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1 **The IITM Earth System Model: Transformation of a Seasonal Prediction Model to a Long**
2 **Term Climate Model**

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20 **Abstract**

21 With the goal of building an Earth System Model (ESM) appropriate for detection, attribution
22 and projection of changes in the South Asian monsoon, a state-of-the-art seasonal prediction
23 model, namely the Climate Forecast System version 2 (CFSv2) has been adapted to a climate
24 model suitable for extended climate simulations at the Indian Institute of Tropical Meteorology
25 (IITM), Pune, India. While the CFSv2 model has been skillful in predicting the Indian summer
26 monsoon (ISM) on seasonal time scales, a century-long simulation with it shows biases in the
27 ocean mixed-layer, resulting in a 1.5°C cold bias in the global mean surface air temperature, a
28 cold bias in the sea surface temperature (SST) and a cooler-than-observed troposphere. These
29 biases limit the utility of CFSv2 to study climate change issues. To address biases, and to
30 develop an Indian Earth System Model (IITM-ESMv1), the ocean component in CFSv2 was
31 replaced at IITM with an improved version, having better physics and an interactive ocean
32 biogeochemistry. A 100-year simulation with the new coupled model (with biogeochemistry
33 switched off) shows substantial improvements, particularly in global mean surface temperature,
34 tropical SST and mixed layer depth. The model demonstrates fidelity in capturing the dominant
35 modes of climate variability such as the ENSO and Pacific Decadal Oscillation. The ENSO-ISM
36 teleconnections and the seasonal lead-lags are also well simulated. The model, a successful result
37 of the Indo-US collaboration, will contribute to the IPCC-AR6 simulations, a first from India.

38 **Capsule Summary**

39 This work documents the fidelity of the newly-developed IITM climate model simulations, and
40 demonstrates its suitability to address the climate variability and change issues relevant to South
41 Asian Monsoon.

42 **1. Introduction**

43 The Ministry of Earth Sciences, Govt. of India and National Ocean and Atmospheric
44 Administration (NOAA), USA entered into a formal agreement for collaboration to implement
45 the NCEP weather and seasonal prediction system in India in 2011. Under this collaboration, the
46 India Meteorology Department (IMD) and National Centre for Medium Range Weather
47 Forecasts (NCMRWF) implemented the high resolution (T574, L64) atmospheric Global
48 Forecasting System (GFS) model with 3-DVar data assimilation at IMD for short and medium
49 range weather forecasts. Also, the coupled ocean-atmosphere model, Climate Forecast System
50 version 2 (CFSv2) model with a high resolution atmosphere (T382, L64) was implemented for
51 seasonal prediction at the Indian Institute of Tropical Meteorology (IITM). To address the long
52 term critical need in India for a climate model that would provide reliable future projections of
53 Indian monsoon rainfall, IITM planned to build an Earth System Model (ESM) based on the
54 CFSv2 framework. Further, under the Monsoon Mission (see <http://www.tropmet.res.in/>) India is
55 committed to improve the CFSv2 model for providing more skillful predictions of seasonal
56 monsoon rainfall, which would also benefit the short and medium range predictions at IMD.
57 Therefore, the extension of the seasonal prediction model to a long term climate model would
58 establish a seamless prediction system from weather time scales to seasonal and decadal time
59 scales in India. In this paper, we describe how the seasonal prediction model has been converted
60 to a model suitable for long term climate studies.

61

62 The NCEP CFS (Saha et al. 2006), the predecessor of the CFSv2, used to provide
63 coupled ocean-atmospheric forecasts since 2004, demonstrated good skill in simulating and
64 predicting ENSO (Wang et al. 2005; Zhang et al. 2007), and the South Asian summer monsoon

65 variability (Achuthavarier and Krishnamurthy 2010; Yang et al. 2008; Pattanaik and Kumar
66 2010; Chaudhari et al. 2013; Pokhrel et al. 2012, 2013). With substantial changes compared to
67 CFSv1, the CFSv2 (Saha et al. 2013) demonstrated better prediction skills for ENSO, the tropical
68 Atlantic sea surface temperatures (SST), global land precipitation, surface air temperature, and
69 the Madden–Julian Oscillation (Yuan et al. 2011; Weaver et al. 2011; Jiang et al. 2013; Hu et al.
70 2012). Importantly, exhaustive hindcast experiments on seasonal and extended timescales carried
71 out at IITM demonstrated that the CFSv2 model was one of the few models that predicted the
72 general distribution of Indian summer monsoon rainfall during June through September
73 (henceforth ISMR) and its intraseasonal and interannual variability with statistically significant
74 skill (Roxy et al. 2012; Chaudhari et al. 2013).

75 To address issues related to longer time-scale climate variability, beyond the seasonal
76 time-scale, a climate model needs to simulate the observed mean climate reasonably well.
77 Moreover, for a region like South Asia, a realistic simulation of the climatology and variability
78 of the ISM and the drivers of its variability is imperative. Equally important is the ability to
79 replicate the observed sensitivity in temperature to the increasing greenhouse gases (GHGs).
80 However, despite its good seasonal prediction skill, several 100-year simulations carried out at
81 IITM demonstrated a cold bias in global mean temperature and a lack of the observed sensitivity
82 to GHG increase in CFSv2, limiting its utility as a climate change model (e.g. Roxy et al. 2012).
83 The model also exhibits a dry bias over Indian subcontinent during the June-September (JJAS)
84 monsoon season, along with a colder-than-observed SST in the Arabian Sea (Roxy et al. 2012),
85 and eastern tropical Indian Ocean (Chaudhari et al. 2013). Roxy et al., (2012) also noticed a
86 systematic bias in the thickness of the mixed layer in the ocean component of CFSv2. While
87 model systematic biases tend to affect the simulation of long-term mean climate as well as long-

88 term projected trends, improved representation of oceanic processes is one approach towards
89 minimizing systematic biases (see Semtner and Chervin, 1992). For example, such an effort has
90 substantially improved the simulation of many key climate features in GFDL CM2.5 (Delworth
91 et al. 2012), a state of the art model. These works provide motivation for possible alleviation of
92 systematic biases in the CFSv2 model through improved representation of ocean processes in
93 the coupled model.

94 As the first step towards adapting the CFSv2 as an ESM, an ocean model with
95 biogeochemistry, and a better physics for improving the biases of the current ocean component
96 in CFSv2 was incorporated. In this study, we document the formulation of the IITM-Earth
97 System Model version 1 (IITM-ESMv1), and discuss improvements in simulations of various
98 important ocean-atmospheric processes, and variability.

99 The paper is organized as follows. Section 2 describes the model configuration, coupling
100 strategy, experimental design, and initialization details of the climate simulations. Section 3
101 presents a comparative assessment of simulated annual mean climate, and biases therein,
102 between the simulations of CFSv2 and ESMv1. Section 4 describes the fidelity of simulated El
103 Nino-Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO), dominant modes of
104 climate variability on interannual and decadal scales, and teleconnection of ENSO to ISM. The
105 results are summarized in Section 5.

106

107 **2. Brief Description of the IITM-ESMv1**

108 The IITM-ESMv1 has been developed by replacing the ocean component Modular Ocean
109 Model [MOM4p0, (Griffies et al. 2004)] of the CFSv2, by MOM4p1 (Griffies et al. 2009)

110 retaining the land and atmospheric components.. The MOM4p1 has a better physics compared to
111 MOM4p0, and also an interactive ocean bio-geochemistry (BGC) component (Dunne et al.
112 2012). The major differences between the ocean components of IITM-ESMv1 and CFSv2 are
113 summarized in Annex-I.

114

115 **Ocean and sea-ice components**

116 The ocean component (MOM4p1) in IITM-ESMv1 is a hydrostatic model using
117 Boussinesq approximation, and has a rescaled geopotential vertical coordinate (Stacey et al.
118 1995; Adcroft and Campin 2004) for a more robust treatment of free surface undulations. Key
119 physical parameterizations include a KPP surface boundary layer scheme of (Large et al. 1994),
120 which computes vertical diffusivity, vertical viscosity and non-local transport as a function of the
121 flow and surface forcing. Griffies et al (2009) provide a detailed description about the model
122 equation, physics, dynamics, time stepping schemes, and further subgrid scale parameterizations.

123 The IITM-ESMv1 ocean model has 40 vertical levels from surface to 4500 m, identical to
124 that of the CFSv2. It has 27 levels in the upper 400m of water column in an attempt to capture
125 surface boundary layer processes. Bottom topography is represented by the partial cell method
126 described by (Adcroft et al. 1997) and (Pacanowski and Gnanadesikan 1998). Both the ocean and
127 sea ice models use the Arakawa B-grid (Arakawa and Lamb 1977). The zonal resolution is 0.5°
128 and the meridional resolution is 0.25° between 10°S and 10°N , becoming gradually coarser
129 through the tropics, up to 0.5° poleward of 30°S and 30°N . The use of the (Murray 1996) bipolar
130 grid facilitates removal of the coordinate singularity from the Arctic Ocean domain.

131 The sea ice component of IITM-ESMv1 is the GFDL Sea Ice Simulator (SIS) (Delworth
132 et al. 2006; Winton 2000), which is an interactive dynamical sea ice model with three vertical
133 layers, one snow and two ice, and five ice thickness categories.

134

135 **Atmosphere and land components**

136 The atmospheric component of IITM-ESMv1 is based on the NCEP GFS model, and has
137 a spectral triangular truncation of 126 waves (T126) in the horizontal ($\sim 0.9^\circ$ grid) and a finite
138 differencing in the vertical with 64 sigma-pressure hybrid layers. It employs the Simplified
139 Arakawa-Schubert convection scheme, with cumulus momentum mixing. The land surface
140 model is the Noah LSM, with 4 layers (Ek et al. 2003, p. 200), same as in CFSv2. Further details
141 can be availed in (Saha et al. 2010).

142 **Coupling and initialization**

143 The component models pass fluxes across their interfaces through an exchange grid
144 system, which enforces the conservation of energy, mass and tracers.
145 The atmosphere, land, and sea ice exchange quantities such as, heat and momentum fluxes every
146 10 minutes, with no flux adjustment or correction. The ocean tracer and atmosphere-ocean
147 coupling time step is 30 minutes. The individual model components were initialized with 1
148 December, 2009 initial conditions derived from the NCEP CFS Reanalysis. The model has been
149 integrated forward for a 100-year period without any changes in radiative forcing. Importantly,
150 the biogeochemistry and ecosystem modules were switched off to facilitate a comparison of the
151 simulated climate statistics with those from the CFSv2. For convenience, we refer to this
152 simulation as the ESMv1 run. For comparison, we utilize the results from a 100 year run we

153 carried out earlier with the CFSv2, which also started with the same initial conditions. Unless
154 specified, the last 50-years of the simulations from both models are used for the comparison.

155

156 **Observation-based datasets used for evaluating the simulations**

157 For the evaluation of the model simulations, we use the SST data from World Ocean
158 Atlas (WOA, 2009, Locarnini et al. 2010) and a density-based mixed layer depth data (de Boyer
159 Montégut et al. 2004). We also use the HadISST1.1 dataset (Rayner et al. 2003), gridded rainfall
160 data from IMD (Rajeevan et al. 2006) for the period 1930-2010 and gridded monthly rainfall
161 data based on the TRMM Microwave Imager (TMI; Huffman et al. 2007) for 1998-2012, the
162 NCEP and National Center for Atmospheric Research (NCEP/NCAR) reanalysis (Kalnay et al.
163 1996) circulation fields for the period 1980-2010. Global surface air temperature anomalies are
164 obtained from NASA (Hansen et al. 2006), for the period of 2000 to 2010 and sea ice
165 concentration data from HadISST (Rayner et al. 2003) for the period 1950-2010 is also utilized
166 for the study.

167 The climatology for the ESMv1, and that for the CFSv2 are computed for the last 50 years of
168 simulation. The simulated biases for any variable are computed by subtracting the observed
169 value from the corresponding simulated value. The statistical significance of the bias is estimated
170 based on 2-tailed Student's t-test.

171

172 **3. Mean state in ESMv1**

173 **Annual mean surface temperature and SST**

174 The time evolution of the global mean annual mean surface temperature and SST using
175 ESMv1 and CFSv2 are examined (Figure 1). During the initial 30 years of the 100-year run, the

176 CFSv2 simulations undergo a rapid cooling from a global mean surface temperature (T_s) of 14.4
177 °C to 13°C (Figure 1a), around which it lingers thereafter. This value is substantially less than the
178 observed global T_s of 14.6 °C (Hansen et al. 2006), indicating a bias of at least 1.6 °C in the
179 simulated global surface temperature. However, the initial cooling of simulated T_s by the ESMv1
180 is nearly about 0.6 °C (Figure 1a), and the T_s remains around 14.2 °C thereafter. Importantly, the
181 drift in the SST simulated by the ESMv1, averaged globally or in tropics, is only about 0.4°C, as
182 compared to an SST bias of 1.4°C in CFSv2 (Figures 1b & 1c).

183 The spatial map of the annual mean SST bias (Figure 2) indicates that the ESMv1
184 captures observed features well, at par with several other state-of-art coupled models (Figure not
185 shown). The spatial map of SST bias, computed as the difference between the observed annual
186 mean SST from that of the HadISST and over the last 50 years of simulations is shown for
187 ESMv1 and CFSv2 in Figures 2b and 2c respectively. The 10% level of statistical significance of
188 the SST bias estimated based on student's t-test are shown as contours in Figure 2. The results
189 confirm a significant reduction in cold bias in the tropics between 30°S to 30°N, also as
190 evidenced by the RMSE of 0.79 and 0.89 for the ESMv1 and CFSv2, respectively. A similar
191 reduction of the biases is seen in northern subtropical gyres. One of the potential reason for the
192 better reduction of cold bias in the regions of northern subtropical gyres in ESMv1 is the use of
193 the parameterization for the effect of sub-mesoscale mixed layer eddies (Fox-Kemper et al.
194 2011), which avoids mixed layer depths becoming excessively deep (Hallberg 2003); Figure 4a,
195 and discussion in the following section). The improvements in ESMv1 have been further
196 ascertained by comparing the simulations with the WOA (Figures not shown).

197 In both the models, particularly CFSv2, however, the cold bias lingers in the North
198 Atlantic Current east of Newfoundland, which is a region of very sharp gradients in SST. Small
199 errors in the paths of ocean boundary currents can lead to such large SST biases (Griffies et al.
200 2011). While there is a notable and a general improvement in the tropical SST simulation, the
201 warm bias in the far-eastern Pacific cold tongue, and in the Southern Ocean has increased. We
202 also note that warm biases are found in the Southern Ocean and in the upwelling region off the
203 western coast of South America (Fig. 2b and 2c) in both the models, particularly in the ESMv1.
204 The simulated warm bias in the southern ocean in ESMv1 is higher compared to CFSv2 and is
205 due to the weaker-than-observed simulated lower level zonal winds (Figure not shown). A re-
206 computation of the SST biases, after removing the mean global SST (Figure not shown) indicate
207 that the difference between ESMv1 and CFSv2 is mainly reflected in the mean, and the spatial
208 patterns of both ESMv1 and CFSv2 are nearly the same, with a significantly high pattern
209 correlation ($r=0.9$), implying that the large scale features in both the models remains the same. e
210 We note that most of the CMIP5 models exhibit similar biases with weaker-than-observed zonal
211 winds in the southern ocean region (e.g. Fig. 5, Lee and Wang 2014)

212

213 **Mean precipitation**

214 The distributions of boreal summer monsoon (June-September) precipitation bias from
215 ESMv1 and CFSv2 are shown in Figure 3. The 10% level of statistical significance of the
216 precipitation bias estimated based on student's t-test are shown as contours in Figure 3. Both
217 CFSv2 and ESMv1 models reproduce observed precipitation patterns reasonably well, though
218 they show larger-than-observed precipitation in the tropical western and eastern Pacific and the
219 South Pacific convergence zone. However, there is improvement in the oceanic precipitation in

220 ESMv1 in comparison with CFSv2, with a reduction of excess oceanic precipitation over the
221 equatorial Maritime Continent region, eastern equatorial Indian Ocean and western tropical
222 Pacific Ocean as compared to CFSv2.

223 Notwithstanding the improved SST in the tropical and northern Indian Ocean, the ESMv1
224 simulation also depicts a dry bias over India (Figure 3b). In terms of interannual variability of
225 the ISMR, the ESMv1 shows a climatological precipitation rate of 4.3 mm.day^{-1} with a standard
226 deviation of 0.53 mm.day^{-1} giving a coefficient of variation (the variability in relation to the
227 observed mean) of 9%. The corresponding statistics for the observations are 6 mm.day^{-1} , 0.48
228 mm.day^{-1} and 8%, respectively. These results suggest a moderate improvement in the interannual
229 variability of the land precipitation with respect to CFSv2, for which corresponding values are 4
230 mm.day^{-1} , 0.5 mm.day^{-1} and 7.5%, respectively. The ESMv1 also shows slight improvement in
231 terms of intensity and propagation characteristics of monsoon intra-seasonal oscillation (figure
232 not shown).

233

234 **Ocean mixed layer and subsurface characteristics**

235 One major difference between the ESMv1 and CFSv2 is that the former employs the
236 scheme (Simmons et al. 2004) for interior mixing along with mixed layer re-stratification by the
237 sub-mesoscale eddies (Fox-Kemper et al. 2008, 2011), as compared to the prescribed vertical
238 diffusivity (Bryan and Lewis 1979) in the latter. To diagnose the role of such differences, we
239 compare the simulated bias in annual mean ocean mixed layer depth (MLD) with respect to
240 observations (Figure 4).

241 In general, the bias in the annual mean MLD is larger for CFSv2 (Figures 4b) compared
242 to ESMv1 (Figure 4a). Significant improvement is seen in the tropical oceans especially in the

243 Arabian Sea and Bay of Bengal in ESMv1 simulations. The 10% level of statistical significance
244 of the MLD bias estimated based on student's t-test are shown as contours in Figure 4. Notably,
245 Roxy et al. (2012) found that large biases of MLD in CFSv2 in the Arabian Sea during the
246 summer monsoon season lead to an exaggerated SST-precipitation relationship. Indeed,
247 improvements in the ESMv1 simulated MLD and SST also reflect an improvement of
248 precipitation in the tropics (Fig. 3). We however, note a deeper-than-observed MLD in the region
249 of northern subtropical gyres, and shoaling in the southern ocean in simulations by both models
250 (Fig. 4a and 4b). The southern ocean shoaling is relatively larger in ESMv1 simulation, and
251 consistent with the warm SST bias over the region (Fig. 2b). Our sub-surface analysis shows
252 that the warmer temperatures extend deeper in CFSv2 than WOA, and ESMv1, as shown by the
253 position of the 4°C isotherm in the zonally-averaged vertical profiles of temperature (Figure 4c-
254 e). This is also seen in all the three major individual ocean basins (Figure S1). This implies that
255 pumping of heat away from the surface into deeper layers of the ocean takes place in the CFSv2,
256 resulting in the cooling of surface and warming the ocean below.

257

258 **4. Dominant Pacific modes of variability and interactions with Indian summer monsoon**

259 The Pacific Ocean exhibits substantial temporal and spatial variability. The large size of
260 the basin facilitates unique atmosphere-ocean interannual coupled variability in the tropics,
261 which manifests as the El Niño/Southern Oscillation (ENSO; Rasmusson and Carpenter 1983).
262 ENSO affects global climate and weather conditions such as droughts, floods (Ropelewski and
263 Halpert 1987; Trenberth et al. 1998; Wallace et al. 1998; Ashok et al. 2007) and has significant
264 impact on the Asian summer monsoon (Sikka 1980; Webster et al. 1998; Wallace et al. 1998;
265 Kumar et al. 1999; Krishnamurthy and Goswami 2000; Lau et al. 2000; Ashok et al. 2004;

266 Shukla 1995; Keshavamurty 1982). In this section, we evaluate the fidelity of the simulated
267 ENSO and its interaction with Indian summer monsoon. We also focus our attention on the
268 fidelity of the simulated Pacific Decadal Oscillation (PDO). We use the last 75 years of ESMv1
269 and CFSv2 simulations, and qualitatively compared them with statistics from the 75 years (1935-
270 2010) of HadISST data.

271

272 **El Niño/Southern Oscillation (ENSO)**

273 The largest observed SST variability (Figure 5a) is localized across the central-eastern
274 equatorial Pacific, and is predominantly associated with the canonical ENSO. The models
275 qualitatively reproduce the basic pattern of the observed SST anomaly variability. The
276 coefficient of variation (contours) in Figure 5 indicates that the interannual variability is about
277 5% of the mean in observation and is well captured in ESMv1. However, the simulated variance
278 in CFSv2 is significantly weaker as (Figure 5c) compared to the observations. The ESMv1, on
279 the other hand, performs better both in terms of the magnitude and the extension of the variance
280 maxima from the east through the dateline in the equatorial Pacific (figure 5b). In the CFSv2
281 simulations, the maximum variance is confined mostly to the eastern portion of the eastern
282 equatorial Pacific. This is consistent with slightly flattened thermocline slope from central to
283 eastern equatorial Pacific in CFSv2 compared to ESMv1 (Fig 5d). However, it is to be noted
284 that the EMSv1 slightly overestimates the westward extension of the variance in comparison
285 with observations and CFSv2. The thermocline is also relatively shallow in the west and deeper
286 in the east for ESMv1, showing less improvement with respect to CFSv2.

287 In order to illustrate the fidelity of the spatial pattern of inter-annual variability associated
288 with ENSO, the gravest EOF pattern for boreal winter (December-February) SST anomalies over

289 the Pacific from the HadISST data and that from two models are presented in Figure 6. The
290 horseshoe pattern in the Pacific associated with the observed ENSO variability, with unipolar
291 loadings in the central and eastern equatorial Pacific, and oppositely signed loadings west of the
292 dateline (Fig. 6a) is qualitatively captured by both the models (Figures 6b and 6c). The 31.5%
293 variance explained by the EOF1 from the ESMv1 is reasonably close to corresponding value of
294 37% from the observations. The corresponding explained variance from the CFSv2 is slightly
295 smaller, at 29.5%.

296 The time-mean global wavelet spectrum from a wavelet analysis on the observed PC1,
297 which is associated with ENSO, shows a broad peak in the range of 2–7 years, with maximum
298 power at ~5 years (Fig. 7d). Both models capture this broad peak reasonably well (Figures 7e &
299 7f). The ESMv1 also exhibits a decadal modulation of interannual variability (Figure 7b, 7e),
300 similar to the observations (Figure 7a). Though longer time series are required to adequately
301 characterize the ENSO (Wittenberg 2009), many of the simulated ENSO events appear to be
302 episodic, spanning a range of frequencies over the course of one or two events.

303

304 **ENSO-monsoon relationship in the coupled simulations**

305 The ENSO-monsoon teleconnection, to a good extent, depends on the Walker circulation
306 to deliver the Pacific SST signal to the Indian Ocean and Indian land sector (Krishnamurti 1971;
307 Shukla and Paolino 1983; Webster and Yang 1992). Hence, for a better representation of the
308 Indian summer monsoon and its variability, a model should adequately reproduce the spatial,
309 seasonal, interannual and decadal aspects of the ENSO–monsoon connection.

310 We next compare the simulated ENSO-monsoon teleconnection in the climate
311 simulations of ESMv1 and CFSv2 with one another, and also with that from observations. Figure
312 8 shows the lead-lag correlation between the ISMR and the monthly Niño-3.4 index. This will
313 give a general idea on the mean ENSO-monsoon relationship, though it may not hold for its
314 inter-decadal variability as the teleconnection changes on decadal time scales (eg:
315 Krishnamurthy and Goswami 2000, Kriplani and Kulkarni 1998). The observed simultaneous
316 negative correlation (Shukla and Paolino 1983) between Niño-3.4 SST and ISMR, along with the
317 peak correlation after the monsoon, is reasonably simulated by the ESMv1. However, in CFSv2
318 simulations, the negative correlations unrealistically start developing 12 months prior to the
319 monsoon season. Further, the correlation peaks just at the beginning of the monsoon season, 2-3
320 months earlier than observed. In fact, this is a common problem among most of the climate
321 models, including a significant number of CMIP3 and CMIP5 models (Jourdain et al. 2013;
322 Achuthavarier et al. 2012).

323 To understand the spatial variability of rainfall associated with ENSO, we project the
324 summer monsoon rainfall onto the PC1 obtained from the EOF analysis (Figure 6) of the SST
325 anomalies. The regression pattern from both the simulations show (Supplemental Figures S2)
326 below normal rainfall over most the Indian region, with an excess of rainfall over northeast India
327 similar to the observed pattern (Figure not shown) depicting the role of ENSO on Indian summer
328 monsoon.

329 **Pacific Decadal Oscillation (PDO)**

330 The PDO is the dominant mode of inter-decadal variability in the Pacific characterized by
331 warm SST anomalies near the equator and along the coast of North America, and cool SST

332 anomalies in the central North Pacific in its positive phase (Mantua et al. 1997; Zhang et al.
333 1997; Power et al. 1999). Studies have shown that the PDO-related interdecadal variability can
334 modulate the ENSO (Wang 1995) and the ENSO-related interannual variabilities. The PDO,
335 with a periodicity of 20-30 years is shown to have significant impact on the climate around the
336 Pacific Ocean and beyond (Krishnan and Sugi 2003; Power et al. 1999).

337 Following Mantua et al. (1997) we have performed an EOF analysis of detrended
338 monthly SST anomalies over the domain 120E-120W; 20N-60N for the last 75 years of
339 simulations to explore the simulated the PDO signal. For comparison, an EOF analysis is also
340 performed on HadISST data for the period 1935-2010 over the same domain. The EOF1 from the
341 model and observations are shown in Figures 9. EOF1 pattern from HadISST data, explains
342 about 30.3% variance, with a unipolar signal in the central North Pacific surrounded by the
343 oppositely phased loadings hugging along the west coast of North America (Fig. 9a). This is the
344 distinguishing feature of the warm phase of PDO (e.g. Fig.1, Krishnamurthy and Krishnamurthy
345 2013). The corresponding EOF1 from the ESMv1 (Fig9b) captures the pattern and associated
346 explained variance reasonably. On the other hand, the analogous EOF1 for the CFSv2 (Fig 9c)
347 explains only 24.4% of total variance, and the spatial pattern shows relatively weak negative
348 loadings in the north Pacific. This may be associated with the strong cold SST bias in the
349 subtropical Pacific.

350 A wavelet power spectrum analysis on the observed PC1 (Fig. 9) indicates a dominant,
351 and statistically significant, power in the band of 16-32 years (Figures 10a and 10d). The
352 ESMv1 successfully reproduces this dominant peak (Figures 10b and 10e). However, in the
353 CFSv2 simulations, it is weaker and not statistically significant (Figure 10c and 10f).

354 Further, a regression of the December-February surface winds on to the PC1 indicates an
355 enhanced counterclockwise wind stress anomalies over the North Pacific (Supplemental Fig.
356 S3a) associated with the PDO. Such an association is also seen in the simulations from the
357 ESMv1 (Fig. S3b). The location of the anticyclonic winds and their magnitude are well
358 simulated. However, the counter-clockwise surface circulation is weaker in CFSv2 simulations
359 (Fig. S3c) as compared to observation and ESMv1 simulation. These, along with weaker-than-
360 observed westerlies over subtropical Pacific and south-easterlies over North American coast are
361 consistent with a weak PDO signal.

362

363 **PDO and Indian Summer Monsoon**

364 Krishnan and Sugi (2003) suggest that a warm phase of PDO can amplify the impact of
365 El Niño, resulting in the weakening of Indian summer monsoon. Krishnamurthy and
366 Krishnamurthy (2013) have shown that the PDO is associated with deficit rainfall anomalies
367 mainly north of 18°N, with stronger anomalies in the eastern central India. Indeed, a regression
368 of the observed boreal summer monsoon rainfall (Rajeevan et al. 2006), for the period 1935-
369 2010 on to the concurrent PDO index from the HadISST (Fig. 11a) conforms to these earlier
370 observational works. The corresponding results from the simulations, (Figures 11b and 11c) are
371 in qualitative agreement with Fig. 11a. However, the regression pattern from the CFSv2
372 simulation shows a slightly weaker-than-observed signal.

373 **5. Summary and Conclusion**

374 This paper documents the development of the first prototype of the IITM Earth System
375 Model (ESMv1). Derived from the NCEP CFSv2, this model is being developed to be used in

376 studies on the detection, attribution, and projections of climate change and its impact on the
377 South Asian region. The effort particularly involved, as a first step towards the development of
378 the IITM ESM, inclusion of an ocean bio-geochemistry and ecosystem module and improved
379 physics by replacing the ocean component of the CFSv2. 100-year simulations were performed
380 with the ESMv1 and CFSv2, using the same initial conditions, and compared. The new ocean
381 formulation has led to a significant reduction of cold atmospheric temperature bias (from 1.5°C
382 to 0.6°C) and SST bias as compared to that in the CFSv2. The improvement in SST is
383 particularly prominent in the tropical Indian and Pacific oceans. As a result, the precipitation
384 over the tropical oceans has also improved considerably.

385 In addition, the simulations with IITM-ESMv1 also show improvements in the mean state
386 and near-surface biases in the northern subtropical gyres as well, implying the role of ocean
387 physics in the coupled climate simulations. Importantly, the model demonstrates a realistic
388 global mean temperature and reasonable sensitivity to the ambient CO₂, an essential pre-requisite
389 for a climate model to be used for climate change studies.

390 In terms of the spatial pattern and the periodicity, the ESMv1 simulations of climate
391 variability are more realistic as compared to those of NCEP CFSv2. An example is the simulated
392 PDO signal in CFSv2, which is much weaker than that observed. Importantly, the ENSO-
393 Monsoon relationship in CFSv2 shows an unrealistic strong, negative correlation maximum
394 between the Indian summer Monsoon rainfall and Niño-3.4 index 6-9 months prior to the
395 observations, which may result in unrealistic monsoon variations. This is a common problem in
396 many of the CMIP5 models (Jourdain et al. 2013). However, the ESMv1 captures the observed
397 concurrent negative simultaneous correlations between the monsoons and ENSO, as well as a
398 reasonable lead-lag relationship between these two. All these features demonstrate the ability of

399 the ESMv1 to capture the crucial monsoon-ENSO links, which are important in manifesting the
400 interannual variability of the South Asian summer monsoon. A companion study (Shikha et al.
401 2014) also demonstrates that the ESMv1 also simulates a realistic evolution of the Indian Ocean
402 Dipole (Saji et al. 1999; Webster et al. 1999; Murtugudde 2000) and its variability (figure not
403 shown).

404 A preliminary analysis of the simulated Atlantic Meridional Overturning Circulation
405 (AMOC) indicates (Figure not shown), that the full AMOC has not been yet established in the
406 simulation, and warrants the extension of the current integration by a few more hundreds of
407 years. Such a longer run will also result in more robust tropical climate statistics (e.g. Wittenberg
408 2009) We have also analyzed the distribution of sea-ice concentration (Figure S4) in the
409 northern hemisphere from ESMv1 and CFSv2 for January-March (JFM) and June-September
410 (JJAS). The northern hemisphere sea-ice concentration in ESMv1 is comparable with HadISST
411 data during JFM, the season when the sea ice coverage is largest in the northern hemisphere, but
412 it is found to be lower than observations during boreal summer season (JJAS). Further, the
413 southern hemisphere sea ice concentration is lower than observed (Figure not shown) and more or
414 less similar to that of the CFSv2. Importantly, Huang et al. (2014) note that the low sea ice
415 concentration in CFSv2 has led to a weaker-than-observed AMOC in CFSv2, and improvement
416 in sea ice concentration can be achieved by improving the sea ice albedo. Therefore, we plan to
417 improve the sea ice parameters and also the coupling according to Huang et al. (2014) and
418 extend the integration further to study the relevance of AMOC changes for the monsoon
419 variability.

420 The model's fidelity in terms of the mean climate and seasonal cycle simulations, are at
421 par with those of some other state of art models, the model has yet a few limitations such as a
422 warm bias in the southern ocean region, which are common across a wide spectrum of the
423 CMIP5 models (Lee and Wang 2014). Another important issue is that the CFSv2 has a top of the
424 atmosphere energy imbalance of 6Wm^{-2} , which is fairly constant over a 100-year simulation
425 (figure not shown). A similar signal is also associated with ESMv1. Since the temperature has
426 stabilized, the imbalance could be due to some unaccountable source of energy that is not tracked
427 as part of model integration, for example, due to the lack of dissipative heating of the turbulent
428 kinetic energy (TKE, e.g. Fiedler 2007), or neglecting the radiative impact of precipitating
429 hydrometeors (Waliser et al. 2011). Sun et al (2010), Huang et al. (2007) and Hu et al. (2008)
430 have pointed out that CFS has low cloud cover, this may be one of the possible reasons for the
431 top of the atmosphere energy imbalance in ESMv1. In this context, it is worth noting that the
432 annual average absorbed shortwave and outgoing long wave radiation across the ITCZ regions
433 for the ensemble average of CMIP3 GCMs were shown biases as reported by Trenberth and
434 Fasullo (2010). Trenberth and Fasullo (2010) also find that many of the CMIP3 models poorly
435 simulate the energy budget in the southern hemisphere. This aspect needs further attention.
436 Importantly, a recent study by Bombardi et al. (2014) shows that, despite such biases,
437 retrospective decadal forecasts by the CFSv2 model show high predictive skill over the Indian,
438 the western Pacific, and the Atlantic Oceans. Another issue that needs further attention is that
439 despite an improvement in the oceanic precipitation, the dry bias over the Indian subcontinent
440 associated with the CFSv2 simulations is still seen in the ESMv1 simulations as well. These
441 issues will be addressed in the next version of the model. Significantly, a few recent sensitivity
442 experiments carried out using the CFSv2 model (Hazra et al. 2014) suggest that improving the

443 cloud microphysics will alleviate this problem substantially. In addition, parallel efforts are also
444 towards including an aerosol module into the ESM.

445 Summing up, the ESMv1 is a promising development to facilitate future projections
446 relevant to South Asian climate, specifically those that envisage the next 3-5 decades horizon.

447

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454

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675

676 **Figure Captions:**

677 Figure 1. Time evolution of the globally-averaged annual mean fields (°C) of (a) near surface
678 temperature (b) sea surface temperature and (c) tropical sea surface temperature (30°S-30°N).
679 The ESMv1 (CFSv2) simulations are in red (blue). The corresponding annual mean
680 observational values are 14.6 °C, 18.6 °C and 26.1 °C respectively

681 Figure 2. Spatial distribution of annual mean SST ($^{\circ}\text{C}$) from (a) HadISST and the bias for (b)
682 ESMv1 and (c) CFSv2. The contours represent 10% level of statistical significance based on
683 student's t-test. The rms errors for the ESMv1 are, 1.1°C (global), 0.79°C (30°S - 30°N), and for
684 CFSv2, 1.1°C (global), 0.89°C (30°S - 30°N).

685

686 Figure 3. Spatial map of mean summer monsoon precipitation (JJAS; mm day^{-1}) from the (a)
687 TRMM and the biases for (b) ESMv1 and (c) CFSv2. The contours represent 10% level of
688 statistical significance based on student's t-test.

689

690 Figure 4a. Spatial maps of bias in annual mean mixed layer depth for ESMv1 and (b) CFSv2.
691 The model results are computed over the last 50 years of simulation. Biases are in meter. The
692 contours represent 10% level of statistical significance based on student's t-test. (c) vertical
693 distribution of the global ocean zonal mean temperature ($^{\circ}\text{C}$) from WOA (d) and (e) same as (c)
694 except for ESMv1 and CFSv2 respectively.

695

696 Figure 5. Standard deviation of interannual SST anomalies ($^{\circ}\text{C}$, shaded) for (a) HadISST (b)
697 ESMv1 and (c) CFSv2. The coefficient of variation (%) are overlaid as contours. (d) depth of 20
698 $^{\circ}\text{C}$ isotherm (m) in the equatorial Pacific (5°S - 5°N) for WOA, ESMv1 and CFS2

699

700 Figure 6. The leading EOF pattern of boreal winter (December-February) SST anomalies ($^{\circ}\text{C}$) in
701 the pacific for (a) HadISST data for the period 1935-2010 (b) ESMv1 and (c) CFSv2. The model
702 results are computed over the last 75 years of simulations.

703

704 Figure 7. Time series of wavelet power spectra of the gravest principal component from the EOF
705 analysis of the pacific winter SST ($120^{\circ}\text{E}-80^{\circ}\text{W}, 60^{\circ}\text{N}-60^{\circ}\text{S}$; see Fig. 6) for (a) HadISST (b)
706 ESMv1 and (c) CFSv2. The corresponding time-averaged power spectra are shown for (d)
707 HadISST (e) ESMv1 and (f) CFSv2.

708

709 Figure 8. Lead–lag correlations between All Indian Summer Monsoon derived from the IMD
710 datasets (June–September) rainfall and monthly Nino-3.4 index from the HadISST, for the 1935-
711 2010 period (black line), ESMv1 (red line), CFSv2 (blue line). Note that the model results are
712 computed over the last 75 years of simulations for comparison.

713

714 Figure 9. The leading EOF pattern of detrended monthly SST anomalies ($^{\circ}\text{C}$) in the north Pacific
715 ($120^{\circ}\text{E}-120^{\circ}\text{W}, 20^{\circ}\text{N}-60^{\circ}\text{N}$) (a) HadISST data for the period 1935-2010 (b) ESMv1 and (c)
716 CFSv2. The model results are computed over the last 75 years of simulations.

717

718 Figure 10. Time series of wavelet power spectra of the gravest principal component from the
719 EOF analysis of the northern pacific SST ($120^{\circ}\text{E}-120^{\circ}\text{W}, 20^{\circ}\text{N}-60^{\circ}\text{N}$; see Fig. 9) for (a)
720 HadISST (b) ESMv1 (c) CFSv2 and the black contour is the 10% significance level. (d) the
721 corresponding time-averaged spectra. The dashed line is the 10% significance for the time-averaged
722 power spectra.

723

724 Figure 11. Spatial map of JJAS rainfall anomalies (mm day^{-1}) regressed on to the gravest
725 principal component from EOF analysis of northern pacific ($120^{\circ}\text{E}-120^{\circ}\text{W}, 20^{\circ}\text{N}-60^{\circ}\text{N}$; see

726 Figure 9) from (a) Observations (for the period 1935-2010) (b) ESMv1 and (c) CFSv2. The
727 model results are computed over the last 75 years of simulations.

728

729 **Supplementary figures:**

730 Figure S1. Vertical distribution of the global ocean zonal mean temperature ($^{\circ}\text{C}$) for individual
731 ocean basins (Pacific : top panel, Indian : middle panel and Atlantic : bottom panel) from (a)
732 WOA (b) ESMv1 and (c) CFSv2.

733

734 Figure S2. Spatial map of JJAS rainfall anomalies (mm day^{-1}) regressed on to the gravest
735 principal component from EOF analysis of the pacific SST ($120^{\circ}\text{E}-80^{\circ}\text{W}$, $60^{\circ}\text{N}-60^{\circ}\text{S}$; see Figure
736 6) from (a) Observation (for the period 1935-2010) (b) ESMv1 and (c) CFSv2. The model results
737 are computed over the last 75 years of simulation.

738

739 Figure S3. Spatial map of DJF surface wind anomalies (ms^{-1}) regressed on to the gravest
740 principal component from EOF analysis of the Pacific SST ($120^{\circ}\text{E}-120^{\circ}\text{W}$, $20^{\circ}\text{N}-60^{\circ}\text{N}$; see
741 Figure 9) from upon the wind anomalies from (a) Observation (NCEP reanalysis) (b) ESMv1 and
742 (c) CFSv2.

743

744 Figure S4. Sea ice concentration in the northern hemisphere north of 60°N during January-March
745 (JFM) from (a) HadISST (b) ESMv1 and (c) CFSv2, (d) –(e) same as (a)-(c) except during June-
746 August (JJA).

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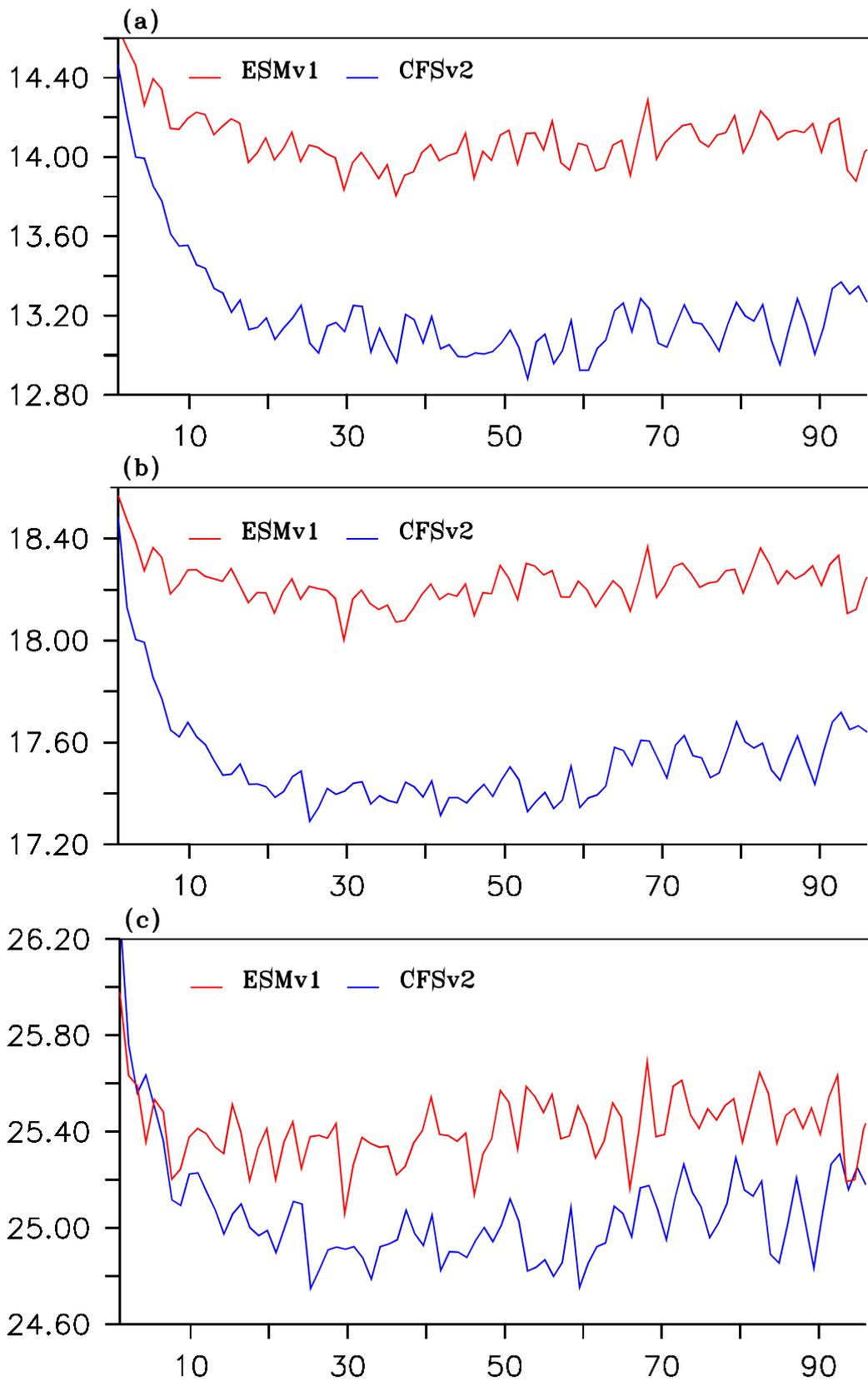


Figure 1. Time evolution of the globally-averaged annual mean fields ($^{\circ}\text{C}$) of (a) near surface temperature (b) sea surface temperature and (c) tropical sea surface temperature (30°S - 30°N). The ESMv1 (CFSv2) simulations are in red (blue). The corresponding annual mean observational values are 14.6°C , 18.6°C and 26.1°C respectively

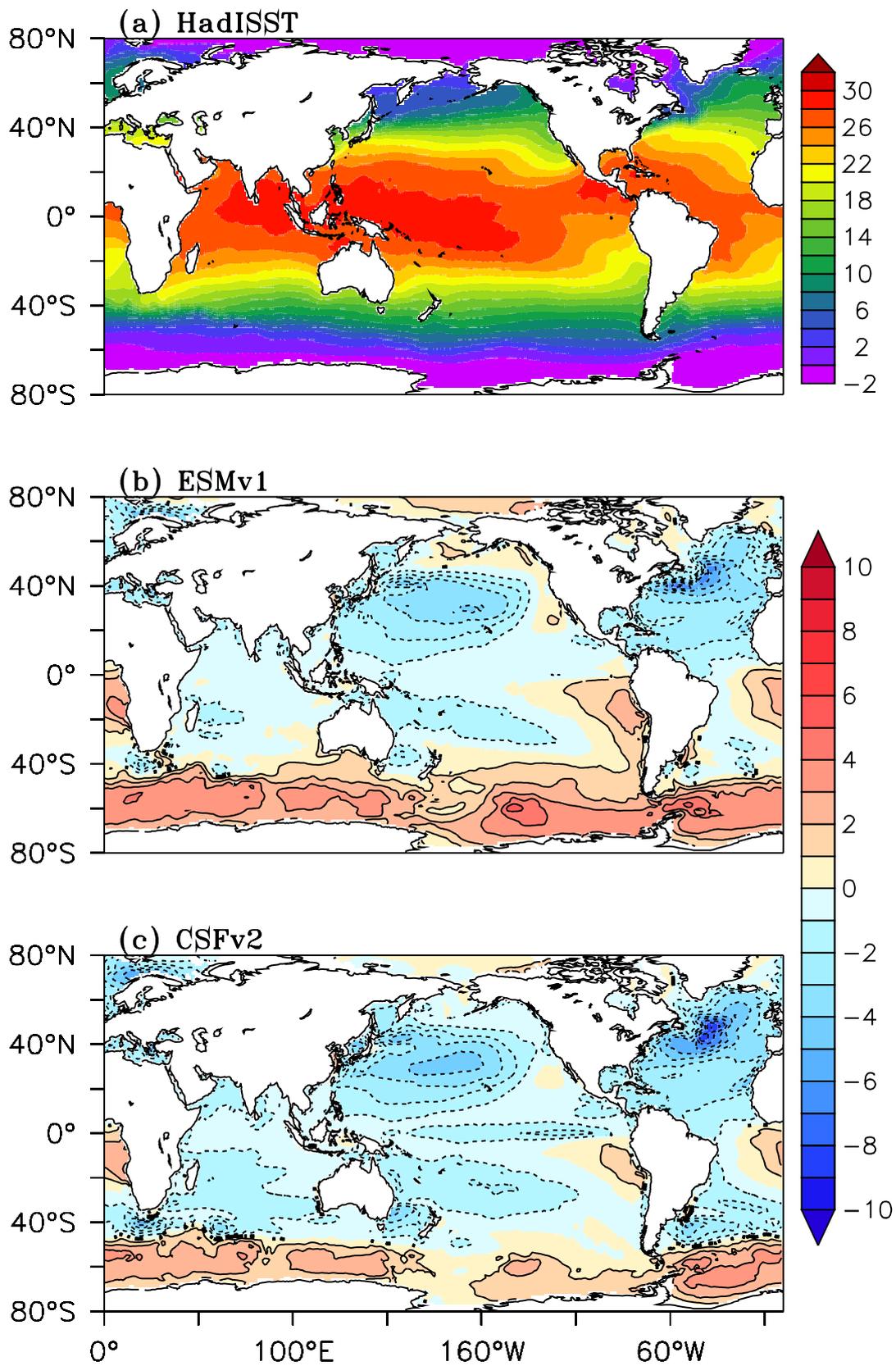


Figure 2. Spatial distribution of annual mean SST ($^{\circ}\text{C}$) from (a) HadISST and the bias for (b) ESMv1 and (c) CFSv2. The contours represent 10% level of statistical significance based on student's t-test. The rms errors for the ESMv1 are, 1.1°C (global), 0.79°C (30°S - 30°N), and for CFSv2, 1.1°C (global), 0.89°C (30°S - 30°N).

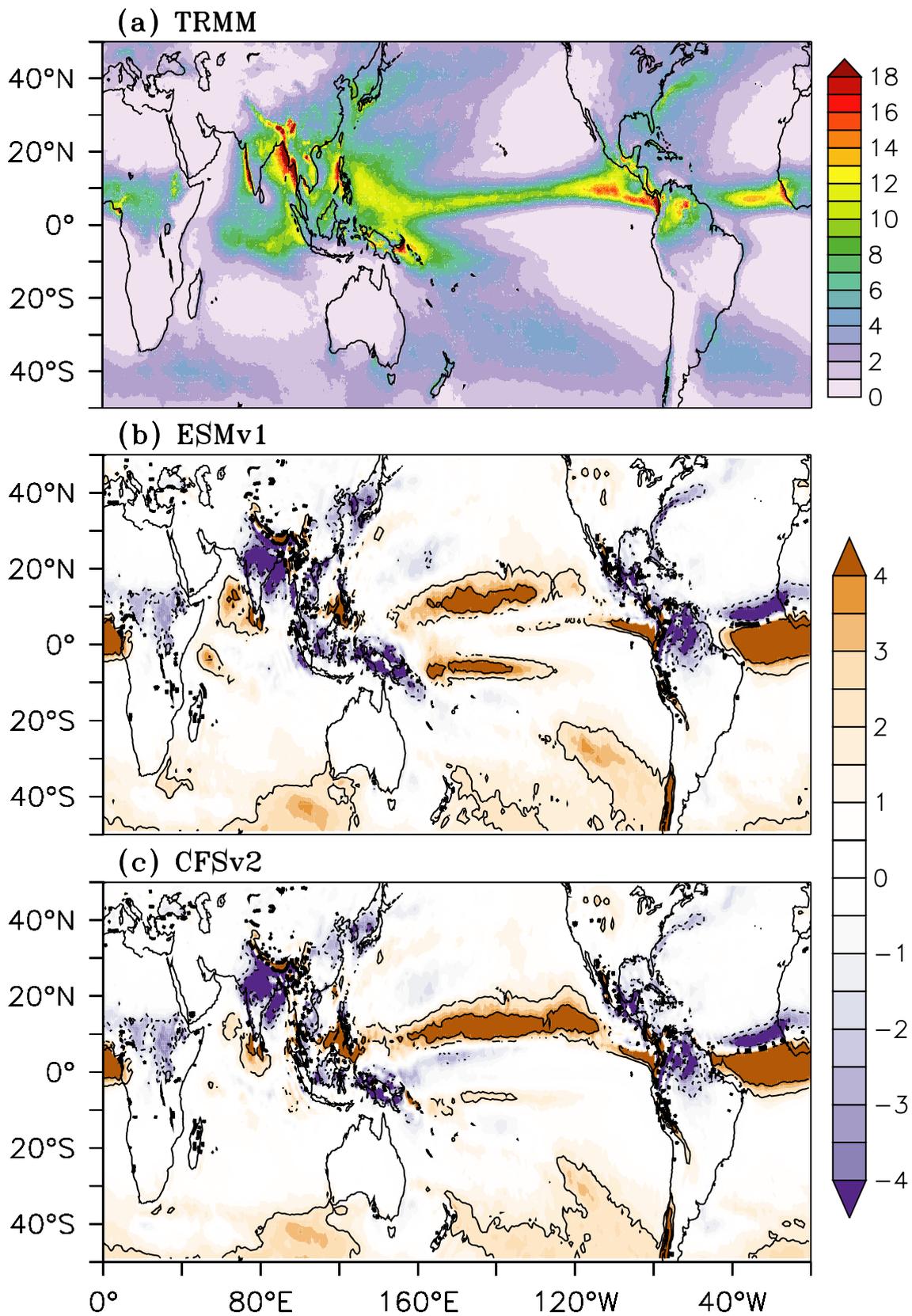


Figure 3. Spatial map of mean summer monsoon precipitation (JJAS; mm day⁻¹) from the (a) TRMM and the biases for (b) ESMv1 and (c) CFSv2. The contours represent 10% level of statistical significance based on student's t-test.

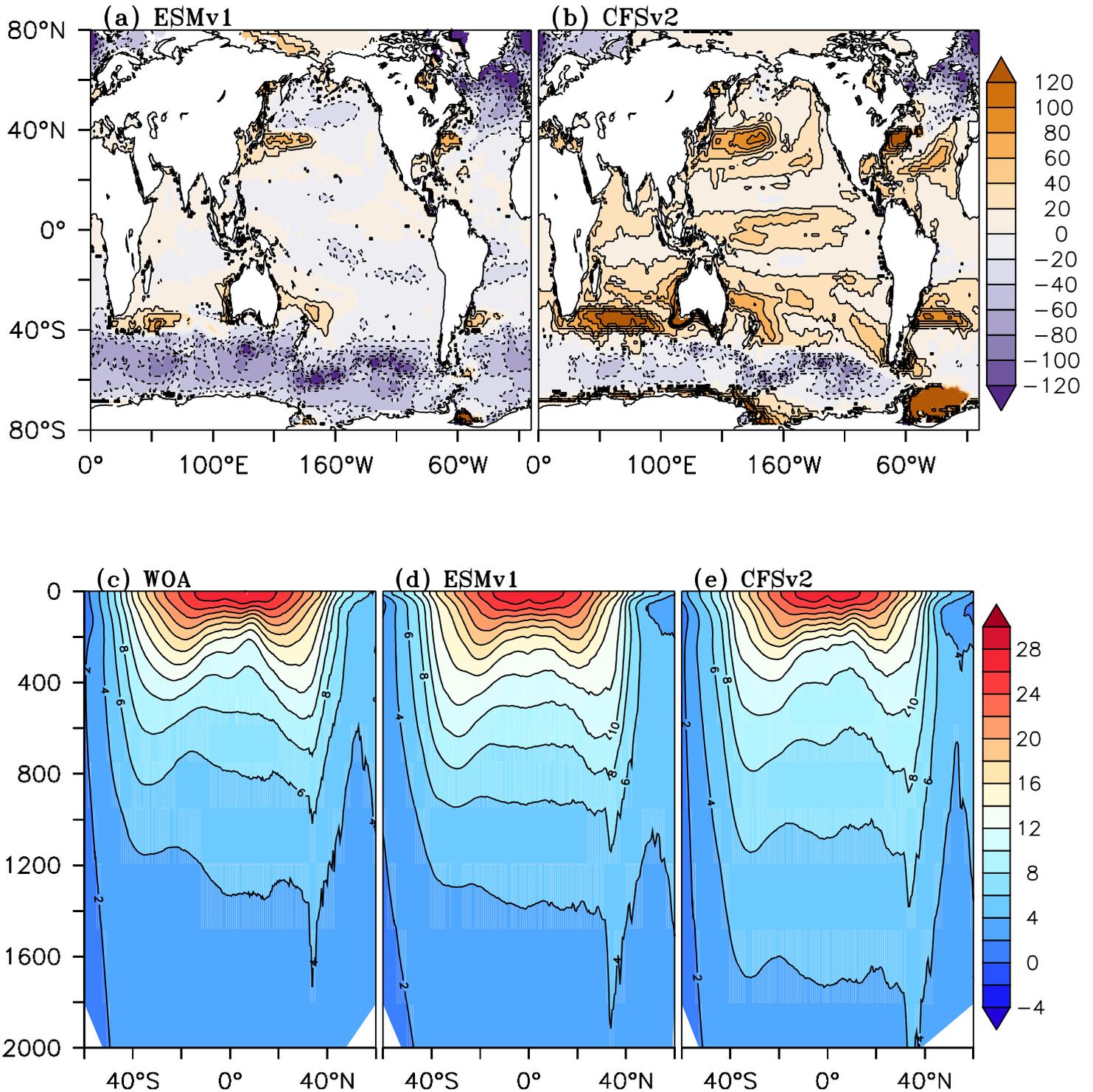


Figure 4a. Spatial maps of bias in annual mean mixed layer depth for ESMv1 and (b) CFSv2. The model results are computed over the last 50 years of simulation. Biases are in meter. The contours represent 10% level of statistical significance based on student's t-test. (c) vertical distribution of the global ocean zonal mean temperature (°C) from WOA (d) and (e) same as (c) except for ESMv1 and CFSv2 respectively.

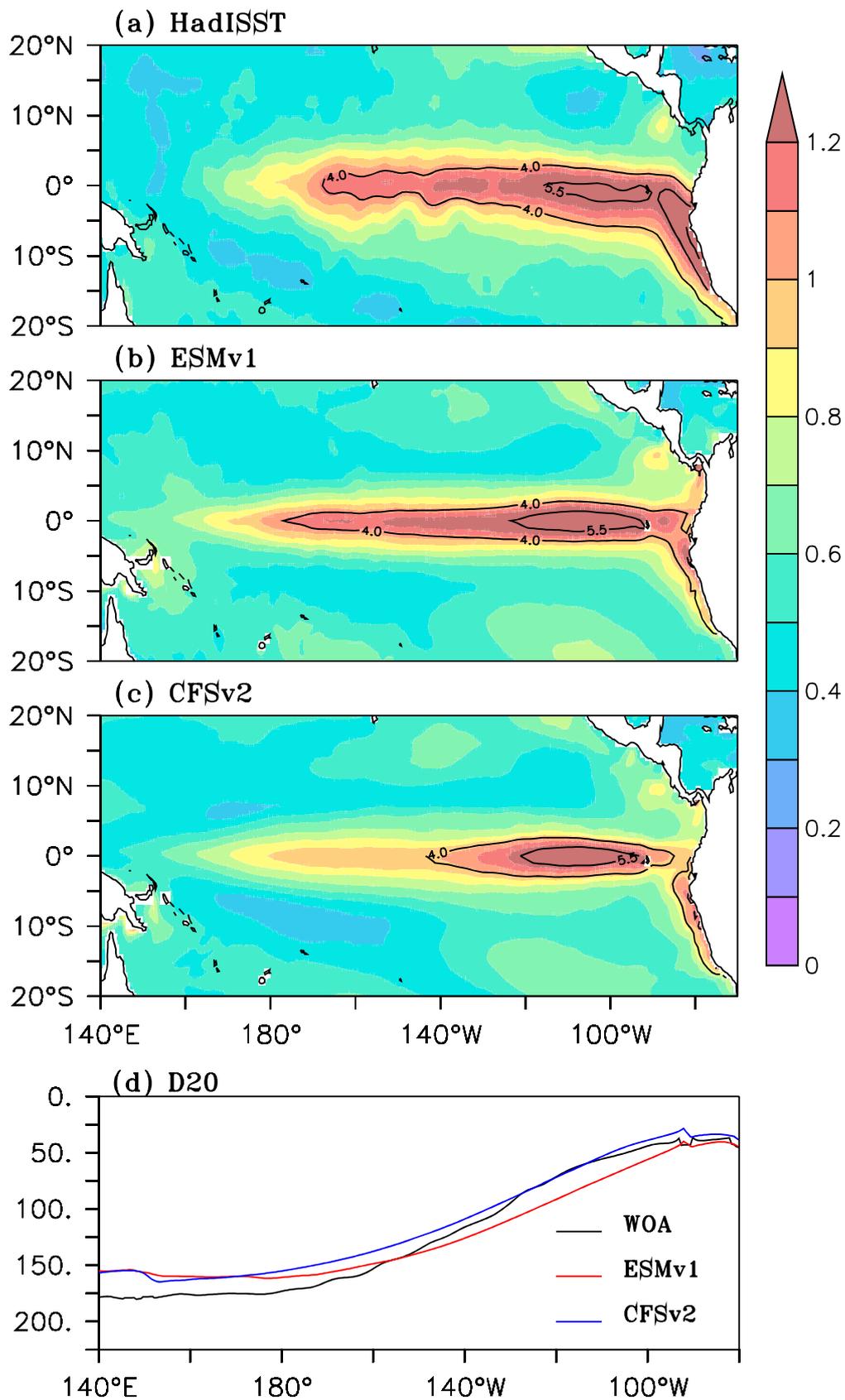


Figure 5. Standard deviation of interannual SST anomalies ($^{\circ}\text{C}$, shaded) for (a) HadISST (b) ESMv1 and (c) CFSv2. The coefficient of variation (%) are overlaid as contours. (d) depth of 20°C isotherm (m) in the equatorial Pacific (5°S - 5°N) for WOA, ESMv1 and CFSv2

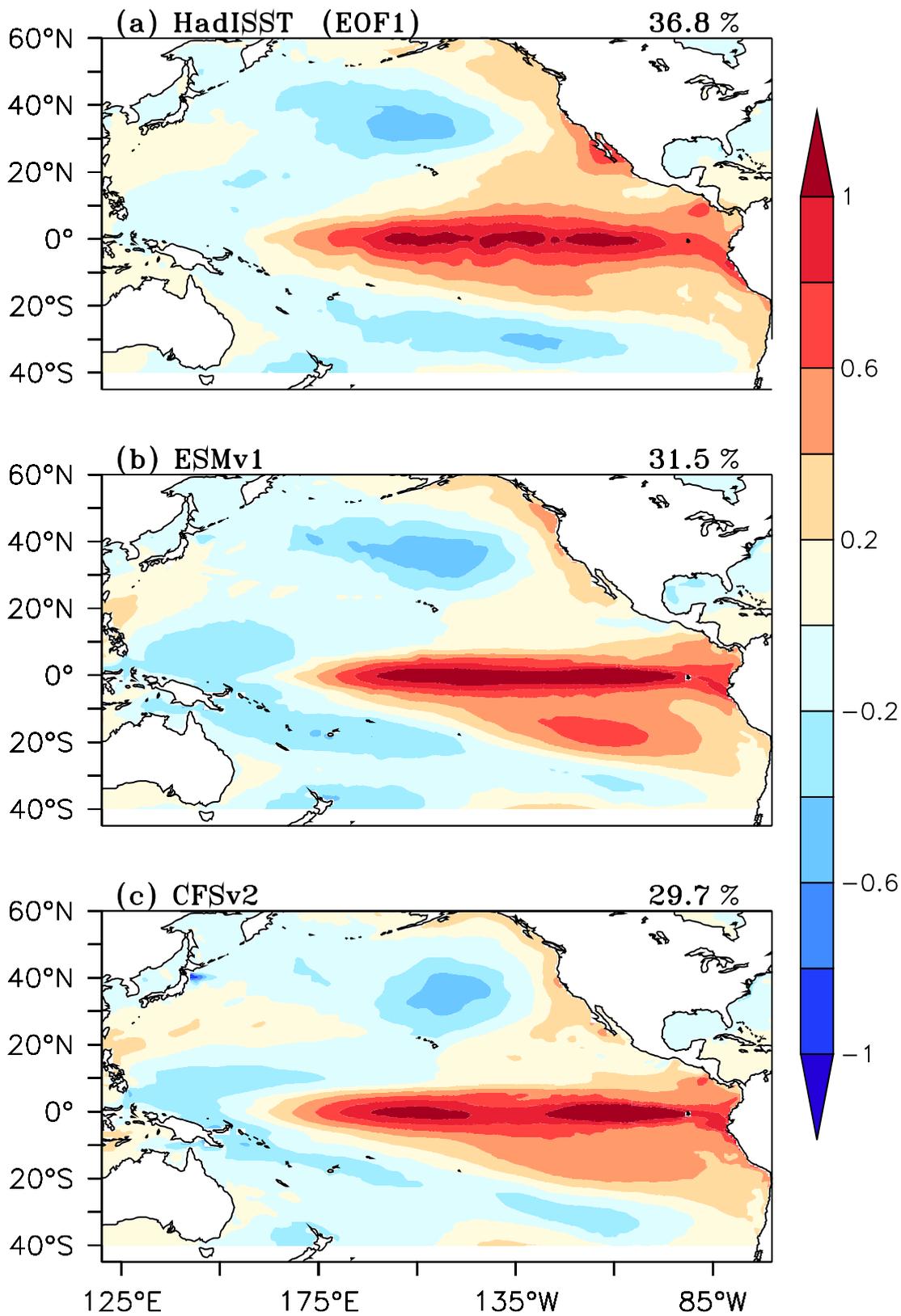


Figure 6. The leading EOF pattern of boreal winter (December-February) SST anomalies (°C) in the Pacific for (a) HadISST data for the period 1935-2010 (b) ESMv1 and (c) CFSv2. The model results are computed over the last 75 years of simulations.

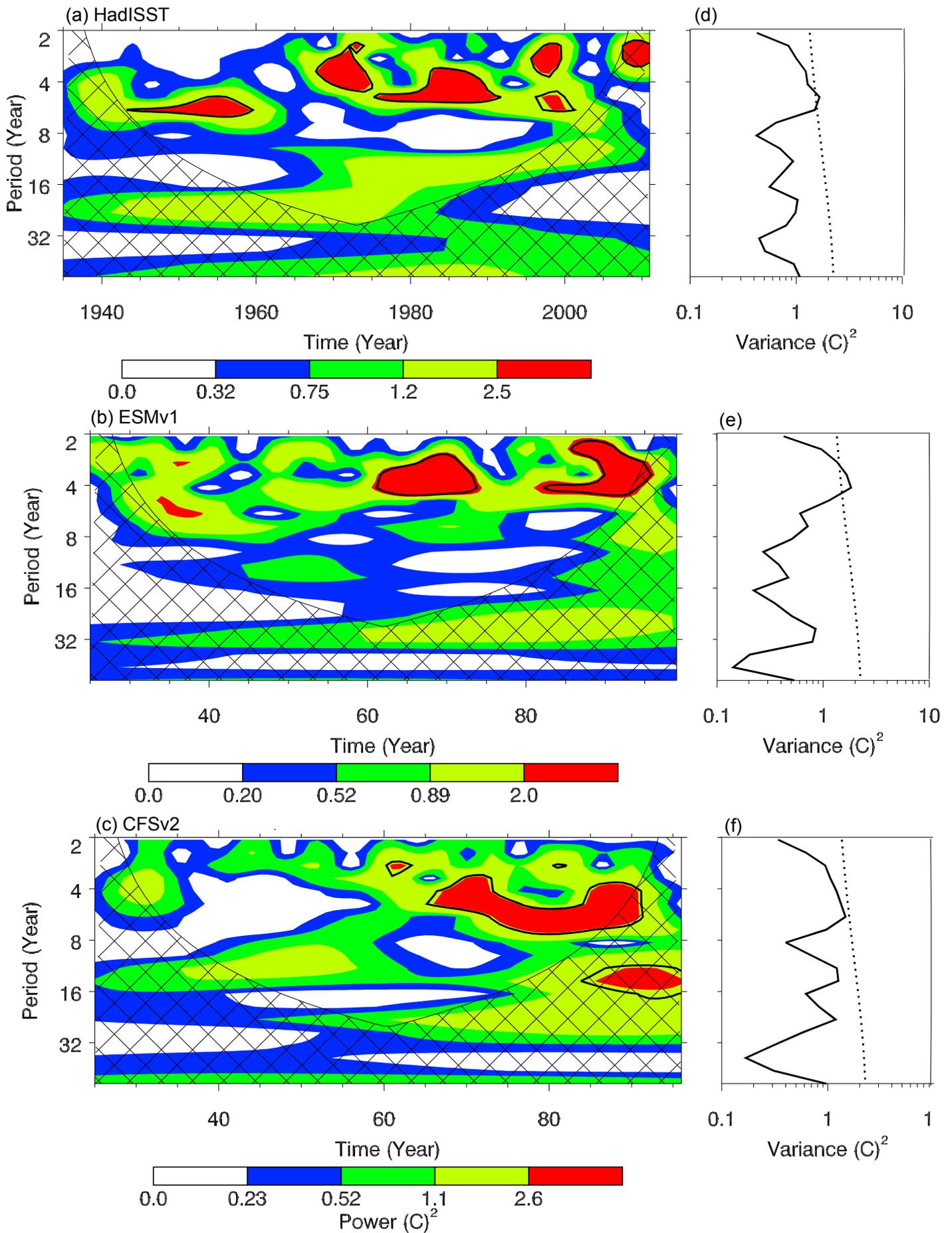


Figure 7. Time series of wavelet power spectra of the gravest principal component from the EOF analysis of the Pacific winter SST (120°E - 80°W , 60°N - 60°S ; see Fig. 6) for (a) HadISST (b) ESMv1 and (c) CFSv2. Black contour is the 10% significance level. The corresponding time-averaged power spectra are shown for (d) HadISST (e) ESMv1 and (f) CFSv2. The dashed line is the 10% significance for the time-averaged power spectra.

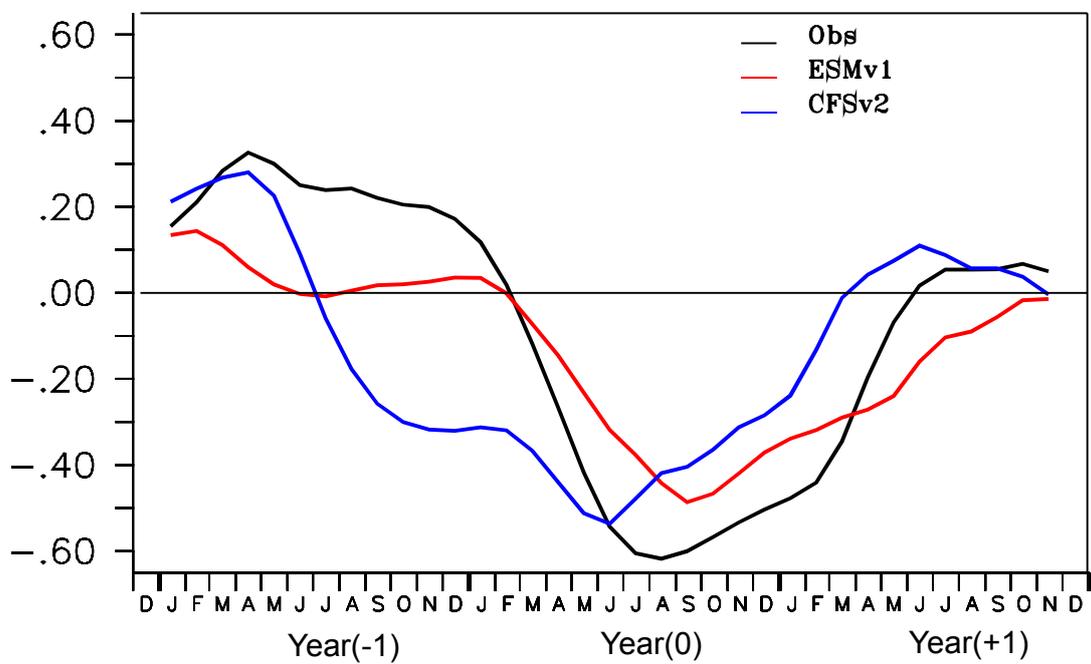


Figure 8. Lead-lag correlations between All Indian Summer Monsoon derived from the IMD datasets (June-September) rainfall and monthly Niño-3.4 index from the HadISST, for the 1935-2010 period (black line), ESMv1 (red line), CFSv2 (blue line). Note that the model results are computed over the last 75 years of simulations for comparison.

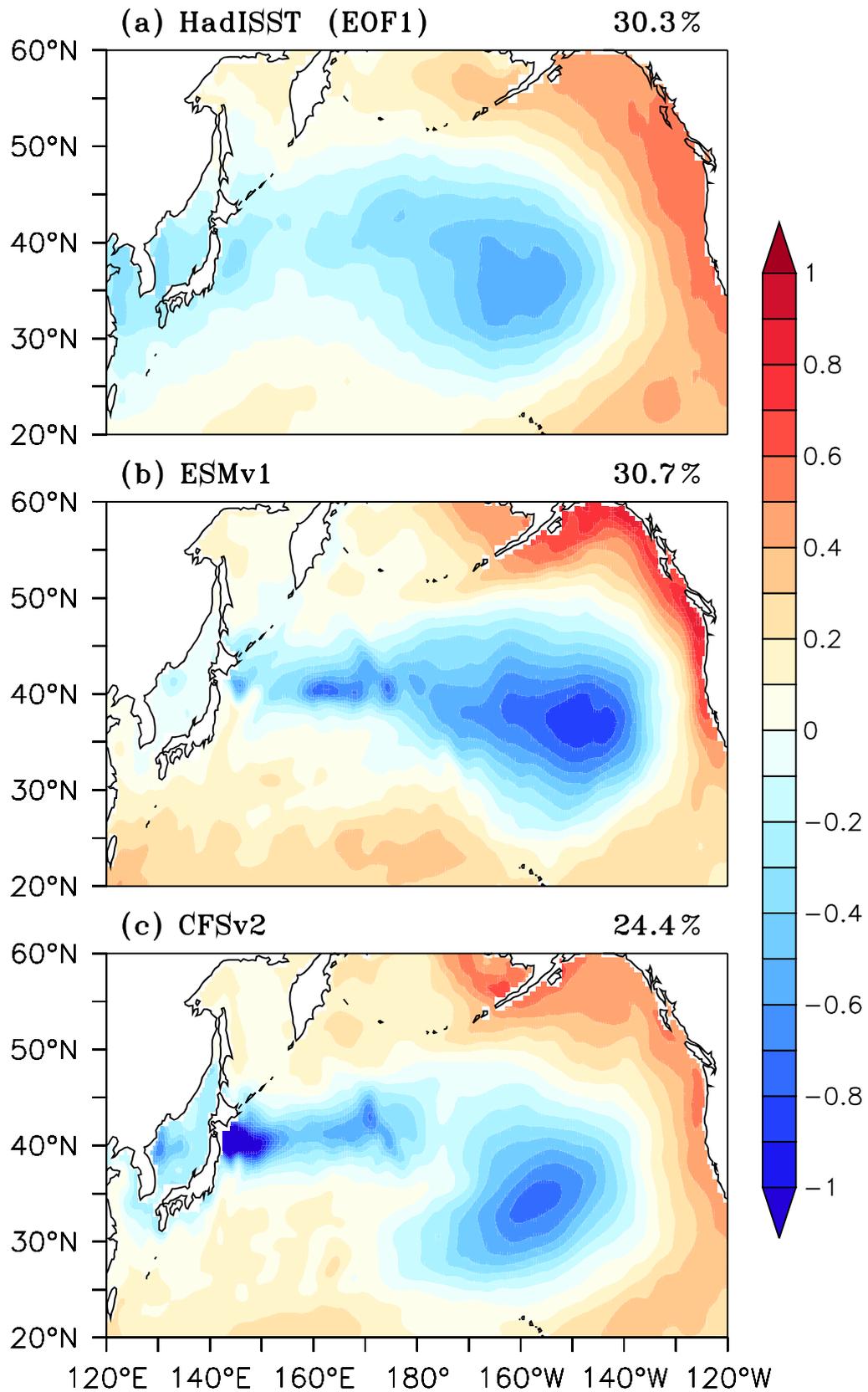


Figure 9. The leading EOF pattern of detrended monthly SST anomalies ($^{\circ}\text{C}$) in the north Pacific (120°E - 120°W , 20°N - 60°N) (a) HadISST data for the period 1935-2010 (b) ESMv1 and (c) CFSv2. The model results are computed over the last 75 years of simulations.

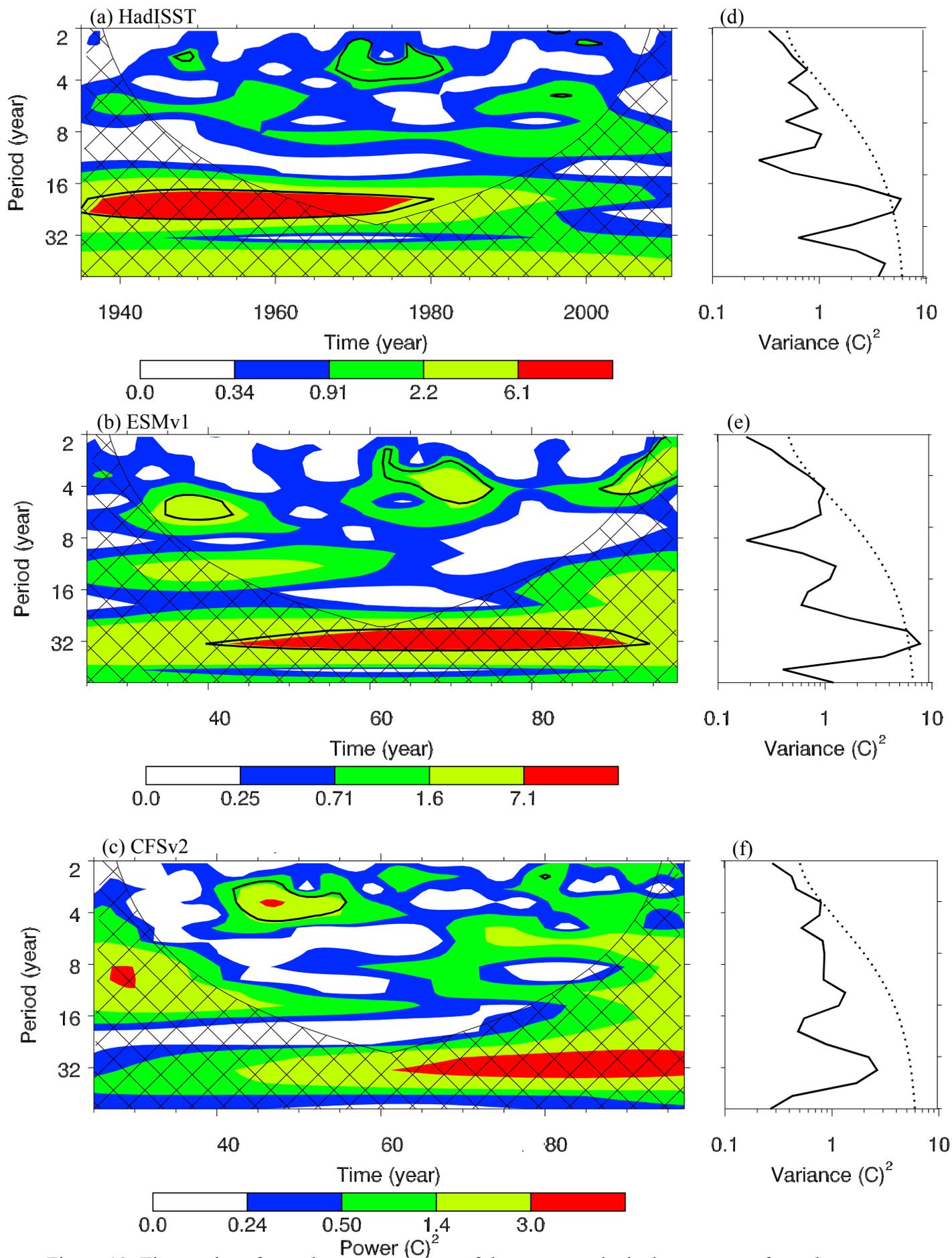


Figure 10. Time series of wavelet power spectra of the gravest principal component from the EOF analysis of the northern pacific SST (120°E-120°W,20°N-60°N; see Fig. 9) for (a) HadISST (b) ESMv1 (c) CFSv2 and the black contour is the 10% significance level. (d) the corresponding time-averaged spectra. The dashed line is the 10% significance for the time-averaged power spectra.

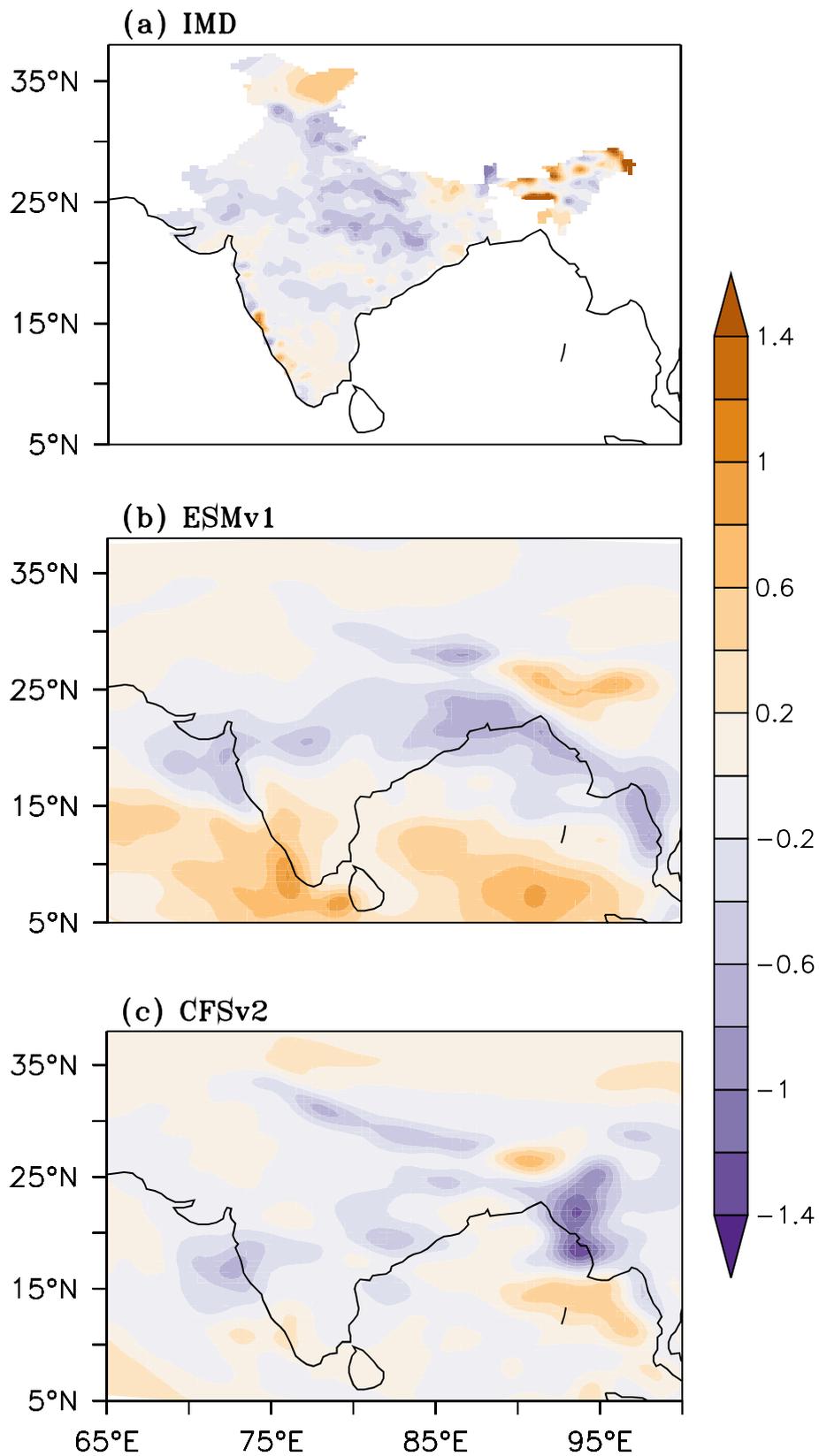


Figure 11. Spatial map of JJAS rainfall anomalies (mm day^{-1}) regressed on to the gravest principal component from EOF analysis of northern pacific ($120^{\circ}\text{E}-120^{\circ}\text{W}, 20^{\circ}\text{N}-60^{\circ}\text{N}$; see Figure 9) from (a) Observations (for the period 1935-2010) (b) ESMv1 and (c) CFSv2. The model results are computed over the last 75 years of simulations.