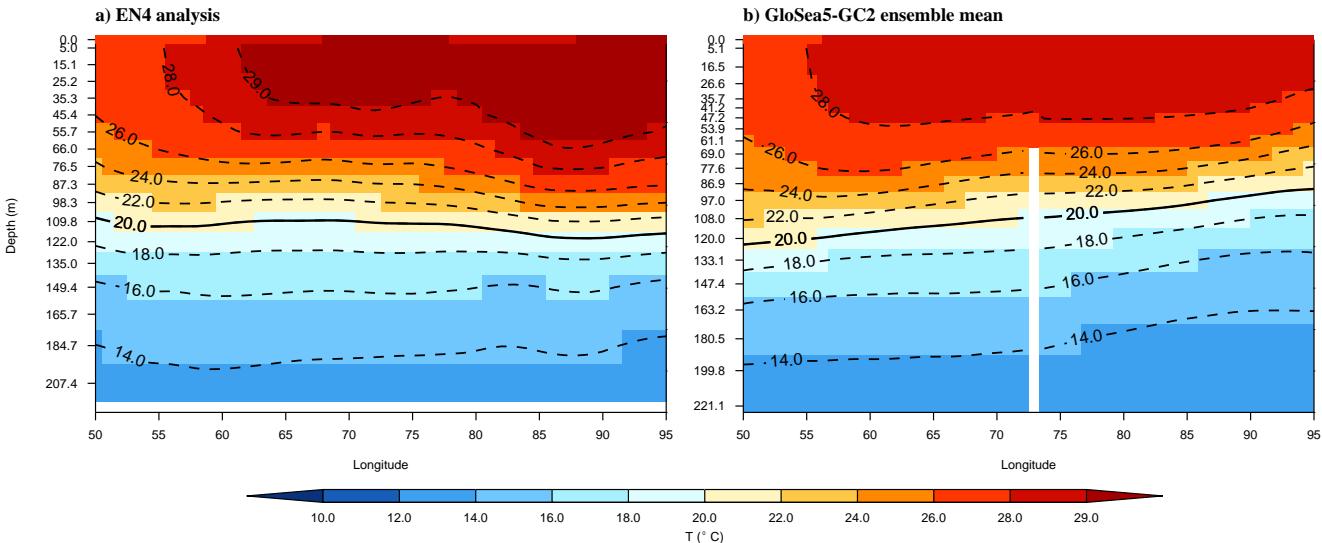


Fig. 10 Vertical profiles of Indian Ocean temperature at the equator, averaged from 3°N to 3°S , in (a) GloSea5-GC2 SST analysis and EN4 subsurface analysis and (b) the GloSea5-GC2 ensemble mean. Each dataset is plotted on a similar set of its own levels which are listed on the y-axis. The solid line marks the 20°C isotherm, a proxy for thermocline depth. The white gap in the GloSea5-GC2 hindcast data is due to missing data at the location of the Andaman Islands.

753 state biases and result in a better representation of the
 754 IOD SST anomalies in HiGEM. Improving this
 755 coupled mean state bias would likely improve AIR predi-
 756 cation skill and prediction skill in the Indian Ocean basin
 757 more broadly.

758 5.2.3 Atlantic Niño

759 As suggested by Kucharski et al (2007, 2008), the ob-
 760 servations show a negative regression between the At-
 761 lantic index and AIR, indicating warm tropical Atlantic
 762 SSTs decrease AIR or, conversely, that cool tropical At-
 763 lantic SSTs increase AIR. However, the hindcast sam-
 764 ples show a wide distribution created by the ensemble
 765 spread in GloSea5-GC2, that peaks at a slightly positive
 766 value and has tails extending to $\pm 2 \text{ mm day}^{-1} \text{ }^{\circ}\text{C}^{-1}$.
 767 While the Niño-3.4 and IOD regression coefficients in
 768 GloSea5-GC2 have similar standard errors to the stan-
 769

770 dard errors derived from observations (Table 3), the
 771 Atlantic index regression coefficient has nearly double
 772 the standard error in the hindcast samples than in the
 773 observations, indicating that the regression values are
 774 not as constrained in GloSea5-GC2 as they are in the
 775 observations. These results motivate a more detailed
 776 analysis of the representation of the mechanism linking
 777 Atlantic SST anomalies to AIR in GloSea5-GC2.

778 Kucharski et al (2007, 2008) use an ensemble of at-
 779 mospheric GCM integrations, coupled only in the In-
 780 dian Ocean, to compare experiments forced by interan-
 781 nually varying Atlantic SSTs with control integrations
 782 forced by climatological Atlantic SSTs. Their experi-
 783 ments show an equatorial Rossby wave response to At-
 784 lantic Niño anomalies which creates a quadrupole struc-
 785 ture in upper level eddy stream function and modifies
 786 the low level circulation in the Indian Ocean (Kucharski
 787 et al, 2007, Figure 6). Cool anomalies create anomalous

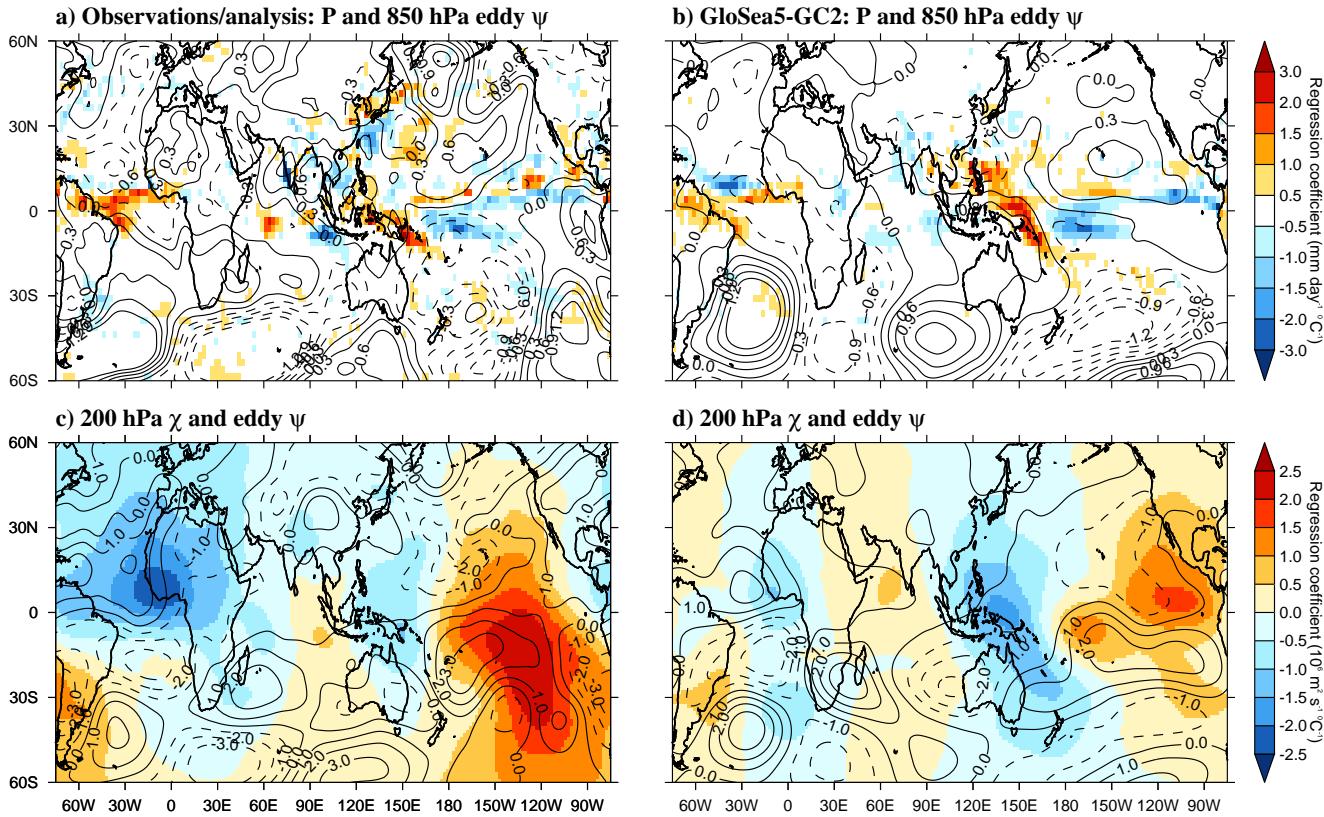


Fig. 11 Maps of regression coefficients of precipitation (shading, a and b), 850 hPa eddy stream function (contours, a and b), 200 hPa eddy stream function (contours, c and d) and velocity potential (shading, c and d) regressed against the Atlantic index in GPCP, ERA-interim and the GloSea5-GC2 hindcast samples that are within 0.05 of the observed Atlantic regression value in Figure 8. First, each grid point of each of these fields was regressed against the Niño-3.4 index. Then the residual was regressed against the Atlantic Niño index, creating the regression coefficients shown here. 850 hPa stream function contours are spaced by $0.3 \text{ } 10^6 \text{ m}^2 \text{ s}^{-1} \text{ } ^\circ\text{C}^{-1}$ and 200 hPa stream function contours are spaced by $10^6 \text{ m}^2 \text{ s}^{-1} \text{ } ^\circ\text{C}^{-1}$.

787 low level cyclones in the equatorial Indian Ocean on ei-809
 788 either side of the equator which increase moisture con-810
 789 vergence and precipitation over India (Kucharski et al,811
 790 2008, Figure 3).

791 To determine whether this mechanism is acting in 813
 792 GloSea5-GC2, we regressed maps of the precipitation, 814
 793 850 and 200 hPa eddy stream function, and 200 hPa ve-815
 794 locity potential against the Atlantic index. The Kucharski 816
 795 et al (2007, 2008) study included the effects of ENSO in 817
 796 both the experiments and the control, so the effects of 818
 797 ENSO should be excluded from their results. To anal-819
 798 yse as similar a diagnostic as possible, we first regress 820
 799 the GloSea5-GC2 fields against the Niño-3.4 index and 821
 800 then regress the residual against the Atlantic index. To 822
 801 clarify the response, we calculate the regression maps 823
 802 individually for 768 of the 3×10^4 GloSea5-GC2 hind-824
 803 cast samples which have Atlantic regression coefficients 825
 804 between -0.59 and -0.69 (within 0.05 of the observed 826
 805 value, Figure 8). We averaged the sample regression 827
 806 maps to create the final maps shown in Figure 11. We 828
 807 also show the equivalent regression maps derived from 829
 808 GPCP and ERA-Interim.

As the hindcast samples were selected based on the proximity of their rainfall regression value to the observed regression value, it is not surprising that negative rainfall anomalies over India are associated with positive Atlantic SST anomalies in both GPCP and the GloSea5-GC2 samples in Figure 11. However, the smooth response of the velocity potential and the quadrupole structure in upper level stream function shown in Kucharski et al (2007) are not present in the GloSea5-GC2 hindcast samples or ERA-Interim. The low level Indian Ocean cyclones shown in Kucharski et al (2008), which would correspond to the low level anti-cyclones in Figure 11, are also missing in GloSea5-GC2. Instead, anomalous upper level divergence is seen broadly over the Atlantic and west Pacific, and upper level convergence is seen in the east Pacific and Indian Ocean, though the magnitude and pattern differ considerably between ERA-Interim and the GloSea5-GC2 samples. There is a low level anti-cyclone present over India in ERA-Interim, but it is not mirrored south of the equator. There is no clear wave-like pattern that is consistent between ERA-Interim and GloSea5-GC2 in upper or lower level

stream function. Similar maps made using all 3×10^4 hindcast samples give similar results (not shown).

Pottapinjara et al (2014) introduced another diagnostic of the influence of tropical Atlantic SSTs on the Indian monsoon. Using NCEP reanalysis (Kanamitsu et al, 2002) and the HadISST sst dataset (Rayner et al, 2003), they correlate Atlantic SST indices with global tropospheric temperature anomaly (1000 hPa to 200 hPa) maps after the influence of ENSO has been removed from both. This reveals a Gill-type (Gill, 1980) tropospheric temperature heating response to warm SSTs in the tropical Atlantic that extends into the tropical Indian Ocean (Pottapinjara et al, 2014, Figure 10). They argue that the tropospheric temperature increase in the Indian Ocean reduces the meridional temperature gradient that drives the South Asian monsoon, reducing Indian rainfall. This is consistent with the Kucharski et al (2007, 2008) results showing cool tropical Atlantic SSTs increase Indian rainfall.

We reproduce this Pottapinjara et al (2014) diagnostic in ERA-Interim reanalysis and the 768 GloSea5-GC2 hindcast samples that agree with the observed Atlantic AIR regression coefficient and show it in Figure 12. In ERA-Interim, tropospheric temperature warming is correlated with the Atlantic index over the tropical Atlantic and Indian Ocean. However it does not extend as far into the Indian Ocean, or correlate as strongly with the Atlantic index as shown in Pottapinjara et al (2014). In GloSea5-GC2 the correlation over the tropical Atlantic is weaker and it does not extend to the Indian Ocean. The Atlantic index used in this study is different than the Atlantic index used in Pottapinjara et al (2014), but repeating the analysis with their At3 index does not change the results.

We conclude that the wave mechanisms described in Kucharski et al (2007, 2008) are not acting in GloSea5-GC2, even in the hindcast samples with a similar regression coefficient to the coefficient derived from observations. That ERA-Interim also does not show the mechanisms prompts questions about the validity and robustness of these mechanisms. Kucharski et al (2007, 2008) study 1950 to 1999 and Pottapinjara et al (2014) study 1979 to 2012, so it is possible that decadal variability has altered or obscured this mechanism in the 1992 to 2011 time period we analyse here. Further study of the Atlantic Niño-AIR teleconnection and its variation over time is needed to unify these results.

5.2.4 HimTP snow

Turner and Slingo (2011) and Senan et al (2015) show using experiments that initialise anomalous snow on April 1, that increased HimTP snow cover reduces sur-

face sensible and long wave heating as proposed by Blanford (1884), which delays the onset of the monsoon and significantly reduces monsoon rainfall in June. In these experiments, snow anomalies persist from April through June. The snow anomalies' impact on June monsoon rainfall combines two effects: the effect previous, spring snow cover had on the tropospheric temperature gradient that initiated the monsoon and the effect current, June snow cover has on current surface temperatures and radiative balances. In order to consider ensemble members from all initialisation dates in the GloSea5-GC2 hindcast set as one ensemble, we must analyse the impact of snow anomalies at a time sufficiently removed from the hindcast initialisation dates. Consequently, we do not consider snow before June in this analysis. This means we only analyse the relationship between summer snow cover anomalies and monsoon rainfall anomalies. For consistency with our JJA analysis, we initially examine the relationship between JJA snow anomalies and JJA rainfall anomalies, but later in this section we examine the relationship between June snow anomalies and June rainfall anomalies, where we would expect to see a larger impact.

In the observations, HimTP snow shows a positive regression with AIR in JJA. This is the opposite of the expected relationship via the Blanford mechanism (Blanford, 1884). A 1σ variation in JJA HimTP snow cover results in an increase of 0.1 mm day^{-1} in JJA rainfall (using Tables 2 and 3), indicating almost no relationship between JJA HimTP snow and JJA AIR. The hindcast samples are consistent with this lack of relationship.

However, Turner and Slingo (2011) showed that the main impact of HimTP snow on AIR is in June, and its relationship with June precipitation may not be strong enough to be detectable in JJA precipitation. To test the representation of the relationship in June, we repeated the entire multiple regression analysis with June indices and, in Figure 13 and Table 3, we show the HimTP snow regression coefficients. The June regression derived from observations is indeed negative, but roughly the same magnitude as the JJA regression. June snow in ERA-Interim/Land has a higher interannual standard deviation, 0.21 cm SWE , than JJA snow, so 1σ variation in June snow leads to a slightly larger impact on June rainfall, 0.3 mm day^{-1} . The hindcast samples have a broad distribution, peaking at the observed value, suggesting GloSea5-GC2 is correctly representing this small negative impact current snow cover has on June Indian rainfall.

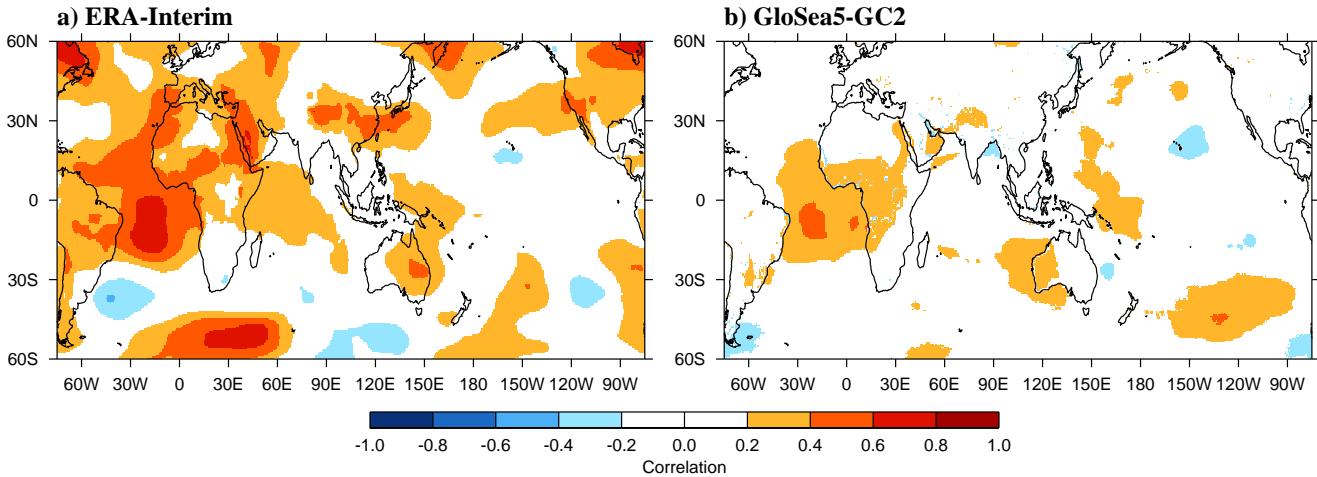


Fig. 12 Correlation of the JJA tropospheric temperature anomaly (averaged from 1000 to 200 hPa) with the JJA Atlantic SST index, after a regression against Niño-3.4 has been removed from each. a) ERA-Interim. b) Average correlation of the GloSea5-GC2 hindcast samples that are within 0.05 of the observed Atlantic regression value in Figure 8.

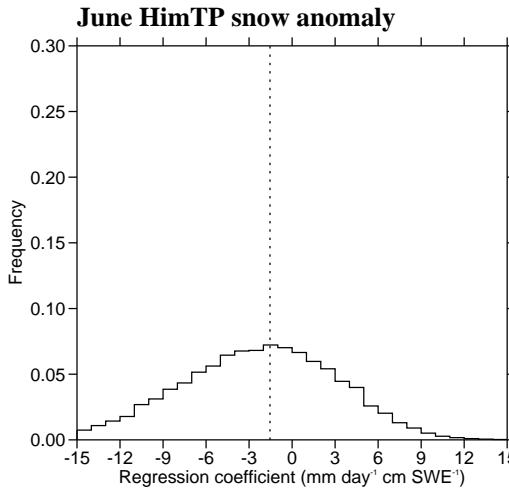


Fig. 13 HimTP snow index regression coefficients in the five parameter June multiple regression analysis. The dashed line is the observed value, and the distribution in the solid line shows the results from many June series selected from the ensemble members in the GloSea5-GC2 hindcast set.

944 In both the observations and GloSea5-GC2, the Niño-
 945 3.4 and IOD indices are most important in explaining
 946 the interannual variability in AIR over the hindcast pe-
 947 riod. Their combined R^2 values are 0.53 and 0.46 in the
 948 observations and hindcast samples, respectively, com-
 949 compared to R^2 value when all five indices are included of
 950 0.66 and 0.56 (listed in Tables 3 and 4). The remaining
 951 three indices add similar, smaller contributions to the
 952 R^2 in observations and GloSea5-GC2. This means it is
 953 difficult to separate them in order of importance, and
 954 we consequently focus on the differences in R^2 for the
 955 Niño-3.4 index and the IOD index.

956 In Table 4, we summarise the results of the forward
 957 selection for the Niño-3.4 and IOD indices. In the ob-
 958 servations, the IOD index explains most of the variance
 959 in AIR, with a single R^2 of 0.27, while in GloSea5-GC2,
 960 Niño-3.4 explains most of the variance with a single R^2
 961 of 0.39. The two indices are similarly correlated with
 962 each other in the GloSea5-GO3 analysis (0.33) and the
 963 GloSea5-GC2 ensemble mean (0.28), indicating the re-
 964 lationship between ENSO and the IOD is consistent
 965 between the observations and GloSea5-GC2. The com-
 966 bined results from the forward selection and multiple
 967 regression analysis suggest that the weakness of the re-
 968 lationship between AIR and the IOD causes AIR to re-
 969 spond too consistently to ENSO anomalies in GloSea5-
 970 GC2, as seen in other forecast systems (Kim et al.,
 971 2012), and consequently Niño-3.4 explains too much of
 972 the variance in AIR in GloSea5-GC2 and the IOD in-
 973 dex explains too little. If the relationship between AIR
 974 and the IOD were correctly represented, it would at
 975 times reinforce the AIR anomaly forced by ENSO, and
 976 at times counteract that anomaly, leading to a weaker
 977 overall correlation between ENSO and AIR and less

932 5.3 Forward selection

933 To assess the importance of each of these indices to
 934 this regression, we use forward selection (Section 2.3.2).
 935 In this technique, indices are each regressed separately
 936 against AIR. The index with the highest R^2 value is
 937 then regressed against AIR in combination with each of
 938 the remaining indices in turn. The process is repeated
 939 until all of the indices are included as independent vari-
 940 ables in the regression. The ordering of the indices and
 941 the increase in R^2 as each index is added, reflect the
 942 importance of the index in explaining the interannual
 943 variability of AIR.

Table 4 Summary of results from forward selection. R^2 for a single regression of Niño-3.4 or the IOD index against AIR is shown in the first two rows, the R^2 for the combined regression of both indices against AIR is shown in the third row.

	Observations and Analysis	Hindcast sample median
Niño-3.4	0.10	0.39
IOD	0.27	0.02
Niño-3.4 & IOD	0.53	0.46

interannual variability explained by ENSO, consistent with the observations.

6 Discussion and Conclusions

We have assessed the seasonal prediction skill of summer all-India rainfall (AIR) and the representation of mechanisms contributing to predictability of AIR in the GloSea5-GC2 coupled ensemble seasonal forecast system. GloSea5-GC2 has notable mean state biases, including equatorial SST cold biases in all basins. The Indian Ocean has the lowest JJA precipitation and circulation signal-to-noise ratios and prediction skill in the tropics, consistent with other state-of-the-art seasonal forecast systems (Rajeevan et al, 2012).

GloSea5-GC2 has moderate skill in predicting JJA AIR ($0.41, p < 0.1$). However, it has much higher skill in predicting the large scale circulation (0.66 for the Webster-Yang dynamical index, $p < 0.01$), consistent with other forecast systems. ENSO, the most widespread mode of interannual SST variability, and the relationship between ENSO and AIR are well represented in GloSea5-GC2. This indicates that the AIR interannual variability related to the large-scale circulation in GloSea5-GC2 is well represented. However, the basin-scale relationship between AIR and the IOD is weak in GloSea5-GC2. Our analysis showed this likely due to a coupled mean state bias in the Indian Ocean which alters the amount of anomalous SST cooling/warming that results from anomalous wind forcing, giving erroneous IOD SST anomalies. Known difficulties in representing convective precipitation over India may also play a role (e.g. Bush et al, 2015). Due to the lack of response to the IOD, AIR responds more consistently to ENSO in GloSea5-GC2 than in observations, which manifests itself in an erroneously high correlation between ENSO indices and AIR.

Our analysis did not show a teleconnection from the tropical Atlantic Niño region to the Indian subcontinent in GloSea5-GC2. However, when analysed over the time period available from the GloSea5-GC2 hindcast set, this teleconnection was not clear in ERA-Interim.

either. This suggests further work is needed to confirm the validity and establish the robustness of the Kucharski et al (2007, 2008) mechanism connecting the the Atlantic Niño region to AIR. Our analysis also indicated the response of June Indian rainfall to June HimTP snow anomalies in GloSea5-GC2 agrees with observations, but is small in both.

Due to the relatively few years in our hindcast set, we analysed all years in our hindcast set together, rather than studying years with an especially strong anomaly in a given index, such as ENSO events. In twenty years there are only a few events of any type, so analysis of strong anomaly years would be very dependent on the GloSea5-GC2 performance in a few individual years. However, A limitation of our analysis is that our general conclusions may not apply to an individual year. For example, we cannot conclude from our analysis that the 1997 forecast bust is necessarily due to a misrepresentation of the IOD-AIR relationship rather than a misrepresentation of the ENSO-AIR relationship. We can conclude that the IOD-AIR relationship is generally misrepresented in GloSea5-GC2, and improving it will improve forecast skill over the hindcast period as a whole, independent of whether it improves forecast skill in a specific year such as 1997.

In agreement with our analysis, recent assessments of seasonal forecast skill have generally found that ENSO anomalies and the response of AIR to the ENSO anomalies are well represented in GCMs (Kim et al, 2012; Rajeevan et al, 2012; Nanjundiah et al, 2013). The representation of the relationship between AIR and the IOD is increasingly recognised as a source of error. Consistent with our analysis of the coupled Indian Ocean SST/wind bias, Rajeevan et al (2012) showed in the ENSEMBLES and DEMETER samples of coupled seasonal forecast systems that air-sea coupling in the Indian Ocean basin is too strong. Nanjundiah et al (2013) studied five coupled seasonal forecast systems from the ENSEMBLES sample and found that the relationship between AIR and the equatorial Indian Ocean zonal wind anomalies is generally poorly represented.

In GloSea5-GC2, the application of mean state bias correction techniques to reduce the error in circulation and equatorial SSTs in the Indian Ocean may improve both the representation of IOD anomalies, as Marathayil (2013) showed for the coupled GCM HiGEM, and the relationship between the IOD and AIR. As the IOD is the major mode of interannual variability in the Indian Ocean, we expect that an improved representation of the Indian Ocean mean state and the IOD would have a significant impact on precipitation and circulation seasonal prediction skill in the Indian Ocean (Fig-

ure 3), and would likely improve AIR prediction skill as well.

Conditions in the equatorial Indian Ocean are important for the correct initiation and propagation of the boreal summer intraseasonal oscillation (e.g. Sperber and Annamalai, 2008). The propagation and amplitude of the BSISO are weak in GloSea5-GC2 (Jayakumar et al, 2016). Given the similarity in pattern between the leading mode of interannual variability in monsoon circulation and a component of the intraseasonal variability, and that the frequency of occurrence of this intraseasonal variability projects onto interannual variations (Sperber et al, 2000), poor simulation of Indian Ocean intraseasonal variability may also therefore impact on the skill of interannual rainfall prediction. Further analysis should address the relationship between errors in the Indian Ocean mean state, the IOD and intraseasonal variability in seasonal forecast systems.

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