Evaluation of CMIP5 models on sea surface salinity in the Indian Ocean

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Abstract. Prior to future climate assessment of the 5th Coupled Model Intercomparison (CMIP5) experiments, how well CMIP5 models simulate present climate should be examined. Sea surface salinity (sss) play important role in ocean stratification and indirectly affects air sea interaction. However, few studies have been carried out to evaluate sss in CMIP5 models. In this study, performance of CMIP5 models in simulating sss in Indian Ocean was examined with respect to the observation. Our results showed that multi model ensemble (MME) mean of CMIP5 models displayed annual and seasonal salinity bias in three regions i.e. Western Indian Ocean (WIO), Bay of Bengal (BOB) and Southeastern Indian Ocean (SEIO). CMIP5 models overestimate sss in BOB about 1.5 psu and underestimate sss in WIO and SEIO about 0.4 psu. Biases in WIO and BOB were mainly attributed to bias in precipitation. CMIP5 models overestimated (underestimated) precipitation in WIO (BOB) with greater bias found during Boreal summer to winter. Meanwhile, advection process was responsible for negative SSS bias in SEIO.

1. Introduction
Influence of seas surface salinity (sss), as proxy of upper ocean salinity, on ocean upper ocean stratification has attracted many studies. Low salinity water influences the mixed layer depth in several places in the tropical ocean [1,2] by increasing stratification in ocean mixed layer that leads to barrier layer (BL) formation in Indian Ocean, BL exist in Bay of Bengal (BOB) [3], Eastern Indian Ocean (EIO) [4,5] and Southeastern Arabian Sea [6]. Recent studies also discussed the mechanism of how low salinity changes mixed layer density and forming BL formation. Presence of BL formation induced by low salinity water may prevent entrainment of cool water and maintains mixed layer warms [7,1,2]. As consequence, changes in mixed layer may further influence air-sea interaction and local-global weather/climate.

Low salinity water in Bay of Bengal is attributed to large excess of freshwater from precipitation and river discharge during summer-autumn. Ocean dynamics plays important role in salinity
distribution through advection process. Monsoonal wind affects seasonal variation of current that transport salinity water. In the North of Indian Ocean, monsoon currents facilitate the water exchange between the Arabian Sea and the Bay of Bengal. High-salinity water is advected towards Bay of Bengal during summer while low-salinity water is advected towards southeast Arabian Sea in winter [8,9]. Near the equator of Indian Ocean, seasonal variation of salinity is affected by Yoshida-Wyrtki Jet [10,11], which carries high salinity water eastward in spring and autumn.

Modeling studies of salinity effect by [12,13] discussed the impact of precipitation/freshwater flux on the ocean stratification and equatorial circulation in the TIO which remarked that salinity stratification greatly affect the ocean dynamic and air-sea interaction [14]. The simulations with and without salinity effect in the coupled model reveal a highly seasonal influence of salinity and the barrier layer (BL) on oceanic vertical density stratification, which is in turn linked to changes in sea surface temperature (SST), surface winds, and precipitation [15].

The Coupled Model Intercomparison Project phase 5 (CMIP5) models provide the opportunity to investigate role of salinity on past and projected future climates [16,17]. Previous studies showed that CMIP5 models have common error in equatorial Indian Ocean which simulate positive IOD-like pattern as shown in figure 1 [18] during summer and fall indicated by warm SST bias in WIO and cool SST bias in Eastern Indian Ocean (EIO). This is accompanied by bias and strong easterly wind bias in the Eastern Indian Ocean (EIO) [19,20]. The thermocline is also tilted toward EIO [21]. [22] and [19] also remarked that SST biases over WIO are related to a weaker southwesterly summer monsoon.

Despite evaluation of CMIP5 models in representing SST variations, only few studies has been conducted to evaluate how sea surface salinity (sss) is being represented by CMIP5 in the present climate. Therefore, this study will investigate how CMIP5 models simulate seasonal variation of sss. The purpose of this study is to investigate the underlying cause in salinity bias by considering systematic bias of CMIP5 models in Indian Ocean.

2. Methods
We examined the dataset of CMIP5 that is referred to historical runs covering much of the industrial period from the mid-nineteenth century to near present [17]. Table 1 shows a list of 21 CMIP5 models used in this study. Further information on each model is available online at http://www-pcmdi.llnl.gov. In this study, monthly-mean outputs from 20-year CMIP5 simulations (1985–2004) were examined, including ocean salinity and currents, precipitation and evaporation. The similar averaging period was often used in the previous studies for mixed layer depth (MLD) (e.g., [23]), documenting that the simulated MLD shows weak decadal and longer variability, which was sufficient to analyze the mean seasonal cycle of sss in the tropical Indian Ocean. In order to calculate the multi-model ensemble-mean (MME), outputs of CMIP5 models were horizontally interpolated onto a 1° x 1° uniform horizontal grid and vertically interpolated onto a 5 m uniform vertical grid from ocean surface down to 100 m and 25 m uniform vertical grid below 100m, using linear interpolation. We noted that salinity at 5 m was used as sss in this study because the first ocean vertical level is 5 m in most of the models.

In order to analyze biases of sss in the models, we used the monthly mean ocean salinity provided by the In Situ Data Analysis System (ISAS) 13 [24, 25], which is an averaged over the period 2004–2014 (11 years) with horizontal grid resolution of 0.5° and vertical grid resolution of 152 levels from 0 to 2000m. The levels above 100m have higher vertical resolution with 5m thicknesses. Near-surface winds at the 1000-hPa level were obtained from the European Center for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA) Interim product [26], averaged over the period 1985–2004. The horizontal grid for near-surface wind data is 0.75°. Precipitation data were obtained from the Global Precipitation Climatology Project (GPCP) [27]. Evaporation data were provided by the Woods Hole Oceanographic Institute OAFX project at http://oaflux.whoi.edu [28]. The horizontal grid resolution for precipitation and evaporation are 2.5° and 1° respectively. For ocean current comparison, we used monthly mean ECMWF Ocean Reanalysis System 4 (ORAS4) [29] with 1° horizontal grid resolution. ECMWF ORAS4 data were obtained from http://www.ecmwf.int/en/research/climate-reanalysis/ocean-reanalysis. All observation data were
averaged over the period 1985-2004. Linear interpolation was also applied onto horizontal and vertical grid of the observation for calculating the bias in MME of CMIP5 models.

Table 1. List of the 21 CMIP5 models used in this study.

| Model Name | Institution | Label |
|------------|-------------|-------|
| MRI-CGCM3  | Meteorological Research Institute (Japan) | M01   |
| CMCC-CM    | The Centro Euro-Mediterraneo sui Cambiamenti Climatici Climate Model (Italy) | M02   |
| MRI-ESM1   | Meteorological Research Institute (Japan) | M03   |
| BCC-CM1-1  | The Beijing Climate Center Climate Model (China) | M04   |
| HADGEM2-ES | Met Office Hadley Centre (UK) | M05   |
| IPSL-CM5B  | Institut Pierre-Simon Laplace (France) | M06   |
| CNRM-CM5-2 | Centre National de Recherches Meteorologiques/Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique (France) | M07   |
| ACCESS1.3  | CSIRO-BOM (Australia) | M08   |
| CNRM-CM5   | Centre National de Recherches Meteorologiques/Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique (France) | M09   |
| NorESM1-M  | Norwegian Climate Centre (Norway) | M10   |
| GFDL-CM3   | Geophysical Fluid Dynamic Laboratory (USA) | M11   |
| IPSL-CM5A-LR | Institut Pierre-Simon Laplace (France) | M12   |
| MIROC-ESM  | Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology | M13   |
| GISS-E2-R  | NASA Goddard Institute for Space Studies (USA) | M14   |
| CanESM2    | Canadian Centre for Climate Modeling and Analysis (CCCMA) | M15   |
| MPI-ESM-LR | Max Planck Institute for Meteorology (Germany) | M16   |
| GFDL-CM 2.1 | Geophysical Fluid Dynamic Laboratory (USA) | M17   |
| MPI-ESM-P  | Max Planck Institute for Meteorology (Germany) | M18   |
| CSIRO      | CSIRO Atmospheric Research (Australia) | M19   |
| GFDL-ESM2G | Geophysical Fluid Dynamic Laboratory (USA) | M20   |
| MIROC5     | Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology (Japan) | M21   |

We examined the possible cause of sss bias by using salt budget analysis. Salt budget analysis had been used in similar manner to heat budget analysis to study salinity variability in Northeast Pacific Ocean [30]. In this study, we used fixed depth (50m depth) salt following [31] and [32].

\[
\frac{\partial S}{\partial t} = -u \frac{\partial S}{\partial x} - v \frac{\partial S}{\partial y} - w \frac{\partial S}{\partial z} + \frac{S_o (E-P)}{h} + \text{Residual},
\]

where \( S, u, v, \) and \( w \) represent climatological monthly means of ocean salinity, zonal, meridional, and vertical ocean current velocities respectively, and \( h \) is a thickness of the water column (= 50 m). All the terms were averaged over the top 50 m. Using fixed depth of 50 m avoids complications associated with a multi-model ensemble such as varying mixed layer depth amongst models [32]. \( S_o \) was defined as vertical average of salinity over 50 m. \( E \) and \( P \) were defined as evaporation and precipitation rate respectively.
3. Results

3.1. SST and surface wind bias
In this study, we investigated whether the sss bias was influenced by CMIP5 common bias. Bias in precipitation and evaporation may increase/decrease the ocean salinity. Bias in surface wind may induce changes in evaporation and also affects salt advection through ocean current bias. Multi model ensemble (MME) mean of CMIP5 models used in this study displayed common bias as shown in figure 1 that is consistent with previous CMIP5 studies. Warm SST bias was present during summer (June to August, called JJA) and autumn (September to November, called SON) in the WIO. At the same time, strong easterly bias was pronounced in Eastern Indian Ocean accompanied by cold SST bias. These warm-cold SST bias over India Ocean exhibited similar pattern like positive Indian Ocean Dipole (IOD) SST anomalies. [33] reported that significant biases in annual zonal wind at the equator (figure 1a) resulting too small of an east-west gradient of sea level. Here, our result (figure 1) reaffirmed previous studies in CMIP5 bias.

Figure 1. Seasonal SST bias overlaid by surface wind bias. Here a) MAM (March to May, Boreal spring), b) JJA (June to July, Boreal summer), c) SON (September to November, Boreal autumn), and DJF (December to February, Boreal winter).

3.2. Sea surface salinity bias
Annual mean of sss over Indian Ocean is shown in figure 2a, indicating high sss presents in Arabian Sea and WIO and low sss presents in BOB. Low sss was present in BOB due to large amount of precipitation and low salinity water input from river discharge. Low sss along the coast of Java-Sumatra was attributed to annual precipitation in maritime continent throughout the year. MME CMIP5 models successfully simulated annual mean SSS in Arabian Sea, yet they underestimated annual sss in WIO and SEIO and overestimated sss in BOB (figure 2b-c). We defined box 1 (40-70E; 10S-10N), box 2 (80-100E; 8-20N) and box 3 (90-120E; 20-10S) as illustrated in figure 2c, which correspond to the area where annual sss bias was present, i.e. WIO, BOB and SEIO, respectively. We excluded the maritime continent in this study. More detail discussion for bias in maritime continent must consider influence from Western Pacific Ocean, which is beyond our discussion.
Figure 2. Annual mean of sea surface salinity for a) the observation, b) MME of CMIP5 models and c) MME annual mean bias. The dots in figure 2c shows that the bias is represented by 75% of models. The area of study are denoted by the box i.e. Western Indian Ocean (WIO, 40-70E; 10S-10N), Bay of Bengal (BOB, 80-100E; 8-20N) and Southeastern Indian Ocean (SEIO, 90-120E; 20-10S).

In general, MME mean of CMIP5 models overestimated seasonal variation of sss in BOB while CMIP5 underestimated sss in WIO and SEIO and in the maritime continent. Our study regions (figure 2) displayed significant seasonal sss bias. It is interesting to note that sss biases in the study area are greater in Boreal autumn to winter (December to February, called DJF) season as shown in figure 3 and 4. In particular the bias in the BOB (figure 3b) where most of models failed to simulate realistic sss in SON. MME of CMIP5 models overestimated the sss with bias about 1.5 psu greater than the observation. Meanwhile, MME of CMIP5 models simulated sss lower than the observation in WIO and SEIO with bias about 0.4 psu in SON-DJF. Although there was inter-model variation among CMIP5 models, we confirmed that the bias in three regions was significant which was represented by at least 15 of 21 models (75%) denoted by the dots in figure 4.

Figure 3. Seasonal time series of SSS in a) WIO, b) BOB and c) SEIO are indicated by red solid line. Standard deviation is indicated by error bar. Solid black line denotes the observation. The x and y axis denote time (months) and sss value (psu).

3.3. Precipitation bias
Precipitation is among the key factors controlling the sss. Realistic reproduction of precipitation is challenging task in state-of-the-art GCMs simulation. Positive precipitation bias in WIO existed in all seasons with greater bias presented during autumn and winter (figure 5a-d). Positive precipitation bias had appeared after warm SST bias developed in summer (figure 1c). In BOB, strong negative precipitation bias occured during summer when Indian summer monsoon precipitation emerged. In Eastern Indian Ocean, positive precipitation bias was present in maritime continent throughout the year. In the west of Sumatra, near the equator, negative precipitation bias was present during autumn. Positive bias of precipitation in WIO and negative bias of precipitation in the west of Sumatra exhibited positive IOD-like pattern of precipitation, which was mentioned earlier as common bias in
CMIP5 models. Precipitation bias in SEIO (box 3) was well simulated, except in spring (March to May, called MAM), where positive precipitation bias appeared. Horizontal distribution of evaporation minus precipitation rate (E-P) as proxy of freshwater flux (figure 5e-h) displayed similar pattern as precipitation bias. Positive bias indicated that evaporation exceeded precipitation and vice versa.

![Figure 4. Horizontal distribution of seasonal sea surface salinity bias for a) MAM, b) JJA, c) SON and d) DJF. The boxes denote area of study as defined in figure 2. The dots show that the bias is represented by 75% of models.](image)

3.4. Fixed-depth salt budget analysis
In order to examine the possible cause of bias, we used fixed depth salt budget equations. Time series of fixed-depth salt budget calculation in WIO is shown in figure 6. Salt tendency and advection terms were well simulated by CMIP5 models. CMIP5 models simulated more positive contribution from residual terms, representing diffusion and mixing process. Freshwater flux during summer to winter (red solid line) was more negative than the observation, which was consistent with positive precipitation bias shown in figure 5. Apparently, unrealistic high precipitation was the main cause for negative sss bias in WIO. We obtained similar pattern of horizontal bias distribution between precipitation and sss bias in WIO by comparing figure 4 and 5.

In BOB, CMIP5 models reasonably simulated seasonal variations of all budget terms. CMIP5 simulated more positive freshwater flux and vertical advection during summer and winter respectively. The former one was mainly caused by negative precipitation bias during summer-autumn season. Unfortunately, river discharge was not available in all CMIP5 models outputs. Nevertheless, negative bias of precipitation in India continent (figure 3) may leads to decrease of water discharge from the river to the Bay. As a result, less precipitation and water discharge from the river maintained high sss water in the Bay. Saline waters were then distributed to the entire of the Bay by advection process. Figure 8 shows scatterplot between sss bias in DJF and precipitation. Strong correlation (-0.75) indicated that sss bias in winter (DJF) was mainly influenced by simulated precipitation in JJA (summer). Models that underestimated (overestimated) precipitation in JJA tend to simulate positive (negative) sss bias in BOB.
Figure 5. Horizontal distribution for precipitation bias (a-d) and E-P bias (evaporation minus precipitation) bias (e-h). The boxes denote area of study as defined in figure 2.

Figure 6. Time series of fixed depth salt budget equation for the a) observation and b) CMIP5 models (solid line) in WIO. Black, red, green, blue and purple indicate salinity tendency, freshwater flux, horizontal advection, vertical advection, and residual terms respectively. The x and y axis denote time (months) and sss tendency (psu month\(^{-1}\)).

Figure 7. Same as figure 6 but for BOB
Figure 8. Scatterplot between sss bias (psu) in DJF (x-axis) and precipitation (mm month\(^{-1}\)) in JJA (y-axis).

Figure 9. Same as figure 6 but for SEIO

Figure 10. Horizontal map of seasonal distribution for eastward surface current bias (a-d) and horizontal advection bias (e-h). The boxes denote area of study as defined in figure 2.

Precipitation was not the only cause of negative sss bias since evaporation exceeded precipitation in SEIO as displayed in figure 5. This was shown by salt budget analysis where CMIP5 models simulated more positive freshwater flux compared to the observation throughout the year (figure 9). Figure 5 shows that significant positive bias of precipitation only presents in spring (MAM), which partly contributed to sss bias in this season. Meanwhile, sss bias continued to exist in the rest of season although E-P and precipitation are well simulated by CMIP5 models. These suggested that ocean process was more responsible to cause the bias than precipitation/freshwater flux.
Figure 4 shows that negative sss bias are present in south of Java coast, which is still probably related to positive bias of precipitation in maritime continent. However, the negative sss bias extended further to the SEIO (box 3). Seasonal variation of salt budget terms were well simulated, however horizontal salt advection in CMIP5 models was more negative than the observation during spring to winter (figure 9). Too strong eastward current in SEIO possibly induced this bias during summer-autumn (figure 10b-c). Consequently, negative advection bias (figure 8) distributed low sss from the south of Java coast further to the west (box 3, SEIO).

4. Conclusion
This study examined the sss biases over Indian Ocean in the CMIP5 models. It was evident that CMIP5 models underestimated sss in WIO and SEIO and overestimated sss in BOB. Precipitation bias was found as the primary cause for sss bias in WIO and BOB, while horizontal advection and precipitation were responsible for negative sss bias in SEIO. Salt budget analysis indicated that CMIP5 overestimated precipitation shown by negative bias of freshwater flux in the WIO. Negative bias of precipitation/freshwater flux in BOB during summer monsoon was responsible for positive sss bias during winter. In SEIO, CMIP5 simulated strong eastward current bias in SEIO, transporting low salinity water during summer-autumn which caused negative sss bias.

Our analysis revealed the cause of common bias in CMIP5 on sss in Indian Ocean was closely related to systematic bias in CMIP5 models. Precipitation bias in BOB was indirectly caused by weak southwesterly summer monsoon wind in CMIP5 models, which considerably decreased moisture transport towards Indian continent. Bias of sss in WIO was attributed to unrealistic simulation of precipitation that very related to positive IOD-like bias where positive precipitation bias developed during autumn. Meanwhile, strong eastward current bias in SEIO was induced by strong easterly wind considered as systematic bias in CMIP5 that emerged in summer to autumn near the equator. Bias in SEIO was related to systematic bias where most of models tend to simulate too strong easterly wind near equator.

This study illustrated that most of CMIP5 models fail to simulate the seasonal variations of sss over the tropical Indian Ocean, which has not been fully examined in previous studies. [34] showed that better freshwater forcing and model physics in state-of-the-art GCMs might reduce the sss bias. Better ocean model and the use of high resolution might contribute to improve ocean dynamic biases in climate models. It was documented that the CMIP5 models showed a future IOD-like climate change [35]. Investigation of the process causing the future SSS changes over the Indian Ocean will be performed in future work.

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