How extreme could the near term evolution of the Indian Summer Monsoon rainfall be?

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Abstract
We provide a methodology to estimate possible extreme changes in seasonal rainfall for the coming decades. We demonstrate this methodology using Indian summer monsoon rainfall as an example. We use an ensemble of 1669 realizations of Indian summer monsoon rainfall from selected seasonal prediction systems to estimate internal variability and show how it can exacerbate or alleviate forced climate change. Our estimates show that for the next decade there is a ∼60% chance of wetting trends, whereas the chance of drying is ∼40%. Wetting trends are systematically more favoured than drying with the increasing length of the period. However, internal variability can easily negate or overwhelm the wetting trends to give temporary drying trends in rainfall. This provides a quantitative explanation for the varying trends in the past observational record of rainfall over India. We also quantify the likelihood of extreme trends and show that there is at least a 1% chance that monsoon rainfall could increase or decrease by one fifth over the next decade and that more extreme trends, though unlikely, are possible. We find that monsoon rainfall trends are influenced by trends in sea-surface temperatures over the Niño3.4 region and tropical Indian Ocean, and ∼1.5 ° cooling or warming of these regions can approximately double or negate the influence of climate change on rainfall over the next two decades. We also investigate the time-of-emergence of climate change signals in rainfall trends and find that it is unlikely for a climate change signal to emerge by the year 2050 due to the large internal variability of monsoon rainfall. The estimates of extreme rainfall change provided here could be useful for governments to prepare for worst-case scenarios and therefore aid disaster preparedness and decision-making.

1. Introduction

The Indian summer monsoon rainfall contributes ∼80% of the total annual rainfall received over the country and has widespread influence on the hydrological cycle, agriculture, and the economy (Saha et al 1979, Lobell et al 2011, Auffhammer et al 2012, Jena et al 2015). Over the last century, insignificant changes were observed in the all-India summer monsoon rainfall (Kumar et al 2010). However, significant wetting and drying trends were observed in the past on multidecadal timescales (Mooley and Parthasarathy 1984). For instance, from the mid to late 20th century (i.e. 1950–2000), a significant drying trend was seen in all-India summer monsoon rainfall (e.g. Ramesh and Goswami 2014, Saha et al 2014, Salzmann and Cherian 2015) whereas an increasing trend was reported from the year 2000 onwards (Jin and Wang 2017). The range of possible changes in seasonal rainfall over the next few decades can help the government to prepare for the worst-case scenarios (e.g. floods or droughts) and aid food and water security, disaster management, and decision-making. Therefore, in this study, we provide an estimate of the possible extreme changes in the Indian summer monsoon rainfall for the coming decades.

On multidecadal timescales, trends in rainfall can arise due to the internal variability of the climate system (e.g. trends in El-Niño Southern Oscillation (ENSO), Pacific Decadal Oscillation and internal
variability of the atmosphere) as well as due to the changes in natural or anthropogenic forcings (e.g. changes in anthropogenic emissions, land-use or land-cover, volcanic eruptions, solar radiation). There is abundant evidence that regional and near-term changes in climate variables, including rainfall, contain significant internal variability even on long timescales (e.g. Hegerl et al 2007, Hawkins and Sutton 2009, Kirtman et al 2013, Deser 2020, Maher et al 2020) and several studies have demonstrated the large internal variability in the Indian summer monsoon rainfall (Kucharski et al 2009, Sinha et al 2015, Huang et al 2020). Therefore, we use an ensemble of initialised climate simulations from multiple models to sample a large range of internal variability and provide estimates of the possible extreme changes in the Indian summer monsoon rainfall. We use multiple models and multiple ensemble members with current climate forcings to estimate reasonable worst case scenarios for wetting and drying trends over the coming decades.

Given that the trends over multidecadal timescales could arise due to both internal variability and changes in anthropogenic forcing; a second key question that emerges is when can we expect a clear emergence of a climate change signal in rainfall beyond the envelope of natural internal variability? Several detection and attribution studies have investigated this question and found clear evidence of anthropogenic climate change in atmospheric variables such as near-surface temperature and humidity on a global as well as regional scale (Hawkins and Sutton 2009, 2012, Giorgi and Bi 2009, Hegerl et al 2007, Sippel et al 2020), and detection of anthropogenic change is possible even for modest changes with enough data. However, for rainfall, the detection of anthropogenic change is relatively harder, partly due to the large internal variability in the rainfall (e.g. Hoerling et al 2006, Sarojini et al 2016, Megan et al 2020, Hawkins et al 2020). In this study, we therefore compare the influence of internal variability with forced climate change in the Indian summer monsoon rainfall and determine the emergence time when we can expect the climate change signal to be comparable to internal variability in rainfall trends using future projections from multiple Coupled Model Inter-comparison Project (CMIP) Phase 5 and Phase 6 models.

The historical simulations from the CMIP3, CMIP5 and CMIP6 models indicate a near-unanimous increase in the Indian summer monsoon rainfall over the 20th century (Turner and Annamalai 2012, Menon et al 2013, Saha et al 2014, Jain et al 2019b, 2020a, Katzenberger et al 2021). However, the majority of CMIP models show either positive or no trend in Indian summer monsoon rainfall for the period 1950–2005; neither was an increase in rainfall seen in the observational record for this period. In fact, the observations showed a significant decreasing trend in the Indian summer monsoon rainfall over the 1950–2005 period (Ramesh and Goswami 2014, Saha et al 2014). Therefore, we examine this aspect and show that internal variability provides a quantitative explanation of why the observed rainfall did not increase in the observational record despite climate model simulations showing an increase on average over the late 20th century.

In this paper, we first compare the past changes in the Indian summer monsoon rainfall in the observational record with the changes that can arise due to the internal variability of the climate system (section 3). We provide an estimate of the possible extreme changes in the summer rainfall for the coming decades in the current climate (section 4). We then compare these changes with the anthropogenically forced changes in rainfall for four medium to high greenhouse gas emission scenarios and investigate the time of emergence of climate change signal in JJA rainfall (section 5). Finally, we show an influence of ENSO, Indian Ocean warming and circumboreal Rossby wavetrains on the Indian summer monsoon rainfall changes (section 6). The details on the data and methodology used in the paper are provided in the next section.

2. Data and methods

The rainfall observations are obtained from the India Meteorological Department (IMD). We use IMD daily gridded rainfall product for 1901–2013, available at $0.25^\circ \times 0.25^\circ$ resolution over the Indian land region (Pai et al 2014). The IMD climatological June–July–August (JJA) total rainfall averaged across the period 1901–2013 is 690.4 mm.

For the initialized climate simulations, we use seasonal hindcast outputs from multimodel ensembles (MME) collated under the Climate-system Historical Forecasts Project (CHFP, Tompkins et al 2017). We use monthly outputs of precipitation, sea-surface temperatures (SSTs), and winds that are initialized on dates centred around 1st May. We have previously tested the fidelity of eight seasonal prediction systems from the CHFP in representing JJA rainfall over India and found a reasonably realistic simulation of JJA rainfall in most systems (Jain et al 2019a, 2020b). The spatial distributions of JJA rainfall from the CHFP models were comparable to the observations. The models show statistically significant skill in simulating the interannual variability of JJA rainfall and the ENSO-rainfall teleconnections were similar to the observations. We have further analysed the JJA mean rainfall distributions from these prediction systems and tested their performance using fidelity tests for the mean, standard deviation, skewness and kurtosis (Jain et al 2020b, also see Thompson et al 2017, 2019 for the UNSEEN methodology used here). We found five prediction systems to be statistically
indistinguishable from the observations and therefore the hindcast data from these five systems are used in this study (table 1). There are in total 1669 realizations of JJA rainfall available from 63 multimodel ensembles (table 1) which are then used to subsample time-series of different lengths. For the GloSea5 model, the precipitation and SST data are taken from the Seasonal-to-Decadal climate Prediction for the improvement of European Climate Services (SPECS). The wind data at pressure levels for the GloSea5 model is not openly available from SPECS and therefore not analysed here.

In addition to the CHFP MME, we also use future projections of precipitation from CMIP5 and CMIP6 multimodel ensembles for the period 2021–2050 (Eyring et al. 2016). The CMIP precipitation outputs are used for four different scenarios i.e. SSP5-8.5, SSP3-7.0, RCP8.5 and RCP4.5. The details of the models and members from each future scenario used in this study are provided in table 2. The RCP8.5 represents a high greenhouse gas emission scenario with radiative forcing reaching $\sim 8.5 \text{ Wm}^{-2}$ by the end of the 21st century whereas RCP4.5 represents a medium emission scenario with radiative forcing reaching $\sim 4.5 \text{ Wm}^{-2}$ by the end of the 21st century. The SSP3-7.0 represents a medium-high greenhouse gas emission and fossil-fuelled development scenario with baseline scenario SSP3 and radiative forcing reaching $\sim 7.0 \text{ Wm}^{-2}$ by the end of the 21st century. And finally, the SSP5-8.5 scenario represents a high reference scenario lying at the upper edge of the scenarios considered for the CMIP6 simulations (Riahi et al. 2017).

We calculate the trends for the time series of length varying from 10 to 30 year for all three data sources, i.e. IMD, CHFP MME and CMIP MME. For IMD observations, the rainfall data is available for 113 years (1901–2013). For a given length N of the time series, we estimate the trends in JJA total rainfall for all possible trends of length L in the IMD record. The total number of trends is then $N = (L - 1)$ and in the 113 years IMD record, the total possible periods of length 10 year are $113 \times (10 - 1) = 104$. The line of best fit is passed through each time series and linear trend is estimated as the slope of the line of best fit.

For the CHFP MME, the JJA precipitation time series for each ensemble member is bias-corrected removing the climatological difference between the observed rainfall and ensemble mean rainfall for each model's hindcast. For the CHFP data, we then construct 10 000 representative time series of JJA total rainfall for each length by randomly selecting an ensemble member precipitation for each calendar year. Note that the order of calendar years is preserved while resampling and only the ensemble members were resampled to preserve any impact of climate change. For example, for a length of ten years, we randomly selected any ten year period between 1980 and 2012 (CHFP MME hindcast period) and randomly selected one ensemble member for each calendar year. This is repeated to obtain 10 000 time series and corresponding trends for each length.

For the CMIP MME from each scenario, the trends are calculated using the same methodology as IMD where each CMIP ensemble member is treated the same as the observed record. The total possible sample periods of length L in a 30 year period (2021–2050) would be $30 - (L - 1)$. For example, for the CMIP6 SSP5-8.5 scenario, 66 ensemble members are used in this study. Therefore, for time series length L, the total number of possible trend values considering all ensemble members and all periods would be $[30 - (L - 1)] \times 66$.

All rainfall analysis presented in this paper is for June–July–August (JJA) and referred to as summer monsoon rainfall. The JJA total rainfall for both observations and models is obtained by accumulating rainfall from 1 June to 31 August. We use JJA in this paper as it is standard for boreal summer in seasonal forecasting. The observed correlation between the JJA and June–July–August–September (JJAS) rainfall is extremely high $\sim 0.97$ and therefore our results are likely to be insensitive to the inclusion of September in the analysis. All rainfall totals from both observations and models used in this study are calculated for all-India and land-only region. The estimated trends from the IMD observations and CHFP and CMIP models are reported as a percentage change in rainfall with respect to the observed climatological JJA total rainfall for 1901–2013, which is $\sim 690$ mm.

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### Table 1. Details of the rainfall/precipitation data from the observations and CHFP models used in this study.

| Model/source | Centre, country | Period, total calendar years | Ensemble members | Total ensemble years |
|--------------|-----------------|-----------------------------|------------------|----------------------|
| IMD (observations) | IMD, India | 1901–2013, 113 | 1 | $113 \times 1 = 113$ |
| GloSea5 (SPECS) | MetOffice, UK | 1992–2012, 21 | 24 | $21 \times 24 = 504$ |
| ECMWF-S4 (CHFP) | ECMWF, UK | 1981–2010, 30 | 15 | $30 \times 15 = 450$ |
| CFS (CHFP) | NOAA, USA | 1981–2007, 27 | 7 | $27 \times 7 = 189$ |
| MIROC5 (CHFP) | CCSR, Japan | 1980–2011, 32 | 8 | $32 \times 8 = 256$ |
| MPI-LR (CHFP) | MPI-ESM, Germany | 1982–2011, 30 | 9 | $30 \times 9 = 270$ |
| CHFP MME | Multiple sources | 1980–2012, 33 | 63 | 1669 |
Table 2. Details of the precipitation data from the CMIP5 and CMIP6 models used in this study for four different future scenarios. All precipitation data from the CMIP models are for the period of 30 years from 2021–2050.

| Model                  | Centre, country | Total number of ensemble members |
|------------------------|-----------------|---------------------------------|
| ACCESS CM2             | CSIRO, Australia| 1 3 6 6 |
| ACCESS ESM1-5          | CSIRO, Australia| 1 3 1 1 |
| ACCESS1-0              | CSIRO, Australia| 1 3 1 1 |
| AWI-CM1-1-1-MR         | AWI, Germany    | 1 1 1 1 |
| BCC-CSM2-MR            | BCC, CMA, China | 1 1 1 1 |
| BNU-ESM                | BNU, China      | — — 1 1 |
| CAMS-CSM1.0            | MPI, Germany    | 2 2 1 1 |
| CanCM4                 | CCCma, Canada   | — — 1 1 |
| CanESM2                | CCCma, Canada   | — — 5 5 |
| CanESM5                | CCCma, Canada   | 16 20 1 1 |
| CanESM5-CanOE          | CCCma, Canada   | 3 1 1 1 |
| CCSM4                  | Multiple, USA   | — — 6 6 |
| CESM1-CAM5             | NCAR, USA       | — — 1 1 |
| CESM1-CAM5             | NCAR, USA       | — — 3 2 |
| CESM1-WACCM            | NCAR, USA       | — — 3 3 |
| CESM2                  | NCAR, USA       | 2 — — 1 |
| CESM2-WACCM            | NCAR, USA       | 1 3 — — |
| CMCC-CM2-SR5           | CMCC, Italy     | — 1 — — |
| CMCC-CMS               | CMCC, Italy     | — 1 1 1 |
| CMCC-ESM2              | CMCC, Italy     | — 1 — — |
| CNRM-CM5               | CNRM, France    | — 5 1 1 |
| CNRM-CM6.1             | CNRM, France    | 6 6 — — |
| CNRM-ESM2-1            | CNRM, France    | 4 5 — — |
| EC-EARTH               | Multiple, Europe| — 5 7 1 |
| FGOALS-f3-L            | CAS, China      | 1 1 — — |
| FGOALS-G3              | CAS, China      | 1 — — — |
| FIO-ESM                | FIO, China      | — 3 3 1 |
| FIO-ESM-2-0            | FIO, China      | 3 — — — |
| GFDL-CM4               | GFDL, USA       | 1 — — — |
| GFDL-ESM4              | NOAA, USA       | 1 1 — — |
| GISS-E2-1-G            | NASA, USA       | — 1 — — |
| GISS-E2-H              | NASA, USA       | — 1 16 1 |
| GISS-E2-H-CC           | NASA, USA       | — — 1 1 |
| GISS-E2-R              | NASA, USA       | — — 5 — |
| GISS-E2-R-CC           | NASA, USA       | — — 1 1 |
| HadGEM2-CC             | UKMO, UK        | — — 3 4 |
| HadGEM2-ES             | UKMO, UK        | — — 3 4 |
| HadGEM3-GC31-LL        | UKMO, UK        | 2 — — — |
| INMCM4                 | INM, Russia     | — — 1 1 |
| INM-CM4-8              | INM, Russia     | 1 1 — — |
| INM-CM5-0              | INM, Russia     | 1 3 — — |
| IPSL-CM5A-LR           | IPSL, France    | — 2 4 1 |
| IPSL-CM5A-MR           | IPSL, France    | — 1 1 1 |
| IPSL-CM5B-LR           | IPSL, France    | — 1 1 1 |
| IPSL-CM6a-LR           | IPSL, France    | 1 5 — — |
| KACE-1-0-G             | NIMS/KMA South Korea| 1 — — — |
| MIROC5                 | Multiple, Japan | — — 3 3 |
| MIROC6                 | Multiple, Japan | 3 2 — — |
| MIROC-ES2L             | Multiple, Japan | 1 — — — |
| MIROC-ESM-CHEM         | Multiple, Japan | — — 1 1 |
| MPI-ESM1-2-LR          | MPI, Germany    | 4 3 — — |
| MPI-ESM-LR             | MPI, Germany    | — — 3 3 |
| MPI-ESM-MR             | MPI, Germany    | — — 1 3 |
| MRI-CGCM3              | MRI, Japan      | — — 1 1 |
| MRI-ESM1               | MRI, Japan      | — — 1 — |
| MRI-ESM2.0             | MRI, Japan      | 1 3 — — |
| NESM3                  | NUIST, China    | 2 — — — |
| NOR-ESM                | Multiple, Norway| — — 1 1 |
| UKESM1.0-LL            | MOHC, UK        | 4 — — — |
| CMIP MME               | Multiple sources| 66 67 62 74 |
3. Decline and recovery of observed Indian summer monsoon rainfall

Several studies have reported and discussed the decline of the Indian summer monsoon rainfall post-1950s, followed by the recovery from around the year 2000 onwards (Ramesh et al. 2014, Saha et al. 2014, Jin and Wang 2017, Huang et al. 2020). Therefore, we investigate if these, and perhaps even more extreme changes in the rainfall over the multidecadal timescale can be explained simply by the internal variability of the climate system.

As it is difficult to identify the exact year when the trend in rainfall reversed from decreasing to increasing (or vice-versa) in the observational record, we calculate the percentage change in rainfall for every possible 10, 20 and 30 year period in the IMD record (1901–2013) and show the distribution in figure 1. The distribution of percentage change in rainfall in the IMD record is compared with the CHFP MME distribution. The trends sampled using the CHFP MME shows the influence of internal variability in presence of climate change, and therefore provides the range by which chaotic internal variability can exacerbate or alleviate the influence of climate change on rainfall.

Figure 1 shows that the past decline and recovery of the Indian summer monsoon on the multidecadal time scale lies within the range of modelled internal variability, indicating that internal variability is large enough to explain the past changes in rainfall. This is also consistent with Huang et al. (2020), who concluded that the impact of anthropogenic forcing on past rainfall trends is weaker than internal variability and that the recent decline and recovery of Indian monsoon rainfall were largely modulated by the internal variability.

Figure 1 also shows that the rainfall distribution from the CHFP MME for 10 year trends is close to symmetric around zero whereas, for 20 and 30 year timescale, the distribution is shifted progressively towards increasing chance of wetting trends. This could be due to the influence of climate change leading to a wetter monsoon in the modelled ensembles. The later years in the hindcast period (1980–2012) are subject to more forcing and the increase in rainfall is therefore more apparent for trends calculated over a longer time period. In addition, the timing of the ENSO phase for the CHFP hindcast period (1980–2012) could also contribute to the asymmetry as several El Niño events were recorded over the beginning of the CHFP hindcast period (1982, 1987 and 1991) whereas La Niña tended to dominate towards the end of the hindcast period (1999 and 2000). A more detailed analysis of the influence of ENSO on rainfall trends is presented in section 6.

Figure 1 also shows that though the probability of wetting trends is higher for longer periods, drying trends are still likely to occur. Considering that the observations are just one realization of the climate system, this shows that drying trends can occur in the observational record despite the presence of climate change, purely due to internal variability. The chaotic internal variability of the climate system can easily temporarily negate or overwhelm the underlying influence of climate change to give temporary trends of the opposite sign in rainfall. This can explain why the sign of the trends shown by the CMIP models does not match the observed trends. A quantitative estimate of the chance of wet and dry trends on a multidecadal timescale is presented in the next section.

4. Estimates of extreme changes in rainfall for the next decades

In this section, we provide the range and probability of the possible extreme changes in rainfall arising due to internal variability in the current climate. We also compare the changes in rainfall from the CHFP MME with the IMD observational record. Over the IMD observational record (1901–2013), 20%–25% change in rainfall can be seen for the shorter periods (i.e. 10 years) whereas, for longer periods (>10 years),
the change in rainfall is within 10%–15%. However, figure 2 shows that the limited observational record cannot be used to obtain a robust estimate of extreme trends beyond the 1% frequency level and so observations provide only a limited estimate of the chance of wet and dry trends due to the smaller sample size. In contrast, CHFP MME data provide more statistically robust estimates due to the large sample size and these extend out to rarer, more extreme trends. The CHFP MME provides the chance of unprecedented extreme wet and dry multidecadal trends that have not (yet) been seen in the observational record. For example, the worst 10 year drying in the current observational record shows a ∼20% reduction in seasonal total rainfall compared to the observed climatological mean over the 1901–2013 period. Although the probability is low, the CHFP MME shows that there is a probability of ∼1% that the linear trend over a given 10 year period could exceed the most extreme drying seen so far in the observations and there is a 0.1% chance that it could even amount to a 30% decline in summer monsoon rainfall.

For the 20 and 30 year periods, the observations have very few samples to estimate the most extreme trends but the model data show that there is a 1% chance of ∼19% and 16% increases in rainfall, respectively. There is also a 1% probability of ∼10% reduction in rainfall over the next 20 years and 6% reduction in rainfall over the next 30 years respectively. For more extreme scenarios, the model data show that wetting of 20%–30% and drying of 10%–20% are possible at the 0.1% probability level.

Figure 2 also shows that wetting trends are more favoured than drying trends for all periods analysed here. For the length of 10 years, there is a ∼60% chance of wetting trends whereas the chance of drying is ∼40%. With the increasing length of the period considered, the wetting trends are systematically more favoured than drying. For example, for the time series of length 20 and 30 years, the chance of drying trends falls to ∼28% and ∼17%, respectively. This contrasts with single-year events, for which intensity of droughts tend to be more severe and more frequent than floods, not least because of El Niño suppression of monsoon rainfall and ENSO phase asymmetry with El Niño reaching higher magnitude than La Niña (Jain et al 2020b). Figure 2 thus shows that in the current climate, wetting trends are more probable than drying over multidecadal periods. We should add that the analysis so far may be conditional on the particular sequence of ENSO events in the CHFP hindcasts used here and so we also use uninitialized simulations (CMIP) below to gain an additional independent estimate of impending trends.

5. Climate change signal in rainfall trends

We now compare the trends in rainfall arising due to the combination of internal variability and anthropogenically forced trends over the next few decades in the CMIP MME under four different future scenarios with the trends obtained from the CHFP MME. The percentage change in rainfall inferred from the CHFP MME in figure 3 suggest a mean change of around +2% in rainfall by the next decade, reaching +5% by 2050. The CMIP-MME trends under the four future scenarios considered here (i.e. SSP5-8.5,
SSP3-7.0, RCP8.5 and RCP4.5) suggest an increase in rainfall by \( \sim 2\% \) to 6\% by 2050 and this is of similar magnitude to the mean trend obtained from the CHFP MME. Figure 3 shows that the mean change in rainfall from the CMIP MME under all four scenarios lies well within the envelope of internal variability obtained from the CHFP (solid lines lying well within red shading), and it is therefore unlikely that the climate change signal in monsoon rainfall will emerge outside the likely range due to internal variability by 2050 under the medium to high emission scenarios analysed here.

Figure 3 also shows that both the CHFP MME and the CMIP MME under the four future scenarios analysed here show a larger chance of wetting than drying for the coming decades and that the wetting trends again become more probable with the length of the period. However this trend can easily be negated by internal variability and it is unlikely to emerge from the envelope of natural variability as all scenarios show only a few percent of systematic increase over the next three decades. We now examine the influence of background dynamical conditions on the variety of plausible trends in the Indian summer monsoon rainfall.

6. Influence of sea surface temperatures and large-scale circulation on rainfall trends

The impacts of ENSO and Indian Ocean Dipole (IOD) on Indian summer monsoon rainfall variability and trends have been demonstrated extensively in the literature (Sikka 1980, Shukla and Paolino 1983, Ju and Slingo 1995, Torrence and Webster 1999, Webster et al 1999, Saji et al 1999, Krishnamurthy and Goswami 2000, Ashok et al 2001, 2004, Annamalai et al 2013, Cherchi and Navarra 2013, Roxy et al 2014, 2015, Saha et al 2014). Therefore, we investigate the relationship between the trends in JJA precipitation and JJA SSTs over the Niño3.4 region and the Indian Ocean using the CHFP ensemble (figure 4). We show the SST versus precipitation trends calculated for the 20 year period but find similar results for 10 year period and weaker influence of SSTs on precipitation for 30 year periods.

Figure 4 shows that the trends in precipitation are inversely related to the Niño3.4 SSTs. The inverse relation with SST indicates that the transition to predominantly El Niño (warm phases) or La Niña (cold phases) is therefore associated with dry or wet trends.
the Indian monsoon. The trends in SSTs over the Niño3.4 region and summer monsoon precipitation show a modest correlation of $\sim 0.3$ which is significant at the 1% level. The regression line suggests that $\sim 1.5^\circ$ reduction in Niño3.4 SSTs can induce an increase in rainfall of similar magnitude as climate change ($\sim 30$ mm over the 20 years as inferred from figure 3), and with increasing cooling of the Niño3.4 region, an even larger change of up to $\sim 80$ mm over the 20 years is also possible. Similarly, a $\sim 1.5^\circ$ warming of the Niño3.4 region can negate the projected increase in summer monsoon rainfall due to climate change.

Recent research using observational records have highlighted sustained basin-scale warming of the tropical Indian Ocean, with an approximate increase of around 1 °C from 1951 to 2015 (Alory et al 2007, Roxy et al 2014, 2015, 2020). Similar consistent, but slightly higher, warming trends were also noted over the western Indian Ocean ($-5$ to $10^\circ$ N, $50$–$65$ °E) from the year 1900 onwards (Roxy et al 2014). Although the causes and effects of this warming are still debated, there are emerging studies that have related the warming of the Indian Ocean, particularly the western Indian Ocean, to a general decrease in the global land monsoon rainfall including South Asia (Zhou et al 2008, Roxy et al 2014, 2015, Ueda et al 2015). Figure 4 shows a similar relationship between increasing western Indian Ocean SST and decreasing monsoon precipitation, with an opposite but similar-sized effect from the eastern Indian Ocean. The correlation between the Indian Ocean SSTs and precipitation is significant ($p < 10^{-5}$), but it is relatively weaker ($\sim 0.2$) than the Niño3.4 region. Although there is a large scatter in the rainfall trends due to the multiple sources of variability, the regressions for the Indian Ocean regions show changes in the rainfall of equivalent magnitude to that generated by Niño3.4 changes and suggest that the future changes in the IOD could be as important as ENSO. While we demonstrate the independent influence of ENSO and IOD on rainfall trends here but other longer term oscillations, such as Interdecadal Pacific Oscillation (Huang et al 2020) can also influence the decadal rainfall trends and are important.

In addition to the well-known drivers of the variability in Indian monsoon rainfall originating in the tropics, such as ENSO and IOD, there are also global scale circulation patterns that could influence Indian summer monsoon rainfall (Wu et al 2009, Linderholm et al 2011, Feliks et al 2013). Borah et al (2020) have recently reported a teleconnection between Atlantic Rossby wave-trains and Indian droughts over the last century, particularly for the cases when strong ENSO signals were absent. These wave-trains are demonstrated in observational analyses (e.g. Borah et al 2020, Wang et al 2021) and are reported to have a notable influence on Indian summer monsoon rainfall through their influences on the upper tropospheric circulation system, e.g. displacement of the westerly jet over Asia (Chowdary et al 2021, Wang et al 2021). Therefore, here we examine the existence of Rossby wave trains, also referred to as the Silk Road Pattern, and its teleconnection to Indian summer monsoon rainfall in the latest seasonal prediction systems.

To examine this, out of the 10 000 resampled time series of length 20 years, we extracted ten time series that showed the largest positive trends and ten with the largest negative trends. In the extracted time series, we found several instances of extreme wet and dry summer monsoon seasons that lead to relatively larger trends. Therefore, we calculated the difference in upper-level meridional winds ($V_{200}$) for the top ten wettest and driest JJA summer monsoon seasons from each model subsequently averaged to provide a multimodel mean difference (figure 5).

There is a clear Rossby wave train (shown by green and brown color) circumnavigating the globe with the opposite phase in the most extreme wet and dry summer monsoon seasons. The differences in $V_{200}$ are significant (stippled) for almost the entire path of the wave-train. Based on the linear zonal mean theory (James 1994), we have calculated the Rossby wave group velocity (see Scaife et al 2017):
Figure 5. Upper-level wind anomalies for wet and dry JJA Indian summer monsoon. Difference between JJA meridional winds at the 200 hPa pressure level ($V_{200}$) for the top ten wettest and driest JJA summers from each model, subsequently averaged to form the multimodel mean ($V_{200}$ data were not available for the GloSea5 system). Stippling denotes regions for which differences are significant at 1% level using a two-tailed student’s t-test and the tinted region shows the latitude bands for which Rossby wave propagation is not permitted.

\[
c_{gx} = \frac{2\overline{u}^2k^2}{\beta - \overline{u}yy} \quad \quad c_{gy} = \frac{2\overline{u}^2k \left( \frac{\beta - \overline{u}yy}{\overline{u}} - k^2 \right)^{1/2}}{\beta - \overline{u}yy}
\]

where $\beta = $ Rossby parameter, $\overline{u}$ is the zonal mean u-wind at 200 hPa level averaged over all ensemble members and years, $k$ is the zonal wave number. The second derivative of $\overline{u}$ is small in most regions and therefore neglected here. Note that for Rossby wave propagation to occur $c_{gy}$ should be real. The latitudes which do not support Rossby wave propagation are shaded in figure 5.

Figure 5 shows that the tele-connection is contained within the permitted region of Rossby wave propagation. Given that stationary Rossby waves propagate eastwards, it appears that the wave train source lies in the extra-tropics, probably over the North Atlantic sector for this case, and propagates southeastwards towards India. Therefore, variations in the climate of the extratropics, in this case, the Atlantic-European region, are also likely to be important in determining the future of Indian summer monsoon rainfall. Recent studies also indicate possible decadal predictability of these Rossby wave patterns (Monerie et al 2018) thereby providing a potential avenue for future decadal prediction of Indian summer monsoon rainfall trends.

7. Conclusions

We provide the estimates of possible extreme changes in Indian summer monsoon rainfall for the upcoming decades using an ensemble of 1669 realizations of rainfall from the selected seasonal prediction systems that are statistically indistinguishable from the observations. We demonstrate our methodology using an example of Indian summer monsoon rainfall but this methodology could easily be extended to other climate variables, regions and timescales provided model forecasts are representative of the current climate. Our estimates of extreme trends provided here include the effects of both internal variability and climate change.

We find that in the current climate, wetting trends are systematically more favoured than drying especially for longer trends due to climate change signal in monsoon rainfall. For example, there is a $\sim 60\%$ chance of wetting trends for the next decade, which increases to $\sim 70\%$ and $\sim 80\%$ for 20 and 30 year trends, respectively. This contrasts with single summer monsoon events, for which the intensity of droughts is more severe than floods (Jain et al 2020b). The chance of drying trends becomes progressively smaller with increasing length of period but the drying trends can occur in the observational record purely due to internal variability (e.g. $\sim 20\%$ chance for 30 year trends). In the past (from $\sim 1950$ to 2005), observational records have shown a reduction in Indian summer monsoon rainfall but the average of historical simulations from the generations of CMIP models indicated a near-unanimous increase in the Indian summer monsoon rainfall. Given that observed trends are within the range of ensemble simulations used here, internal variability provides a quantitative explanation for the lack of wetting trends in current rainfall observations over India.
The largest 10 year trends in the current observational record (1901–2013) show ∼20% change in JJA total rainfall compared to the observed climatological mean. However, our analysis quantifies the probability of such trends and shows that the JJA rainfall change could even exceed ∼30% over the next decade, although the probability of such a large change is low. We also find that for longer periods (>20 years), the observations give only a poor estimate of the most extreme trends, in contrast to the initialised forecast ensembles which provide a statistically robust estimate. We also investigate the time-of-emergence of climate change signals in rainfall trends and find that it is unlikely for a climate change signal to emerge above internal variability by the year 2050.

We find that the rainfall trends are influenced by the trends in sea-surface temperatures over the Niño3.4 region and the western and eastern Indian Ocean and circumglobal Rossby wave-trains, apparently emanating from the Atlantic region. The actual rainfall change over the next decades will therefore depend on the timing and magnitude of these effects. Nevertheless, our estimates of the chances and intensity of future monsoon trends provide reasonable worst case scenarios for future decadal and multi-decadal trends in the Indian monsoon rainfall.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://archive.ceda.ac.uk/ and https://www.wcrp-climate.org/wgsp-chfp/chfp-data-archive. The IMD rainfall data can be obtained from the following link: https://www.imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data.Download.html.

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