

El Niño Southern Oscillation evolution modulated by Atlantic forcing

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Key Points:

- Model runs show that equatorial Atlantic warming (cooling) triggers subsequent tropical Pacific cooling (warming) 7 months later.
- Pacific wind-SST feedbacks are robust on ENSO timescales, but model sensitivity is large in Pacific wind response to Atlantic forcing.
- El Niño Southern Oscillation predictability is modulated by the Atlantic mean state bias and systematic errors in inter-basin interactions.

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Abstract

The El Niño Southern Oscillation (ENSO) exerts a strong influence on tropical Atlantic variability, but it is also affected by Atlantic forcing. Previous research has proposed three Atlantic precursors for ENSO: the North tropical Atlantic, the equatorial Atlantic, and the entire tropical Atlantic. However, the relative importance of these Atlantic precursors for ENSO remains unclear. Here, we present evidence from a set of multi-model partial ocean assimilation experiments that equatorial Atlantic cooling is the main contributor for weakening equatorial zonal winds in the Indo-Pacific sector and subsequent ocean warming in the tropical Pacific. Opposite tendencies occur for a warmer equatorial Atlantic. The equatorial Atlantic affects the inter-basin climate seesaw between the Atlantic and Pacific through an atmospheric zonal wavenumber 1 pattern. However, model mean-state biases and systematic errors prevent a precise assessment of the response times for the equatorial Pacific trade winds to Atlantic forcing.

Plain Language Summary

El Niño—an unusual surface warming of the tropical Pacific—may be more predictable than previously thought if the prediction of Atlantic climate and its remote impact on the Indo-Pacific region can be improved. In this study, we found that sea surface cooling in the equatorial Atlantic weakens western Pacific trade winds and triggers subsequent tropical Pacific warming through a positive feedback of atmosphere-ocean interactions. This process increases the chance of an El Niño event 7 months later. By assimilating observed ocean data in this simulation, we found that El Niño predictive skill relies not only on the tropical Pacific climate state but also on the Atlantic mean state and its remote impact on the tropical Pacific. Our result suggests that improving model performance in the Atlantic ocean and its remote impacts are crucial for enhancing El Niño predictions.

1 Introduction

Tropical Pacific climate variability has profound impacts not only on the Pacific region but also on global climate, including the Atlantic Ocean. A well-known example is the remote influence of the El Niño Southern Oscillation (ENSO) on Atlantic sea surface temperature (SST) variability, particularly in tropics north of the equator (Timmermann et al., 2018; S. P. Xie & Carton, 2004). The opposite pathway also exists, that is, the

47 Atlantic can affect tropical Pacific climate variability (e.g., Cai et al., 2019, and refer-
48 ences therein). Consistent with this pathway, the tropical Pacific SST predictability is
49 enhanced when precursor signals in the tropical Atlantic Ocean are taken into account
50 in statistical ENSO prediction models (Frauen & Dommenges, 2012; Dayan et al., 2014;
51 Martín-Rey et al., 2015) as well as in a dynamical model (Keenlyside et al., 2013). How-
52 ever, the two-way interaction between the tropical Pacific and the Atlantic makes it chal-
53 lenging to identify the dynamics and mechanisms involved in the Atlantic precursor of
54 ENSO predictability. According to ENSO recharge theory (Jin, 1997), the evolution, ter-
55 mination, and flavors of ENSO events are attributed to upper ocean heat content and
56 trade wind anomalies in the tropical Pacific (Timmermann et al., 2018; Meinen & McPhaden,
57 2000). Whereas heat content variability is controlled by ocean dynamics within the trop-
58 ical Pacific (C. Wang & Picaut, 2004), trade wind variability can be modulated by lo-
59 cal stochastic processes (Timmermann et al., 2018) as well as the remote forcing from
60 the Atlantic (Cai et al., 2019, and references below), the Indian Ocean (S. Xie et al., 2009;
61 Izumo et al., 2010, 2014; Dong & McPhaden, 2018), and the subtropical western North
62 Pacific (S.-Y. Wang et al., 2013; Fosu et al., 2020).

63 To better understand precursors to the remote forcing of ENSO, this study focuses
64 on the Atlantic impact on the trade wind variability and subsequent ENSO evolution.
65 Three precursors of SST variability have been proposed for the tropical Atlantic impact
66 on ENSO: the equatorial cold-tongue (i.e., the Atlantic Niño; Rodríguez-Fonseca et al.,
67 2009; Ding et al., 2012; Keenlyside et al., 2013; Martín-Rey et al., 2014; Polo et al., 2015),
68 the North tropical Atlantic (Ham, Kug, Park, & Jin, 2013; Ham, Kug, & Park, 2013; L. Wang
69 et al., 2017), and the entire tropical Atlantic (Kucharski et al., 2011, 2016; McGregor
70 et al., 2014; Chikamoto et al., 2015; Li et al., 2015; Ruprich-Robert et al., 2017). On seasonal-
71 to-interannual timescales, the most prominent precursor is the Atlantic cold-tongue, in
72 which an Atlantic Niño during the boreal summer can trigger a Pacific La Niña event
73 in the subsequent winter through modulation of the global Walker circulation (Rodríguez-
74 Fonseca et al., 2009; Keenlyside et al., 2013). This relationship is also found in the op-
75 posite phase (i.e., the Atlantic Niña and the Pacific El Niño). Another precursor is also
76 proposed on seasonal-to-interannual timescales: SST anomalies in the Northern trop-
77 ical Atlantic during the boreal spring can affect ENSO events in the following winter through
78 changes in the North Pacific subtropical high (Ham, Kug, Park, & Jin, 2013; Ham, Kug,
79 & Park, 2013; L. Wang et al., 2017). On decadal-to-multidecadal timescales, by contrast,

80 SST warming in the entire tropical Atlantic could be an important driver for a La Niña-
81 like climate response in the tropical Pacific, which corresponds to more frequent and pro-
82 longed La Niña events for all seasons through the reorganization of the global Walker
83 circulation and subsequent atmosphere-ocean interactions (Kucharski et al., 2011, 2016;
84 McGregor et al., 2014; Chikamoto et al., 2015; Li et al., 2015; Ruprich-Robert et al., 2017).
85 These studies prompt the question about which part of the tropical Atlantic is more im-
86 portant for inter-basin climate interactions on decadal timescales: the North tropical At-
87 lantic associated with the Atlantic Multidecadal Oscillation (Kucharski et al., 2016; Levine
88 et al., 2017; Ruprich-Robert et al., 2017), the equatorial Atlantic (McGregor et al., 2014),
89 or the South tropical Atlantic (Chikamoto et al., 2016; Barichivich et al., 2018). Such
90 differences in perspective may result from seasonal dependencies and model sensitivities
91 in the Atlantic impacts on ENSO. Even without seasonal dependence, a question still
92 remains as to which part of the Atlantic Ocean is most important for modulating the
93 interannual ENSO evolution.

94 To evaluate Atlantic impacts on the tropical Pacific climate variability, several model
95 experiments have been proposed. One of the common approaches is the Atmospheric Model
96 Intercomparison Project (AMIP)-type experiment, in which an atmospheric general cir-
97 culation model is forced by observed SST variability using a slab ocean model (e.g., Mc-
98 Gregor et al., 2014). AMIP-type experiments can evaluate the direct atmospheric response
99 to Atlantic SST forcing, but they do not capture the time evolution of dynamical atmosphere-
100 ocean responses due to the lack of an ocean dynamical model. To retain dynamical atmosphere-
101 ocean interactions in response to ocean remote forcing, some studies conducted the At-
102 lantic forcing experiments using an intermediate complexity atmospheric model (so-called
103 SPEEDY) coupled with a 1.5 layer reduced gravity ocean model (Rodríguez-Fonseca et
104 al., 2009) or ocean general circulation model (Kucharski et al., 2016). However, those
105 experiments required flux adjustment to avoid artificial "model drift" during the sim-
106 ulations, which can obscure the identification of crucial mechanisms. This issue moti-
107 vates advanced model experiments using a fully coupled dynamical model, such as pace-
108 maker experiments by nudging the model to the observed SST (Ding et al., 2012; Keenly-
109 side et al., 2013; Kosaka & Xie, 2013; Li et al., 2015) or partial assimilation experiments
110 as described below.

111 To identify the most prominent Atlantic precursor for modulating the interannual
112 ENSO evolution without seasonal dependence (i.e., focusing on a 12-month mean instead

113 of a seasonal mean), this study applies a partial ocean assimilation approach based on
114 three sets of experiments. In these partial assimilation experiments, observed 3-dimensional
115 ocean temperature and salinity fields for the targeted region are assimilated into the ocean
116 component of the global climate models. By assimilating the observed fields only in the
117 Atlantic Ocean as described in Section 2, we can estimate the Atlantic contribution to
118 tropical Pacific climate variability. Using these experiments, Section 3 illustrates the pro-
119 cess by which Atlantic Ocean variability affects the evolution of ENSO as well as the sen-
120 sitivity in those processes. Results are discussed in Section 4 and summarized in Sec-
121 tion 5.

122 **2 Model setup and Data**

123 **2.1 Model experiments**

124 Main configurations of the partial ocean assimilation experiments are based upon
125 the decadal climate prediction systems developed from two global climate models: MIROC3.2
126 (Nozawa et al., 2007) and CESM1.0 (Shields et al., 2012). Both models consist of fully
127 coupled general circulation models of atmosphere, land, ocean, and sea-ice components.
128 MIROC3.2 has a T42 spectral grid for atmosphere and land components whereas ocean
129 and sea-ice components consist of a latitude-longitude coordinate with an approximately
130 $0.56\text{-}1.4^\circ$ horizontal grid. The CESM1.0 has lower resolution than the MIROC3.2: a T31
131 spectral grid for atmosphere and land components and a curvature grid with a displaced
132 North Pole for ocean and sea-ice components (approximately 1° latitude and 3° longi-
133 tude grid near the equator). Those decadal climate prediction systems consist of three
134 basic model experiments (Table 1a): 20^{th} century historical simulations, global ocean
135 assimilation runs, and hindcast runs. In the 20^{th} century historical simulations, we pre-
136 scribed the natural and anthropogenic radiative forcings (e.g., greenhouse gas and aerosol
137 concentrations, solar cycle variations and major volcanic eruptions) for 1850–2005. Af-
138 ter 2005, we prescribed the A1B-type emission scenario for MIROC and the RCP4.5 sce-
139 nario for CESM. These experiments consist of 10 ensemble members conducted with ini-
140 tial conditions obtained from 10 random years of the pre-industrial control simulations.
141 In the global ocean assimilation runs, we use the same model configuration with the his-
142 torical simulations but assimilate the observed 3-dimensional ocean temperature and salin-
143 ity anomalies into the ocean component of global climate models. In the assimilation pro-
144 cess, the monthly observations were linearly interpolated to daily fields. Analysis incre-

145 ments are estimated from a temporally, spatially, and vertically invariant model-to-observation
146 ratio in analysis errors and added as forcing into the model’s temperature and salinity
147 tendency equations during an analysis interval of one day (Mochizuki et al., 2010; Tatebe
148 et al., 2012) using an Incremental Analysis Update scheme (Bloom et al., 1996; Huang
149 et al., 2002). Observations were derived from the objective analysis compiled by the Japan
150 Meteorological Agency (referred to as ProjD; Ishii & Kimoto, 2009) for 1945–2010 in MIROC,
151 and from the ECMWF ocean reanalysis product version 4 (Balmaseda et al., 2013) for
152 1958–2014 in CESM. The initial 5 and 2 years of model integrations were excluded in
153 MIROC and CESM, respectively, as the model spin-up period. Climatological fields are
154 calculated based on each observation and model historical simulations for a reference pe-
155 riod of 1971–2000. Whereas 3-dimensional oceanic anomalies are derived from the cli-
156 matological fields in MIROC (Mochizuki et al., 2010), the model biases of historical sim-
157 ulations are further adjusted in CESM (Chikamoto et al., 2019). More detailed descrip-
158 tions and the performance of these decadal climate prediction systems are found in pre-
159 vious studies for the MIROC (Mochizuki et al., 2010; Chikamoto et al., 2012; Mochizuki
160 et al., 2012; Tatebe et al., 2012; Chikamoto et al., 2013) and the CESM (Chikamoto et
161 al., 2017, 2019).

162 Using the same configurations of global ocean assimilation runs in MIROC3.2 and
163 CESM1.0, we conducted three sets of Atlantic Ocean partial assimilation runs. The three
164 experiments are summarized in Table 1b, namely the MIROC ATL anomaly, CESM ATL
165 anomaly, and CESM ATL full runs. In all of these ATL runs, observed 3-dimensional
166 fields of ocean temperature and salinity in the Atlantic Ocean were assimilated into the
167 ocean components of MIROC and CESM, in the same way as the global ocean assim-
168 ilation runs but targeted on the Atlantic Ocean only (50°S–60°N for MIROC and 30°–
169 70°N for CESM). The main advantage in our partial assimilation approach is that, by
170 assimilating 3-dimensional ocean fields, the models are able to simulate ocean variabil-
171 ity in the mixed layer and thermocline more appropriately compared to SST-only assim-
172 ilation runs and pacemaker experiments (Chikamoto et al., 2019; Ding et al., 2012). Whereas
173 the MIROC and CESM ATL ”anomaly” runs assimilate observed ”anomalies” with main-
174 taining model climatological fields, the CESM ATL ”full” run incorporates full-field ob-
175 servations (i.e., observed anomaly plus observed climatology) instead of the anomaly field
176 only. As a result, the CESM ATL full runs have the smallest biases of climatological ocean
177 fields in the assimilated Atlantic region, whereas MIROC and CESM ATL anomaly runs

178 still exhibit model mean state biases but suppress artificial shock for model states dur-
179 ing assimilation (left panels in Fig. 1). It is interesting to note that, even though the cli-
180 matological SST biases in the Atlantic are almost negligible in the CESM ATL full run,
181 we can still find SST and SLP biases in the tropical Pacific (Fig. 1e and f). The SST and
182 SLP biases show different patterns among three Atlantic partial assimilation experiments
183 (Fig. 1) since our multi-model approach tends to cover a diverse set of Atlantic forcing
184 experiments. Therefore, our model experiments provide a perspective on model sensi-
185 tivity, involving model systematic errors (MIROC ATL anomaly vs CESM ATL anomaly
186 runs) and climatological mean state biases (CESM ATL anomaly vs full runs).

187 It is worth noting the difference between "pacemaker experiments" and partial as-
188 similation experiments being conducted here. Both use fully coupled atmosphere-ocean
189 general circulation models without any flux adjustment. In pacemaker experiments, a
190 fully coupled atmosphere-ocean model is forced by the observed SST field for a targeted
191 region but is allowed to evolve freely outside the targeted region. Using the pacemaker
192 experiment targeted for eastern tropical Pacific SST, for example, Kosaka and Xie (2013)
193 demonstrated that the recent global warming hiatus could be mainly attributed to east-
194 ern tropical Pacific SST variability. Ding et al. (2012) also illustrated the Atlantic Niño
195 impact on the amplitude of ENSO events based on pacemaker experiments by prescrib-
196 ing the observed SST field in the tropical Atlantic. However, a recent study in the Cou-
197 pled Model Intercomparison Project Phase 6 (CMIP6) Decadal Climate Prediction Project-
198 Component C coordination pointed out that the Atlantic SST forcing in pacemaker ex-
199 periments may introduce energy and seawater density imbalances due to a lack of salin-
200 ity information, which causes an artificial change in the air-sea interaction and alters the
201 coupled model equilibrium (Boer et al., 2016). In the equatorial Pacific, SST is the main
202 driver for mixed layer dynamics through strong atmosphere-ocean interaction, which can
203 constrain tropical Pacific climate variability. In the Atlantic and extra-tropics, however,
204 subsurface ocean temperature and salinity also play an important role in ocean dynam-
205 ics. Hence, SST-only assimilation is not sufficient to constrain the ocean density struc-
206 ture due to higher-frequency fluctuations. As a result, SST-only assimilation or pace-
207 maker approaches may fail to properly simulate the observed SST variability (Chikamoto
208 et al., 2019). To avoid this situation, pacemaker experiments "strongly" nudge models
209 toward the observed SST (a typical restoring timescale is order 1–10 days for a 50 m mixed
210 layer depth). Such observed SST is usually monthly mean values so that strong nudg-

211 ing damps higher-frequency atmosphere-ocean interaction at sub-monthly timescales. Be-
 212 cause higher-frequency atmosphere-ocean interactions are important for the model to ad-
 213 just toward quasi-equilibrium climate states, the strong SST constraint in pacemaker ex-
 214 periments may cause artificial model drift and energy imbalances. In addition to this en-
 215 ergy imbalance during the nudging process, most global climate models suffer from a cli-
 216 matological SST bias with a colder northern tropical Atlantic and a warmer southeast-
 217 ern tropical Atlantic (Richter, 2015), which distorts the Atlantic impact on tropical Pa-
 218 cific climate variability (Sasaki et al., 2014; McGregor et al., 2018; Kajtar et al., 2018;
 219 Luo et al., 2018). The partial ocean assimilation approach can minimize the artificial in-
 220 fluence of model drift and energy imbalances on inter-basin climate interactions. In this
 221 approach, the observed SST variability is "weakly" assimilated into the models in order
 222 to allow models to adjust the model-simulated quasi-equilibrium condition (a typical restor-
 223 ing timescale is much larger than 10-days). By assimilating subsurface ocean temper-
 224 ature and salinity, the model better simulates lower-frequency ocean dynamics, which
 225 can provide more realistic simulation of observed SST variability compared to SST-only
 226 assimilation (Chikamoto et al., 2019). As a result, partial assimilation experiments, com-
 227 pared to pacemaker experiments, have the advantage of minimizing artificial model drift
 228 in response to prescribed ocean forcing.

229 **2.2 Data sources**

230 We use several gridded observations to minimize observational uncertainty. Observed
 231 sea level pressure (SLP) and zonal winds at 250 (U250) and 850 hPa (U850) are obtained
 232 from NCEP-NCAR (Kalnay et al., 1996) and JRA55 atmospheric reanalyses (Kobayashi
 233 et al., 2015). SST datasets include ERSST version 4 (Huang et al., 2015) and an objec-
 234 tive ocean analysis compiled by the Japan Meteorological Agency (i.e., ProjD; Ishii &
 235 Kimoto, 2009). Anomalies are defined as deviations from the climatological mean for the
 236 50-year period 1960–2009 in each of the model experiments and observations. All anoma-
 237 lies are detrended using a least-squares quadratic trend and are re-gridded into a $2.5^\circ \times$
 238 2.5° latitude-longitude grid. A 12-month running mean filter is applied to all anomalies
 239 to minimize the effect of seasonality. The multi-model ensembles are obtained by aver-
 240 aging the three Atlantic partial assimilation runs after taking the ensemble mean of 10
 241 members for each model experiment during the 1960–2009 period, whereas observational
 242 estimates are based on the average of the two reanalysis products during the same pe-

243 riod as the model. To focus on interannual ENSO variability forced by the Atlantic, the
244 Niño 3.4 index is smoothed by applying a 12-month running average to monthly SST
245 anomalies over the Niño 3.4 region (5°S – 5°N , 120°W – 170°W) in observations and ATL
246 runs individually. Whereas the observed Niño 3.4 index shows a prominent seasonality
247 with a peak during boreal winter, such seasonality for the model simulated Niño 3.4 in-
248 dex is much reduced in the ATL runs even at monthly resolution (Fig. 2a). This result
249 suggests that the Atlantic impact on ENSO can occur in any season even though the At-
250 lantic Niño is prominent during the boreal summer (Fig. 2b).

251 **3 Results: Tropical Pacific climate response to Atlantic forcing**

252 To depict the temporal evolution of ENSO, we first produced the lead-lag corre-
253 lation maps of SST and SLP anomalies associated with the Niño 3.4 index (5°S – 5°N ,
254 120°W – 170°W) in the observation-based data and multi-model ensembles of the three
255 ATL runs (Fig. 3). Observational analysis demonstrates the zonal gradients of SST and
256 SLP anomalies between the western and eastern tropical Pacific during the decaying stage
257 of La Niña events at -18 month lag (Fig. 3a) and then an opposite phase of those gra-
258 dients during the mature stage of El Niño events at 0-month lag (Fig. 3g), confirming
259 previous findings (Timmermann et al., 2018; Meinen & McPhaden, 2000; Jin, 1997). In
260 the tropical Atlantic, unusually cold SST appears around the equator during the devel-
261 oping phase of El Niño at -12 and -6 months lag (Fig. 3c and e) and then decays dur-
262 ing the mature phase of El Niño at 0-month lag (Fig. 3g). This lead-lag relationship be-
263 tween ENSO and equatorial Atlantic SST anomalies accompanies the SLP contrast be-
264 tween the Atlantic and the eastern Pacific, reflecting the reorganization of the global Walker
265 circulation as reported previously (Rodríguez-Fonseca et al., 2009; Ham, Kug, Park, &
266 Jin, 2013; Ham, Kug, & Park, 2013; Cai et al., 2019). In the statistical analysis of ob-
267 servations, however, the causality remains unclear as to whether colder SST in the equa-
268 torial Atlantic is affecting ENSO evolution (Rodríguez-Fonseca et al., 2009; Ding et al.,
269 2012; Keenlyside et al., 2013; Martín-Rey et al., 2014; Polo et al., 2015) or if it is sim-
270 ply a response to the remote impact of ENSO (Enfield & Mayer, 1997; Latif & Grötzner,
271 2000; Handoh et al., 2006; Lübbecke & McPhaden, 2012; Tokinaga et al., 2019).

3.1 Processes

Through the Atlantic Ocean assimilation experiments, the Atlantic impact on ENSO can be revealed more clearly (right panels in Fig. 3). ATL runs constrain only Atlantic Ocean variability and the 10-member ensemble mean in each ATL run filters out the internally generated ENSO variability within the Pacific Ocean, so we can assume that any simulated ENSO variability in the ATL run originates from the Atlantic Ocean forcing. In other words, the ATL run emphasizes the one-way impact from the Atlantic to the Pacific since the observations assimilated into the ATL run may include two-way interactions between these basins. At -18 month lag, the multi-model ensemble of ATL runs shows the initiation of colder SST and higher SLP anomalies in the north tropical Atlantic (Fig. 3b). These Atlantic SST and SLP anomalies in the equatorial band reach maturity from -12 to -6 months lag, coinciding with the developing stage of El Niño (Fig. 3d and f). While the Atlantic SST anomaly develops, a zonal SLP gradient emerges in the equatorial Indo-Pacific region at -12 months lag and then strengthens afterward. This zonal SLP gradient arguably causes anomalous westerly winds in the Indo-Pacific region (i.e., weakened Pacific trade winds). This process is known to trigger equatorial Pacific SST warming through the Bjerknes feedback, leading to the mature stage of El Niño (Rodríguez-Fonseca et al., 2009; Polo et al., 2015). Once the Bjerknes feedback is activated, ENSO can develop through internal tropical Pacific dynamics without much input from the Atlantic (Fig. 3h and j). Regression maps associated with the Niño 3.4 index also show consistent results (Fig. S1).

The multi-model ATL run reveals the most prominent precursor for ENSO from equatorial Atlantic SST with -12 to -6 months lag, which supports previous findings about the influence from the boreal summer Atlantic Niño to the following winter ENSO amplitude (Rodríguez-Fonseca et al., 2009; Ding et al., 2012; Keenlyside et al., 2013; Martín-Rey et al., 2014; Polo et al., 2015). In addition, we also find significant negative correlations of SST anomalies in the Northern tropical Atlantic at -18 and -12 months lag, albeit weaker (Ham, Kug, Park, & Jin, 2013; Ham, Kug, & Park, 2013; L. Wang et al., 2017). These Atlantic SST patterns from -18 to -6 months lag are not identical to the temporal evolution of typical Atlantic Niño that has larger SST anomalies in the southeastern tropical Atlantic (S. P. Xie & Carton, 2004; Rodríguez-Fonseca et al., 2009). In any case, we find that equatorial Atlantic SST variability serves as one of the main drivers for ENSO evolution in our experiments.

305 To facilitate the description of the tropical Pacific response to Atlantic forcing, we
 306 produce Hovmöller diagrams (Figs. 4 and 5) for the lead-lag correlations of SST, SLP,
 307 U850 and U250 anomalies at the equator with the Niño 3.4 index. In the multi-model
 308 ensemble of ATL runs, a local peak of Atlantic SST cooling ($60^{\circ}\text{W}-0^{\circ}$) appears around
 309 7 months before the mature stage of El Niño (at -7 months lag in Fig. 4b), which is com-
 310 parable to the lead-lag relationship between the boreal summer Atlantic Niña and the
 311 boreal winter Pacific El Niño (Rodríguez-Fonseca et al., 2009; Ding et al., 2012; Keenly-
 312 side et al., 2013; Martín-Rey et al., 2014; Polo et al., 2015). This equatorial Atlantic SST
 313 cooling apparently induces positive SLP anomalies over the Atlantic and their subsequent
 314 eastward propagation over the Indian Ocean (S.-Y. S. Wang et al., 2015). Concurrently
 315 with these SLP responses in the Atlantic and Indian Oceans, we also find a delayed re-
 316 sponse of negative SLP anomalies in the central and eastern equatorial Pacific. These
 317 tropical SLP responses consist of an atmospheric wave-number 1 pattern between the
 318 Atlantic-Indian and the Pacific Oceans, resulting in a reorganization of the global Walker
 319 circulation in the process. Similar SST and SLP anomalies are found in individual ATL
 320 runs, despite a difference in timing of Atlantic SST precursors (Fig. 4c-e). Consistent
 321 with the zonal SLP anomaly gradients, anomalous winds in the lower troposphere show
 322 westerlies over the Indian and western Pacific Oceans ($60^{\circ}\text{E}-150^{\circ}\text{W}$) and easterlies over
 323 the eastern Pacific and Atlantic Oceans ($150^{\circ}\text{W}-0^{\circ}$; shading in Fig. 5d). Similar but op-
 324 posite patterns are found in the upper tropospheric zonal winds (Fig. 5b). Specifically,
 325 anomalous westerly winds at 850 hPa correspond to weakened trade winds in the west-
 326 ern equatorial Pacific. The similar changes in the multi-model ATL runs are found in
 327 the observations (Fig. 4a), albeit with a delay in the timing of Atlantic SST cooling, an
 328 earlier peak of Atlantic SLP anomalies, and a longer duration of SST and SLP anom-
 329 lies in the tropical Pacific.

3.2 Timing of evolution

330
 331 To examine the time it takes for ENSO to respond to the Atlantic forcing, we con-
 332 struct additional lead-lag correlations of equatorial Atlantic SST anomalies ($5^{\circ}\text{S}-5^{\circ}\text{N}$,
 333 $50^{\circ}\text{W}-0^{\circ}$) and zonal wind anomalies at 850 hPa in the Indo-Pacific region (averaged in
 334 $5^{\circ}\text{S}-5^{\circ}\text{N}$, $90^{\circ}\text{E}-150^{\circ}\text{E}$) by correlating them with the Niño 3.4 index (Fig. 6). We should
 335 note that the multi-model ATL runs exhibit weaker correlations at negative lags (with
 336 Niño 3.4 leading) compared to those in observations (black lines in Fig. 6b and c). This

337 weaker correlation of the ATL runs suggests that the multi-model ATL runs emphasize
 338 the Atlantic's impact on the response of the zonal winds, whereas this process is obscured
 339 in observational analyses because of the two-way inter-basin interaction. The results of
 340 the multi-model ATL runs demonstrate that Atlantic SST anomalies negatively corre-
 341 late with zonal wind anomalies at 850 hPa over the equatorial Indo-Pacific region with
 342 a local peak at 0-month lag (red line in Fig. 6a). However, there is a time lag of 7 months
 343 in the maximum correlation coefficient between zonal wind anomalies and the Niño 3.4
 344 index (Fig. 6b). In other words, the multi-model ATL runs indicate that the equatorial
 345 Atlantic SST cooling induces weakened trade winds in the equatorial western Pacific al-
 346 most simultaneously as seen in the wave number 1 pattern of SLP anomalies (Fig. 4).
 347 Subsequently, the trade wind changes lead to the delayed response of equatorial Pacific
 348 SST warming by the activation of the Bjerknes feedback. This argument works for the
 349 opposite phases associated with Atlantic SST warming. Consistent with these lead-lag
 350 relationships, the correlation of equatorial Atlantic SST anomalies with the Niño 3.4 in-
 351 dex shows a local peak at 7 months lag (Fig. 6c). Similar results are also obtained when
 352 we apply a 3-month running mean filter (Fig. S2).

353 For verification purposes, we perform additional composite analysis based on equa-
 354 torial Atlantic SST anomalies. Using the multi-model ensemble of the ATL runs (Fig.
 355 7), we extract from the equatorial Atlantic the 7 warmest (Aug 1963, Nov 1968, May 1973,
 356 Jul 1984, Feb 1988, Mar 1996 and May 1998) and 7 coldest SST anomalies (Feb 1965,
 357 Oct 1967, Dec 1971, Aug 1976, Jan 1983, Sep 1992, Apr 1997), regardless of the concu-
 358 rrent ENSO phases. These extracted warmest and coldest years in the ATL runs are iden-
 359 tical to the observed warmest and coldest years of the equatorial Atlantic SST anoma-
 360 lies because the ATL runs incorporate the observed information for that region. When
 361 we create a histogram of anomalous zonal winds in the Indo-Pacific region based on in-
 362 dividual ensemble members, we find a shift in the distribution towards the easterly wind
 363 anomalies in the Indo-Pacific region associated with warmer Atlantic SSTs and the west-
 364 erly anomalies with colder Atlantic SSTs (Fig. 8a). Consistent results are also found in
 365 the western Pacific trade winds (Fig. 8b). Since these changes in the trade winds con-
 366 tribute to the evolution of SST anomalies in the equatorial Pacific, one can infer that
 367 unusually warm Atlantic SSTs enhance the probability of a La Niña event at +7 months
 368 lag (Fig. 8c). This result suggests that equatorial Atlantic SST variability can act as an
 369 external forcing for ENSO dynamics by affecting the ENSO probability at least 7 months

370 before the peak phase of the Atlantic forced ENSO event through a modulation of the
 371 Pacific trade winds. Of course, ocean dynamics within the tropical Pacific is still the main
 372 driver for the development of ENSO even in the presence of external forcing (Jin, 1997;
 373 Timmermann et al., 2018).

374 **3.3 Model sensitivity**

375 We note the present model sensitivity regarding the response timescale of ENSO
 376 to the Atlantic forcing, recalling that equatorial Atlantic SST anomalies are negatively
 377 correlated with the Niño 3.4 index at a lag of +4 months in the CESM ATL anomaly
 378 run (blue solid), +5 months in CESM ATL full run (blue dashed), and +12 months in
 379 MIROC ATL anomaly run (green line in Fig. 6c), respectively. In contrast to this model
 380 sensitivity, the anomalous zonal winds positively correlate with the Niño 3.4 index around
 381 +7 months lag in all runs (blue and green lines in Fig. 6b), indicating a minimal discrep-
 382 ancy when it comes to simulating the Bjerknes feedback. However, a larger model sen-
 383 sitivity was found in the local peaks of correlation coefficients between Atlantic SST anoma-
 384 lies and anomalous zonal winds at -1 , 0 , and $+5$ months lags in the CESM ATL anomaly
 385 (blue solid), CESM ATL full (blue dashed), and MIROC ATL anomaly runs (green line
 386 in Fig. 6a), respectively. These time lags show a larger difference between MIROC and
 387 CESM runs, compared to the difference between CESM ATL anomaly and full runs. In
 388 other words, the Indo-Pacific zonal wind responses to the Atlantic forcing have a larger
 389 sensitivity between MIROC and CESM rather than between the CESM anomaly vs full-
 390 field assimilations.

391 In addition to the large sensitivity in the zonal wind response, we also find a large
 392 difference in Indian Ocean responses to the Atlantic forcing. Figure 9 shows the Hovmöller
 393 diagrams for the lead-lag correlations of U850 and U250 anomalies at the equator with
 394 the Niño 3.4 index. Whereas the MIROC ATL anomaly run demonstrates the signifi-
 395 cant phase changes in U850 anomalies from westerly to easterly over the Indian Ocean
 396 (60°E – 120°E), the signal is less clear in CESM ATL anomaly and full runs (bottom pan-
 397 els in Fig. 9). Associated with these lower-level wind responses, we can find an opposite
 398 sign of upper-tropospheric zonal wind responses aloft in MIROC ATL anomaly run but
 399 an obscured response in the CESM ATL anomaly and full runs (top panels in Fig. 9).
 400 These upper and lower zonal wind anomalies suggest that the Walker circulation response
 401 in Indian Ocean is stronger in the MIROC but weaker in the CESM. Consistent with

402 these wind anomalies, the Indian Ocean SST warming after the mature stage of El Niño
 403 is clear in MIROC ATL anomaly run but unclear in CESM ATL anomaly and full runs
 404 (bottom panels in Fig. 4). Because of this model sensitivity in the Indian Ocean response,
 405 the multi-model ensemble of ATL runs show weaker SST anomalies in the Indian Ocean
 406 compared to observations (Figs. 3 and 4a–b).

407 4 Discussion

408 Since our Atlantic partial assimilation runs assume "perfect knowledge" of Atlantic
 409 Ocean variability, an ENSO anomaly correlation coefficient (ACC) between observation
 410 and model simulation corresponds to the potential predictability of ENSO that is driven
 411 by Atlantic remote forcing. The potential predictability for Niño 4, Niño 3.4, and Niño
 412 3 indices based on the ATL runs (Table 2) is higher in the MIROC ATL anomaly and
 413 CESM ATL full runs (e.g., for Niño 3.4 index, ACC=0.24 and 0.22) than the CESM ATL
 414 anomaly run (ACC=0.06). As a result, we can find higher predictability for the anoma-
 415 lous zonal winds in the Indo-Pacific region: ACC=0.23, 0.46, and 0.18 in the MIROC
 416 ATL anomaly, CESM ATL full, and CESM ATL anomaly runs, respectively. Consistent
 417 with the potential predictability of ENSO, a correlation coefficient between the observed
 418 and the model simulated upper ocean heat content in the western equatorial Pacific is
 419 higher for the MIROC ATL anomaly (R=0.41) and the CESM ATL full runs (R=0.39)
 420 than for the CESM ATL anomaly run (R=0.30; left panels in Fig. S3), though the dif-
 421 ferences are not statistically significant at the 95% level of confidence. These results sug-
 422 gest that ENSO predictive skill relies not only on tropical Pacific climate states but also
 423 on how well models depict the tropical Atlantic SST and Indo-Pacific atmospheric re-
 424 sponses to the Atlantic forcing. Further analysis on monthly mean timescales may con-
 425 tribute to advancing our understanding of ENSO predictability, such as the "spring bar-
 426 rier" of ENSO skill reduction (McPhaden, 2003).

427 Using the statistical and dynamical approaches, previous studies aimed to improve
 428 the predictive skills in ENSO amplitude during the mature stage of ENSO events with
 429 an emphasis on the seasonal relationship between boreal summer Atlantic Niña and the
 430 subsequent winter Pacific El Niño (Frauen & Dommenges, 2012; Keenlyside et al., 2013;
 431 Dayan et al., 2014; Martín-Rey et al., 2015). The results of our multi-model approach
 432 are also consistent with this seasonally dependent relationship between the equatorial
 433 Atlantic and ENSO. By minimizing seasonality in our analysis, we have found that the

434 equatorial Atlantic can influence ENSO predictability not only during its mature stage
435 but also during its onset, decay, and developmental phases. However, there is a large spread
436 for the simulated timing of the Indo-Pacific wind response to the Atlantic forcing. The
437 sensitivity to Atlantic mean state bias therefore introduces an additional source of un-
438 certainty for Atlantic-forced ENSO predictability. Likewise, there is a discrepancy in po-
439 tential ENSO predictability between our ATL runs and the Atlantic pacemaker exper-
440 iments conducted by Ding et al. (2012): higher potential predictive skill in the tropical
441 Pacific SST anomalies is found in the west in our ATL run (Table 2 and Fig. S3) but in
442 the east in the pacemaker experiment (Fig 4 in their paper). This discrepancy provides
443 another perspective on the predictability that involves ENSO diversity (Capotondi et
444 al., 2015), which might be modulated by Atlantic mean state biases, model systematic
445 errors, and assimilation methods (Ding, Keenlyside, et al., 2015; Ding, Greatbatch, et
446 al., 2015; Dippe et al., 2019; Johnson et al., 2020). According to previous studies (Ham,
447 Kug, Park, & Jin, 2013; Ham, Kug, & Park, 2013), the boreal summer Atlantic Niño en-
448 hances occurrences in the eastern Pacific type of ENSO in the subsequent winter, whereas
449 the spring North Atlantic SST anomalies contribute to an increase in the central Pacific
450 type of ENSO events. To investigate these hypotheses regarding the Atlantic impact on
451 ENSO predictability, more research is necessary to engage in multi-model approaches
452 based on different types of climate models and Atlantic experimental design (e.g., pace-
453 maker and partial assimilation experiments), as well as idealized model experiments pre-
454 scribing the Atlantic climate modes such as the Atlantic Niño, the meridional mode, and
455 the Atlantic Multi-decadal Oscillation (Ruprich-Robert et al., 2017; Levine et al., 2018).

456 Previous studies have shown a large inter-model spread regarding the trade wind
457 response to Atlantic forcing on decadal and multi-decadal timescales (McGregor et al.,
458 2018; Kajtar et al., 2018; Luo et al., 2018). Our results show a similar model sensitiv-
459 ity on interannual timescales. Further evaluation is required with a larger number of mod-
460 els to understand the reasons for this model sensitivity. It should also be noted that our
461 results are limited to partial assimilation experiments using only two climate models with
462 anomaly/full field assimilations. Nevertheless, this study provides a blueprint for a multi-
463 model approach using additional climate models and various experimental designs (e.g.,
464 full vs anomaly assimilation, pacemaker experiments, or flux-adjustment method) in or-
465 der to identify the robust processes responsible and quantify the effects of model sen-
466 sitivity.

5 Conclusion

Using an Atlantic Ocean partial assimilation approach, we evaluated the ENSO response to Atlantic forcing on interannual timescales. Our results imply a two-step process on how Atlantic Ocean variability affects ENSO evolution. First, tropical Atlantic SST warming induces a tropical SLP response with an atmospheric zonal wave-number 1 pattern through the reorganization of the Walker circulation, particularly at the equator. This tropical SLP response is accompanied by the strengthened surface trade winds over the western Pacific, which, in turn, affect the probability of a La Niña development by activating the Bjerknes feedback in the tropical Pacific. Since this process takes 7 months from the peak of Atlantic SST forcing to an SST response in the equatorial Pacific, it is possible that ENSO predictability can be extended for a few seasons by utilizing the Atlantic precursor signal as demonstrated by statistical and dynamical predictions (Frauen & Dommenges, 2012; Keenlyside et al., 2013; Dayan et al., 2014; Martín-Rey et al., 2015). Many previous studies have focused on the seasonal relationship how the summer Atlantic Niño affects the following winter Pacific La Niña particularly after 1970 (Rodríguez-Fonseca et al., 2009; Ding et al., 2012; Martín-Rey et al., 2015). Our analysis moves one step further by demonstrating that the equatorial Atlantic impact on the tropical Pacific can be found in any season although the summer Atlantic Niño still elicits the largest contributions to ENSO.

Among our multi-model experiments, there is a different response time between the western Pacific trade wind and the remote forcing from the Atlantic. After the equatorial Atlantic SST anomalies have peaked, we find eastward propagation of SLP anomalies from the Atlantic to the western Pacific via the Indian Ocean (Fig. 4b). The propagation speed over the Indian Ocean is slowest in the MIROC ATL anomaly run and fastest in the CESM ATL anomaly run (Fig. 4c–e). These propagation speeds indicate a model dependency as evident in the different timing for local peaks of correlation coefficients between Atlantic SST anomalies and anomalous zonal winds (Fig. 6a). Consistent with these SLP responses, the MIROC ATL run demonstrates the significant Walker circulation changes over the Indian Ocean and the subsequent SST response, whereas these features are unclear in CESM ATL anomaly and full runs. The impact of Atlantic mean state bias on ENSO potential predictability has an important implication under global warming, since the Atlantic-Pacific connection may weaken in a warmer climate (Jia et al., 2019).

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References

- Balmaseda, M. A., Mogensen, K., & Weaver, A. T. (2013). Evaluation of the ECMWF ocean reanalysis system ORAS4. *Quarterly Journal of the Royal Meteorological Society*, *139*(674), 1132–1161.
- Barichivich, J., Gloor, E., Peylin, P., Brienen, R. J., Schöngart, J., Espinoza, J. C., & Pattayak, K. C. (2018). Recent intensification of Amazon flooding extremes driven by strengthened walker circulation. *Science advances*, *4*(9), eaat8785.
- Bloom, S. C., Takacs, L., da Silva, A. M., & Ledvina, D. (1996). Data assimilation using incremental analysis updates. *Mon. Wea. Rev.*, *124*, 1256-1271.

- 532 Boer, G. J., Smith, D. M., Cassou, C., Doblas-Reyes, F., Danabasoglu, G., Kirt-
 533 man, B., ... others (2016). The decadal climate prediction project (DCPP)
 534 contribution to CMIP6. *Geoscientific Model Development (Online)*, 9(10).
- 535 Cai, W., Wu, L., Lengaigne, M., Li, T., McGregor, S., Kug, J.-S., ... Chang, P.
 536 (2019). Pantropical climate interactions. *Science*, 363(6430). Retrieved
 537 from <http://science.sciencemag.org/content/363/6430/eaav4236> doi:
 538 10.1126/science.aav4236
- 539 Capotondi, A., Wittenberg, A. T., Newman, M., Di Lorenzo, E., Yu, J.-Y., Bracon-
 540 not, P., ... others (2015). Understanding ENSO diversity. *Bulletin of the*
 541 *American Meteorological Society*, 96(6), 921–938.
- 542 Chikamoto, Y., Kimoto, M., Ishii, M., Mochizuki, T., Sakamoto, T. T., Tatebe,
 543 H., ... others (2013). An overview of decadal climate predictability in a
 544 multi-model ensemble by climate model MIROC. *Climate Dynamics*, 40,
 545 1201–1222.
- 546 Chikamoto, Y., Kimoto, M., Ishii, M., Watanabe, M., Nozawa, T., Mochizuki, T.,
 547 ... Jin, F. (2012). Predictability of a stepwise shift in Pacific climate during
 548 the late 1990s in hindcast experiments using MIROC. *J. Meteorol. Soc. Japan*,
 549 90A, 1–21.
- 550 Chikamoto, Y., Mochizuki, T., Timmermann, A., Kimoto, M., & Watanabe, M.
 551 (2016). Potential tropical Atlantic impacts on Pacific decadal climate trends.
 552 *Geophysical Research Letters*, 43(13), 7143–7151.
- 553 Chikamoto, Y., Timmermann, A., Luo, J.-J., Mochizuki, T., Kimoto, M., Watanabe,
 554 M., ... Jin, F.-F. (2015). Skillful multi-year predictions of tropical trans-basin
 555 climate variability. *Nature Communications*, 6, 6869.
- 556 Chikamoto, Y., Timmermann, A., Widlansky, M. J., Balmaseda, M. A., & Stott, L.
 557 (2017). Multi-year predictability of climate, drought, and wildfire in southwest-
 558 ern North America. *Scientific Reports*, 7(1), 6568.
- 559 Chikamoto, Y., Timmermann, A., Widlansky, M. J., Zhang, S., & Balmaseda,
 560 M. A. (2019). A drift-free decadal climate prediction system for the com-
 561 munity earth syetem model. *Journal of Climate*, published online. doi:
 562 doi.org/10.1175/JCLI-D-18-0788.1
- 563 Dayan, H., Vialard, J., Izumo, T., & Lengaigne, M. (2014). Does sea surface temper-
 564 ature outside the tropical Pacific contribute to enhanced ENSO predictability?

- 565 *Climate dynamics*, *43*(5-6), 1311–1325.
- 566 Ding, H., Greatbatch, R. J., Latif, M., & Park, W. (2015). The impact of sea sur-
567 face temperature bias on equatorial Atlantic interannual variability in partially
568 coupled model experiments. *Geophysical Research Letters*, *42*(13), 5540–5546.
- 569 Ding, H., Keenlyside, N., Latif, M., Park, W., & Wahl, S. (2015). The impact of
570 mean state errors on equatorial Atlantic interannual variability in a climate
571 model. *Journal of Geophysical Research: Oceans*, *120*(2), 1133–1151.
- 572 Ding, H., Keenlyside, N. S., & Latif, M. (2012). Impact of the equatorial Atlantic on
573 the El Niño southern oscillation. *Climate dynamics*, *38*(9-10), 1965–1972.
- 574 Dippe, T., Greatbatch, R. J., & Ding, H. (2019). Seasonal prediction of equatorial
575 Atlantic sea surface temperature using simple initialization and bias correction
576 techniques. *Atmospheric Science Letters*, *20*(5), e898.
- 577 Dong, L., & McPhaden, M. J. (2018). Unusually warm Indian Ocean sea surface
578 temperatures help to arrest development of El Niño in 2014. *Scientific reports*,
579 *8*(1), 2249.
- 580 Enfield, D. B., & Mayer, D. A. (1997). Tropical Atlantic sea surface temperature
581 variability and its relation to El Niño-Southern Oscillation. *J. Geophys. Res.*,
582 *102*, 929-945.
- 583 Fosu, B., He, J., & Wang, S.-Y. S. (2020). The influence of wintertime SST variabil-
584 ity in the Western North Pacific on ENSO diversity. *Climate Dynamics*, 1–14.
- 585 Frauen, C., & Dommenges, D. (2012). Influences of the tropical Indian and Atlantic
586 Oceans on the predictability of ENSO. *Geophysical Research Letters*, *39*(2).
- 587 Ham, Y.-G., Kug, J.-S., & Park, J.-Y. (2013). Two distinct roles of Atlantic SSTs in
588 ENSO variability: North tropical Atlantic SST and Atlantic Niño. *Geophysical
589 Research Letters*, *40*(15), 4012–4017.
- 590 Ham, Y.-G., Kug, J.-S., Park, J.-Y., & Jin, F.-F. (2013). Sea surface temperature
591 in the north tropical Atlantic as a trigger for El Niño/Southern Oscillation
592 events. *Nature Geoscience*, *6*(2), 112.
- 593 Handoh, I. C., Matthews, A. J., Bigg, G. R., & Stevens, D. P. (2006). Interannual
594 variability of the tropical Atlantic independent of and associated with ENSO:
595 Part I. The North Tropical Atlantic. *International journal of climatology*,
596 *26*(14), 1937–1956.
- 597 Huang, B., Banzon, V. F., Freeman, E., Lawrimore, J., Liu, W., Peterson, T. C., ...

- 598 Zhang, H.-M. (2015). Extended reconstructed sea surface temperature version
599 4 (ERSST. v4). Part I: upgrades and intercomparisons. *Journal of Climate*,
600 28(3), 911–930.
- 601 Huang, B., Kinter, J., & Schopf, P. (2002). Ocean data assimilation using intermit-
602 tent analyses and continuous model error correction. *Adv. Atmos. Sci.*, 19(6),
603 965–992.
- 604 Ishii, M., & Kimoto, M. (2009). Reevaluation of historical ocean heat content vari-
605 ations with time-varying XBT and MBT depth bias corrections. *J. Oceanogr.*,
606 65(3), 287–299.
- 607 Izumo, T., Lengaigne, M., Vialard, J., Luo, J.-J., Yamagata, T., & Madec, G.
608 (2014). Influence of Indian Ocean Dipole and Pacific recharge on following
609 year’s El Niño: interdecadal robustness. *Climate dynamics*, 42(1-2), 291–310.
- 610 Izumo, T., Vialard, J., Lengaigne, M., de Boyer Montegut, C., Behera, S. K., Luo,
611 J.-J., . . . Yamagata, T. (2010). Influence of the state of the Indian Ocean
612 Dipole on the following year’s El Niño. *Nature Geoscience*, 3(3), 168.
- 613 Jia, F., Cai, W., Wu, L., Gan, B., Wang, G., Kucharski, F., . . . Keenlyside, N.
614 (2019). Weakening Atlantic Niño–Pacific connection under greenhouse warm-
615 ing. *Science advances*, 5(8). doi: 10.1126/sciadv.eaax4111
- 616 Jin, F.-F. (1997). An equatorial ocean recharge paradigm for ENSO. Part I: concep-
617 tual model. *J. Atmos. Sci.*, 54, 811–829.
- 618 Johnson, Z. F., Chikamoto, Y., Wang, S.-Y. S., McPhaden, M. J., & Mochizuki,
619 T. (2020). Pacific decadal oscillation remotely forced by the equatorial
620 pacific and the atlantic oceans. *Climate Dynamics*. doi: doi.org/10.1007/
621 s00382-020-05295-2
- 622 Kajtar, J. B., Santoso, A., McGregor, S., England, M. H., & Baillie, Z. (2018).
623 Model under-representation of decadal Pacific trade wind trends and its link to
624 tropical Atlantic bias. *Climate Dynamics*, 50(3-4), 1471–1484.
- 625 Kalnay, E., Kanamitsu, M., Kistler, R., Deaven, W. C. D., Gandin, L., Iredell, M.,
626 . . . Joseph, D. (1996). The NCEP/NCAR 40-year reanalysis project. *Bull.*
627 *Amer. Meteorol. Soc.*, 77, 437–471.
- 628 Keenlyside, N. S., Ding, H., & Latif, M. (2013). Potential of equatorial Atlantic vari-
629 ability to enhance El Niño prediction. *Geophysical Research Letters*, 40(10),
630 2278–2283.

- 631 Kobayashi, S., Ota, Y., Harada, Y., Ebita, A., Moriya, M., Onoda, H., . . . others
632 (2015). The JRA-55 reanalysis: General specifications and basic characteris-
633 tics. *Journal of the Meteorological Society of Japan. Ser. II*, *93*(1), 5–48.
- 634 Kosaka, Y., & Xie, S.-P. (2013). Recent global-warming hiatus tied to equatorial Pa-
635 cific surface cooling. *Nature*, *501*(7467), 403–407.
- 636 Kucharski, F., Ikram, F., Molteni, F., Farneti, R., Kang, I.-S., No, H.-H., . . . Mo-
637 gensen, K. (2016). Atlantic forcing of Pacific decadal variability. *Climate*
638 *Dynamics*, *46*(7-8), 2337–2351.
- 639 Kucharski, F., Kang, I., Farneti, R., & Feudale, L. (2011). Tropical Pacific response
640 to 20th century Atlantic warming. *Geophys. Res. Lett.*, *38*, L03702.
- 641 Latif, M., & Grötzner, A. (2000). The equatorial Atlantic oscillation and its re-
642 sponse to ENSO. *Climate Dynamics*, *16*(2-3), 213–218.
- 643 Levine, A. F., Frierson, D. M., & McPhaden, M. J. (2018). AMO forcing of multi-
644 decadal Pacific ITCZ variability. *Journal of Climate*, *31*(14), 5749–5764.
- 645 Levine, A. F., McPhaden, M. J., & Frierson, D. M. (2017). The impact of the AMO
646 on multidecadal ENSO variability. *Geophysical Research Letters*, *44*(8), 3877–
647 3886.
- 648 Li, X., Xie, S.-P., Gille, S. T., & Yoo, C. (2015). Atlantic-induced pan-tropical cli-
649 mate change over the past three decades. *Nature Climate Change*. doi: 10
650 .1038/nclimate2840
- 651 Lübbecke, J. F., & McPhaden, M. J. (2012). On the inconsistent relationship be-
652 tween Pacific and Atlantic Niños. *Journal of Climate*, *25*(12), 4294–4303.
- 653 Luo, J.-J., Wang, G., & Dommenges, D. (2018). May common model biases reduce
654 CMIP5’s ability to simulate the recent Pacific La Niña-like cooling? *Climate*
655 *Dynamics*, *50*(3-4), 1335–1351.
- 656 Martín-Rey, M., Rodríguez-Fonseca, B., & Polo, I. (2015). Atlantic opportunities for
657 ENSO prediction. *Geophysical Research Letters*, *42*(16), 6802–6810.
- 658 Martín-Rey, M., Rodríguez-Fonseca, B., Polo, I., & Kucharski, F. (2014). On the
659 Atlantic–Pacific Niños connection: a multidecadal modulated mode. *Climate*
660 *dynamics*, *43*(11), 3163–3178.
- 661 McGregor, S., Stuecker, M. F., Kajtar, J. B., England, M. H., & Collins, M. (2018).
662 Model tropical Atlantic biases underpin diminished Pacific decadal variability.
663 *Nature Climate Change*, *8*, 493–498.

- 664 McGregor, S., Timmermann, A., Stuecker, M. F., England, M. H., Merrifield, M.,
 665 Jin, F.-F., & Chikamoto, Y. (2014). Recent Walker circulation strengthening
 666 and Pacific cooling amplified by Atlantic warming. *Nature Climate Change*,
 667 *4*(10), 888–892.
- 668 McPhaden, M. J. (2003). Tropical Pacific Ocean heat content variations and ENSO
 669 persistence barriers. *Geophysical research letters*, *30*(9).
- 670 Meinen, C. S., & McPhaden, M. J. (2000). Observations of warm water volume
 671 changes in the equatorial Pacific and their relationship to El Niño and La
 672 Niña. *Journal of Climate*, *13*(20), 3551–3559.
- 673 Mochizuki, T., Chikamoto, Y., Kimoto, M., Ishii, M., Tatebe, H., Komuro, Y., ...
 674 Mori, M. (2012). Decadal prediction using a recent series of MIROC global
 675 climate models. *J. Meteorol. Soc. Japan*, *90A*, 373–383. (submitted) doi:
 676 10.2151/jmsj.2012-A22
- 677 Mochizuki, T., Ishii, M., Kimoto, M., Chikamoto, Y., Watanabe, M., Nozawa,
 678 T., ... Mori, M. (2010). Pacific decadal oscillation hindcasts relevant
 679 to near-term climate prediction. *Proc. Natl. Acad. Sci. USA*, *107*, 1833.
 680 (doi:10.1073/pnas.0906531107)
- 681 Nozawa, T., Nagashima, T., Ogura, T., Yokohata, T., Okada, N., & Shiogama, H.
 682 (2007). Climate change simulations with a coupled ocean-atmosphere GCM
 683 called the model for interdisciplinary research on climate: MIROC. *CGER*
 684 *Supercomput. Monogr. Rep*, *12*. (Cent. for Global Environ. Res., Natl. Inst. for
 685 Environ. Stud., Tsukuba, Japan.)
- 686 Polo, I., Martin-Rey, M., Rodriguez-Fonseca, B., Kucharski, F., & Mechoso, C. R.
 687 (2015). Processes in the Pacific La Niña onset triggered by the Atlantic Niño.
 688 *Climate dynamics*, *44*(1-2), 115–131.
- 689 Richter, I. (2015). Climate model biases in the eastern tropical oceans: Causes,
 690 impacts and ways forward. *Wiley Interdisciplinary Reviews: Climate Change*,
 691 *6*(3), 345–358.
- 692 Rodríguez-Fonseca, B., Polo, I., García-Serrano, J., Losada, T., Mohino, E., Me-
 693 choso, C. R., & Kucharski, F. (2009). Are Atlantic Niños enhancing Pacific
 694 ENSO events in recent decades? *Geophysical Research Letters*, *36*(20).
- 695 Ruprich-Robert, Y., Msadek, R., Castruccio, F., Yeager, S., Delworth, T., & Dan-
 696 abasoglu, G. (2017). Assessing the climate impacts of the observed Atlantic

- 697 multidecadal variability using the GFDL CM2.1 and NCAR CESM1 global
698 coupled models. *Journal of Climate*, *30*(8), 2785–2810.
- 699 Sasaki, W., Doi, T., Richards, K. J., & Masumoto, Y. (2014). Impact of the equa-
700 torial Atlantic sea surface temperature on the tropical Pacific in a CGCM. *Cli-
701 mate dynamics*, *43*(9-10), 2539–2552.
- 702 Shields, C. A., Bailey, D. A., Danabasoglu, G., Jochum, M., Kiehl, J. T., Levis, S.,
703 & Park, S. (2012). The low-resolution CCSM4. *Journal of Climate*, *25*(12),
704 3993–4014.
- 705 Tatebe, H., Ishii, M., Mochizuki, T., Chikamoto, Y., Sakamoto, T. T., Komuro, Y.,
706 ... Kimoto, M. (2012). The initialization of the MIROC climate models with
707 hydrographic data assimilation for decadal prediction. *J. Meteorol. Soc. Japan*,
708 *90A*, 275–294. doi: 10.2151/jmsj.2012-A14
- 709 Timmermann, A., An, S.-I., Kug, J.-S., Jin, F.-F., Cai, W., Capotondi, A., ... oth-
710 ers (2018). El Niño–Southern Oscillation complexity. *Nature*, *559*(7715),
711 535.
- 712 Tokinaga, H., Richter, I., & Kosaka, Y. (2019). ENSO influence on the Atlantic
713 Niño, revisited: Multi-year versus single-year ENSO events. *Journal of Cli-
714 mate*, *32*(14), 4585-4600. doi: 10.1175/JCLI-D-18-0683.1
- 715 Wang, C., & Picaut, J. (2004). Understanding ENSO physics—a review. *Earth Cli-
716 mate: Ocean-atmosphere interaction and climate variability*, *147*, 21-48. (Geo-
717 physical Monograph, AGU, Washington D. C.)
- 718 Wang, L., Yu, J.-Y., & Paek, H. (2017). Enhanced biennial variability in the Pacific
719 due to Atlantic capacitor effect. *Nature communications*, *8*, 14887.
- 720 Wang, S.-Y., L’Heureux, M., & Yoon, J.-H. (2013). Are greenhouse gases changing
721 ENSO precursors in the western North Pacific? *Journal of Climate*, *26*(17),
722 6309–6322.
- 723 Wang, S.-Y. S., Jiang, X., & Fosu, B. (2015). Global eastward propagation signals
724 associated with the 4–5-year ENSO cycle. *Climate Dynamics*, *44*(9-10), 2825–
725 2837.
- 726 Xie, S., Hu, K., Hafner, J., Tokinaga, H., Du, Y., Huang, G., & Sampe, T. (2009).
727 Indian Ocean capacitor effect on Indo-western Pacific climate during the sum-
728 mer following El Niño. *J. Climate*, *22*(3), 730–747.
- 729 Xie, S. P., & Carton, J. A. (2004). Tropical Atlantic variability: patterns, mecha-

730 nisms, and impacts. *Earth Climate: ocean-atmosphere interaction and climate*
731 *variability*, 147, 121-142. (Geophysical Monograph, AGU, Washington D. C.)

Table 1. Summary of (a) decadal climate prediction experiments and (b) Atlantic ocean data assimilation experiments. The 5-year and 2-year model spin-up periods for the Atlantic partial assimilation experiments are excluded in MIROC and CESM runs, respectively.

(a) Decadal climate prediction experiment

Experiment	Brief description
Historical runs	Prescribing natural and anthropogenic radiative forcing to climate models.
Assimilation runs	Assimilating the observed ocean anomalies while prescribing the forcing.
Hindcast runs	10-year-long hindcast experiments initialized on January 1 st every year.

(b) Atlantic partial ocean data assimilation experiments

Name	Model	Region	Ocean field	Ensemble	Period
MIROC ATL anomaly	MIROC3.2	Atlantic	Anomaly	10-member	1950–2009
CESM ATL anomaly	CESM1.0	Atlantic	Anomaly	10-member	1960–2014
CESM ATL full	CESM1.0	Atlantic	Full	10-member	1960–2014

Table 2. Potential predictability of Niño 3.4, Niño 4, and Indo-Pacific zonal wind indices (zonal wind anomalies at 850 hPa averaged in 5°S–5°N, 90°E–150°E) measured by an anomaly correlation coefficient between observation and ATL run.

Run	Niño 4	Niño 3.4	Niño 3	zonal wind
MIROC ATL anomaly	0.31	0.24	0.14	0.23
CESM ATL anomaly	0.04	0.06	0.02	0.18
CESM ATL full	0.25	0.22	0.14	0.46
Multi-model	0.27	0.22	0.13	0.36

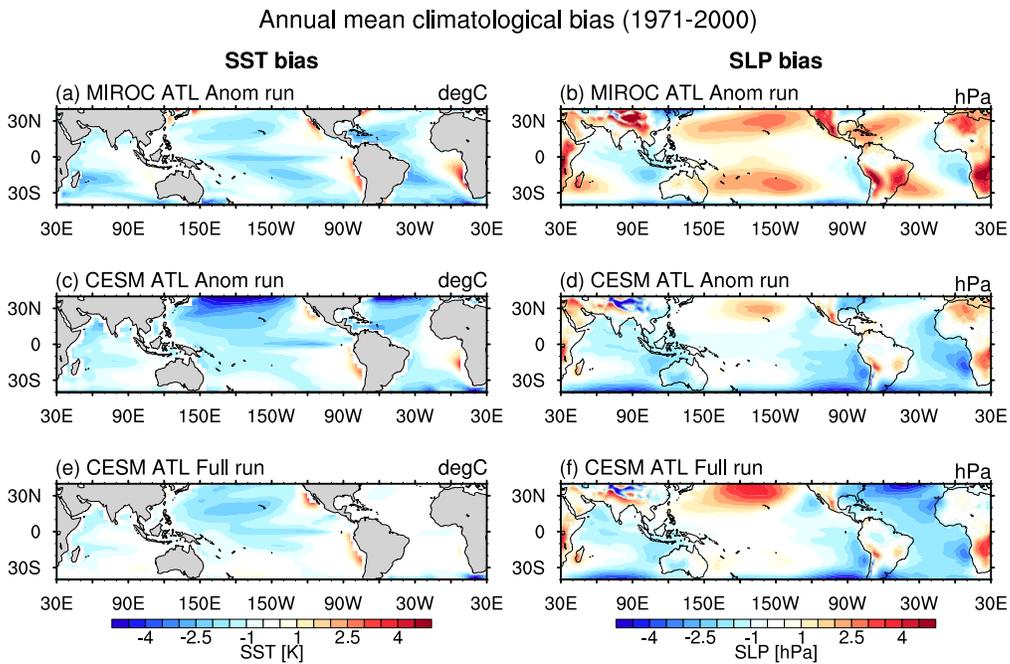


Figure 1. Annual mean climatological biases of SST (left) and SLP (right panels) for (a, b) MIROC ATL anomaly run, (c, d) CESM ATL anomaly run, and (e, f) CESM ATL full run, compared to observations. Annual mean climatology is obtained for a reference period 1971–2000.

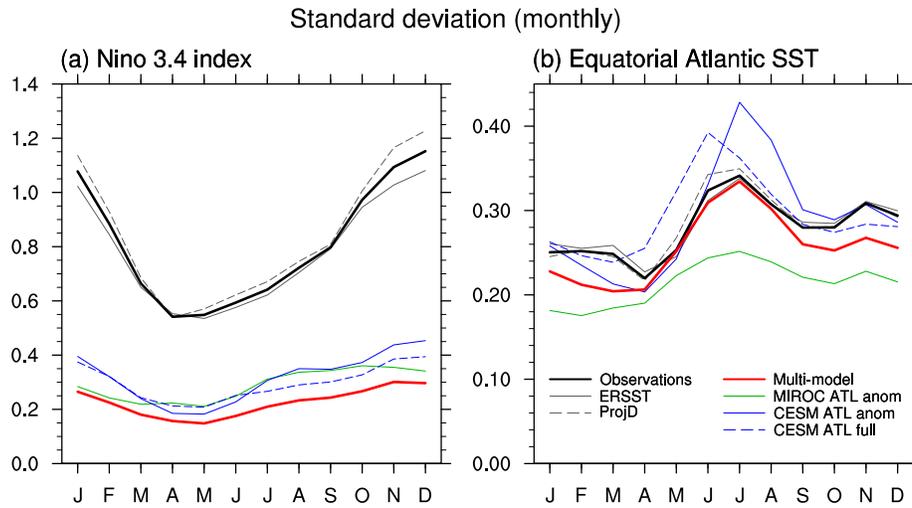


Figure 2. Standard deviations of the monthly (a) Niño3.4 index and (b) SST anomalies averaged over the equatorial Atlantic in observations (black) and the ATL runs (color lines).

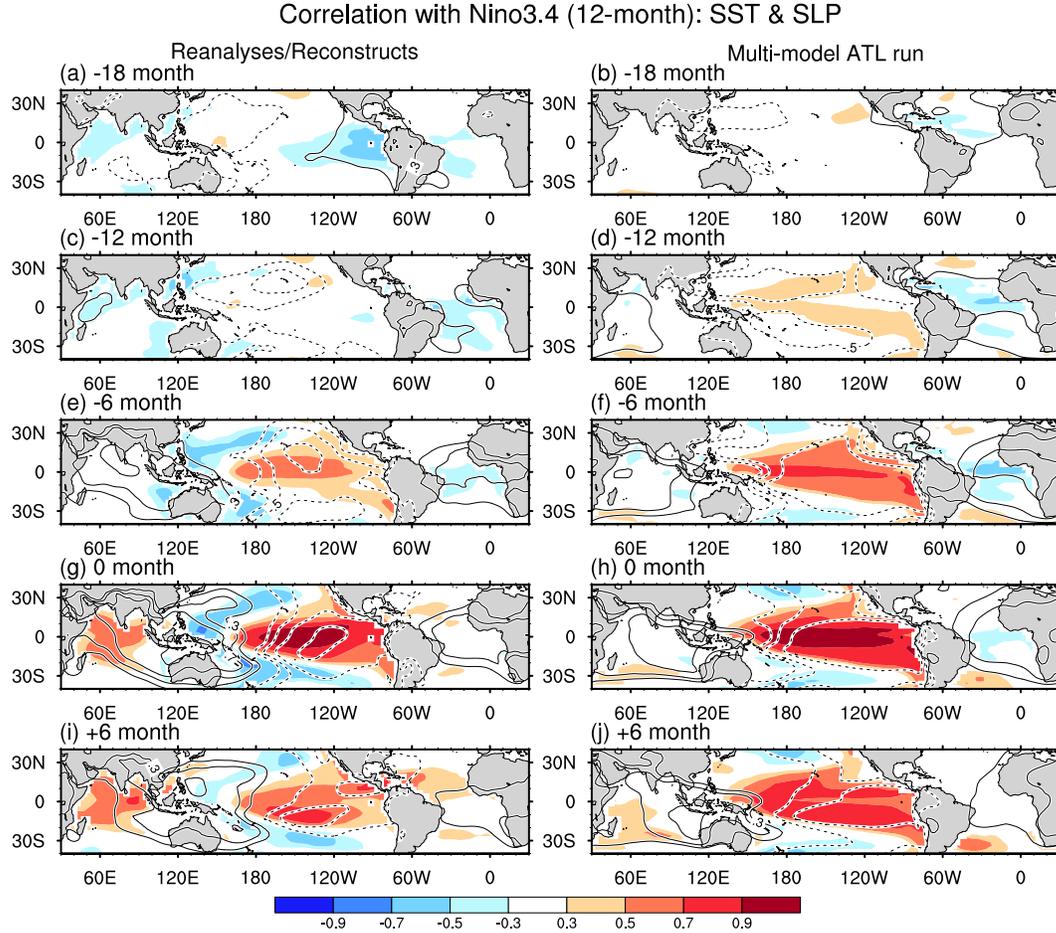


Figure 3. Correlation maps of SST (shaded) and SLP anomalies (contoured) with the Niño 3.4 index in observations (left) and multi-model ensemble of the ATL runs (right panels) at (a,b) -18, (c,d) -12, (e,f) -6, (g,h) 0, and (i,j) +6 month lags. The contour interval is ± 0.3 , ± 0.5 , ± 0.7 , and ± 0.9 . Negative contours are dashed and the zero contour is omitted. A 12-month running mean filter is applied to anomalies after detrending. A correlation coefficient of 0.29 corresponds to the statistical significant at 95% levels with 48 degrees of freedom on the basis of two-side Student's t-test.

SST (shade) & SLP correlations (contour) with Nino3.4 (12-month, 5S-5N)

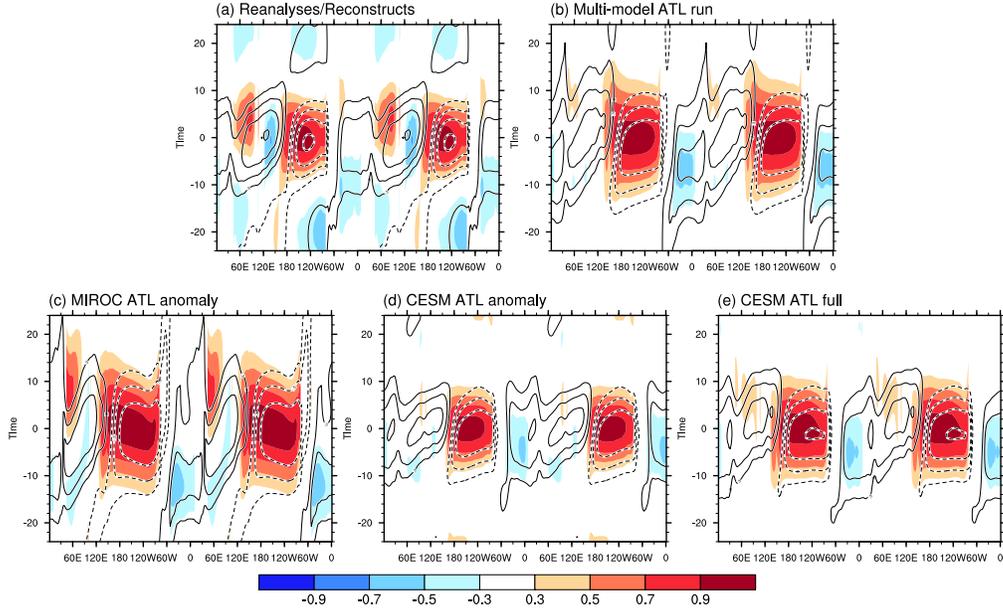


Figure 4. Lead-lag correlations of SLP (contours) and SST anomalies (shaded) correlated with the Niño 3.4 index at the equator (5°S – 5°N) in (a) observations, (b) multi-model ATL run, and its individual experiment for (c) MIROC ATL anomaly, (d) CESM ATL anomaly, and (e) CESM ATL full runs. Note that longitude is repeated twice. Positive (negative) lags indicate that the Niño 3.4 index is leading (lagging) the anomalies. Negative contours are dashed and the zero contour is omitted. The contour interval is ± 0.3 , ± 0.5 , ± 0.7 , and ± 0.9 . A correlation coefficient of 0.29 corresponds to the statistical significant at 95% levels with 48 degrees of freedom on the basis of two-side Student’s t-test.

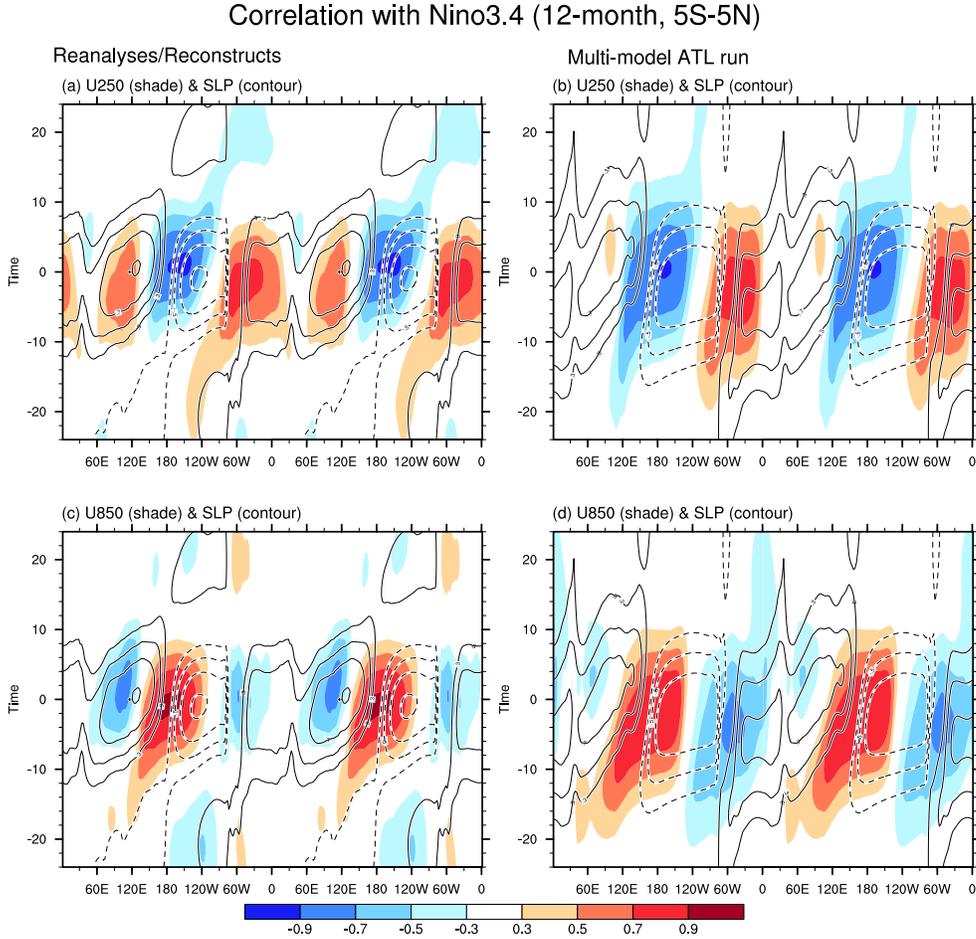


Figure 5. Lead-lag correlations of SLP (contours), (a,b) zonal wind anomalies at 250 hPa (shading) and (c,d) 850 hPa (shading) correlated with the Niño 3.4 index at the equator (5°S – 5°N) in observations (left) and multi-model mean of ATL runs (right panels). Note that longitude is repeated twice. Positive (negative) lags indicate that the Niño 3.4 index is leading (lagging) the anomalies. Negative contours are dashed and the zero contour is omitted. The contour interval is ± 0.3 , ± 0.5 , ± 0.7 , and ± 0.9 . A correlation coefficient of 0.29 corresponds to the statistical significant at 95% levels with 48 degrees of freedom on the basis of two-side Student’s t-test.

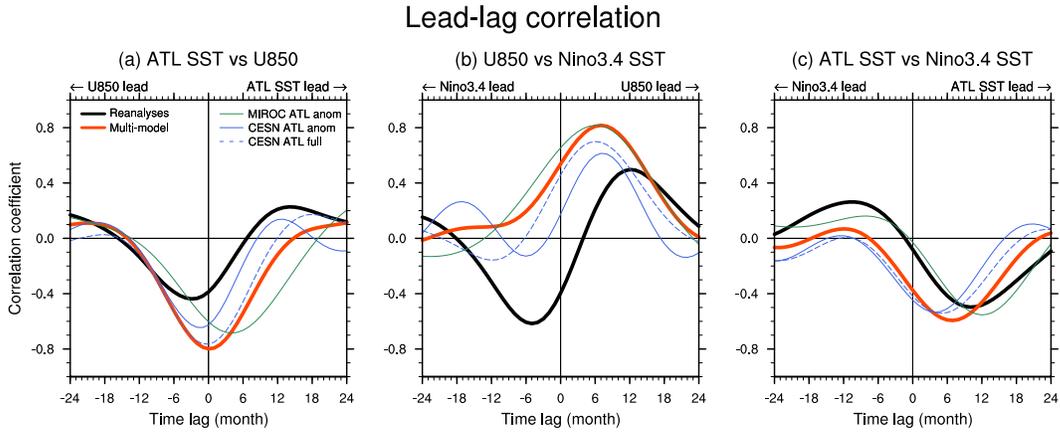


Figure 6. Lead-lag correlations between (a) equatorial Atlantic SST (5°S – 5°N , 50°W – 0°) and zonal wind anomalies at 850 hPa in the Indo-Pacific region (5°S – 5°N , 90°E – 150°E), (b) zonal wind anomalies at 850 hPa in the Indo-Pacific region and Nino 3.4 index (SST anomalies in 5°S – 5°N , 170°W – 120°W), and (c) equatorial Atlantic SST and Nino 3.4 index. Black and red lines are observations and multi-model ensemble of ATL runs, respectively. Green, blue solid and blue dashed lines correspond to the MIROC ATL anomaly, CESM ATL anomaly, and CESM ATL full runs, respectively.

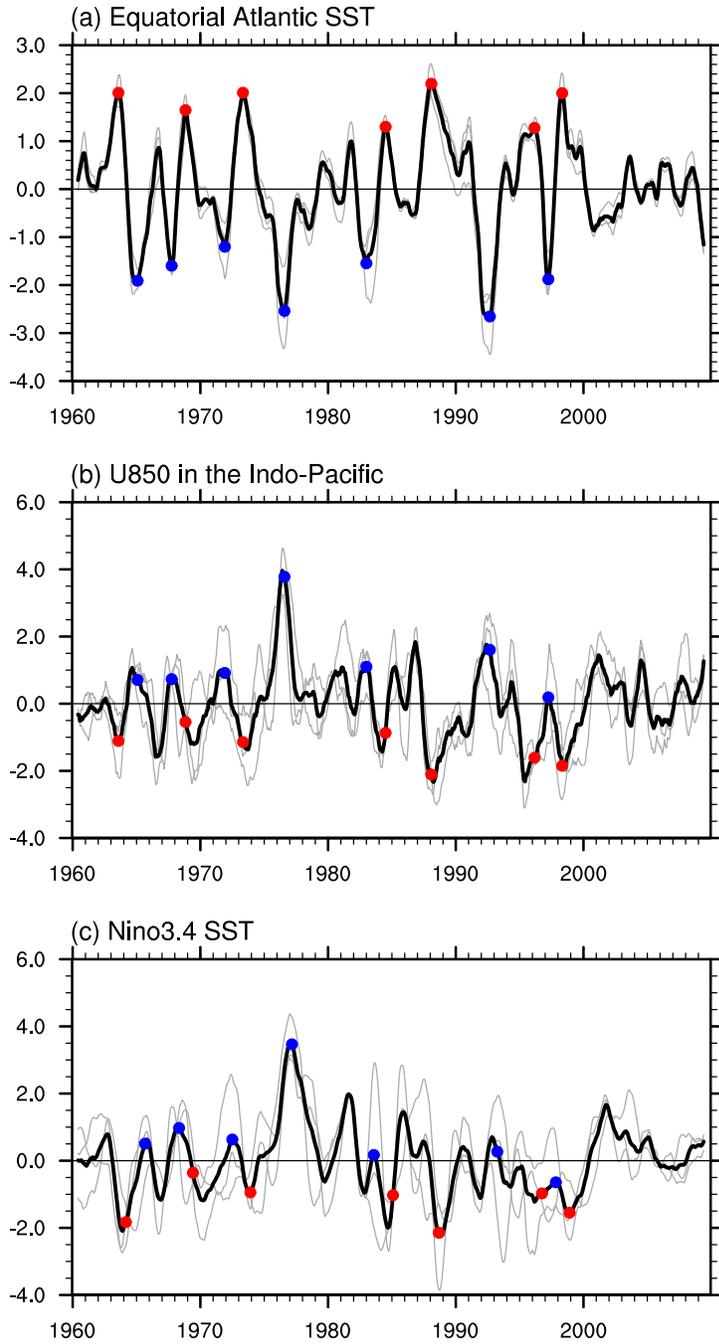


Figure 7. Standardized timeseries of (a) the equatorial Atlantic SST anomalies, (b) anomalous zonal wind at 850 hPa in the Indo-Pacific region, and (c) Niño 3.4 index in the ATL runs. Thick and thin lines are the multi-model ensemble mean of ATL runs and the 10-member ensemble mean of individual ATL run (i.e., CESM ATL anomaly, CESM ATL full and MIROC ATL anomaly runs), respectively. Red and blue circles correspond to the warmer and colder months of equatorial Atlantic SST anomalies in (a, b) but for +7 month lag in (c).

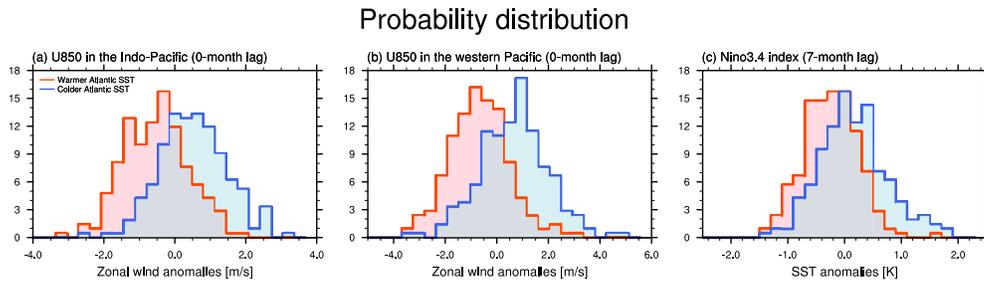


Figure 8. Histograms of (a) zonal wind anomalies at 850 hPa in the Indo-Pacific region (5°S – 5°N , 90°E – 150°E) at 0-month lag, (b) zonal wind anomalies at 850 hPa in the western Pacific region (5°S – 5°N , 120°E – 150°E) at 0-month lag, and (c) SST anomalies in the Niño 3.4 region (5°S – 5°N , 170°W – 120°W) at 7-month lag associated with warmer (red) and colder (blue) tropical Atlantic SST anomalies (blue: 5°S – 5°N , 50°W – 0°) in each member of the ATL run. We extract 7 months of SST anomalies warmer than 1.5 standard deviation: Aug 1963, Nov 1968, May 1973, Jul 1984, Feb 1988, Mar 1996, May 1998; and 7 month colder than 1.5 standard deviation: Feb 1965, Oct 1967, Dec 1971, Aug 1976, Jan 1983, Sep 1992, Apr 1997 (see Fig. 7). There are 210 samples in these distributions ($= 7 \text{ years} \times 10 \text{ members} \times 3 \text{ runs}$).

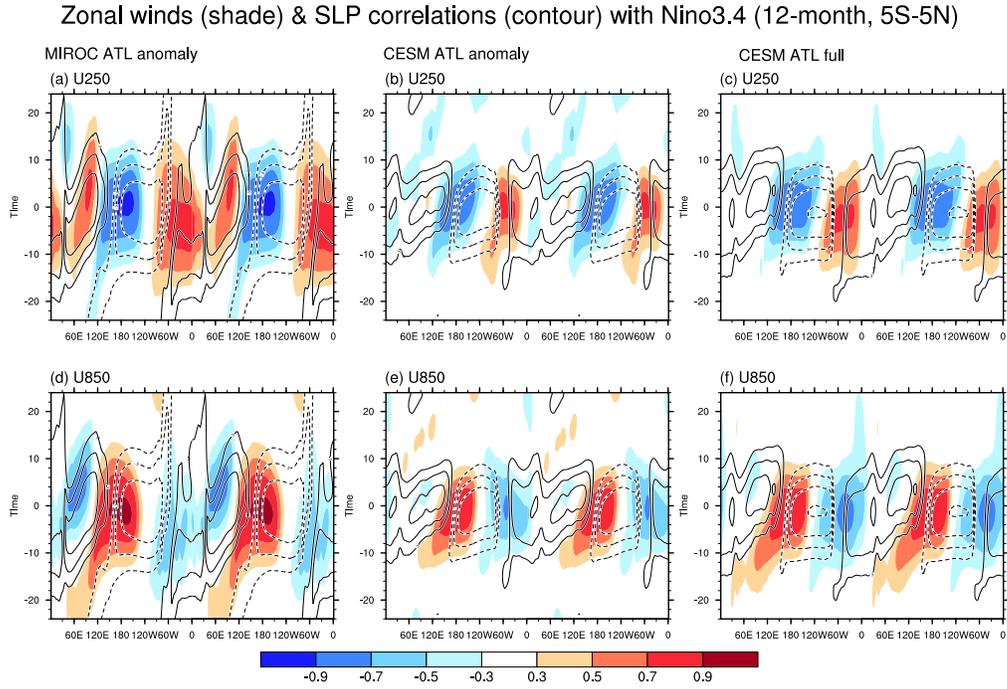


Figure 9. Lead-lag correlations of SLP (contours), zonal wind anomalies at 250 hPa (top) and 850 hPa (bottom) correlated with the Niño 3.4 index at the equator (5°S – 5°N) in MIROC ATL anomaly (left), CESM ATL anomaly (center), and CESM ATL full runs (right panels). Note that longitude is repeated twice. Positive (negative) lags indicate that the Niño 3.4 index is leading (lagging) the anomalies. Negative contours are dashed and the zero contour is omitted. The contour interval is ± 0.3 , ± 0.5 , ± 0.7 , and ± 0.9 . A correlation coefficient of 0.29 corresponds to the statistical significant at 95% levels with 48 degrees of freedom on the basis of two-side Student’s t-test.

Supporting Information for ”El Niño Southern Oscillation evolution modulated by the Atlantic forcing”

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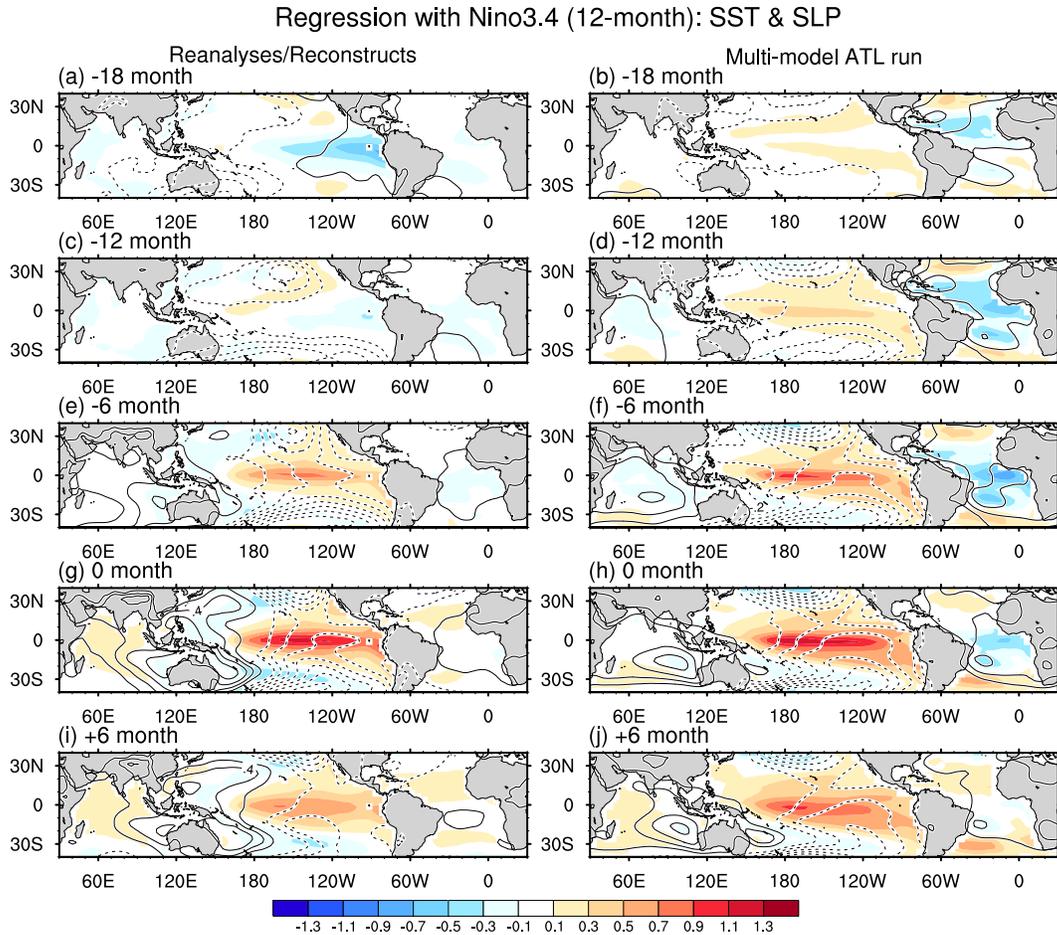


Figure S1. Regression maps of SST (shaded) and SLP anomalies (contoured) with the Niño 3.4 index in observations (left) and multi-model ensemble of the ATL runs (right panels) at (a,b) -18 , (c,d) -12 , (e,f) -6 , (g,h) 0 , and (i,j) $+6$ month lags. The contour interval is ± 0.2 , ± 0.4 , ± 0.6 , ± 0.8 , ± 1.0 , ± 1.2 , and ± 1.3 hPa. Negative contours are dashed and the zero contour is omitted. A 12-month running mean filter is applied to anomalies after detrending.

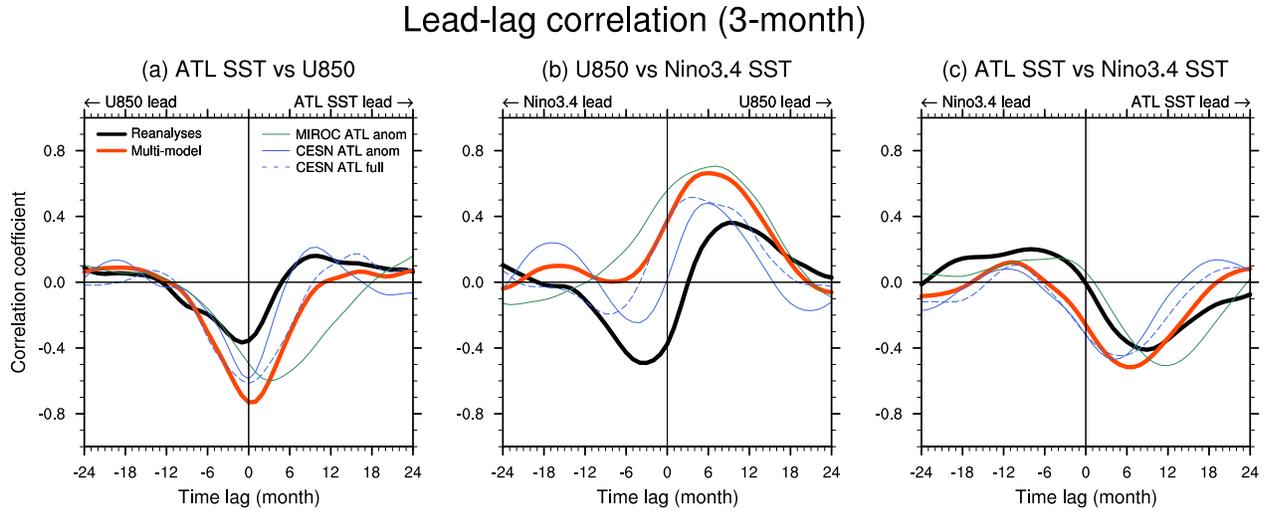


Figure S2. Lead-lag correlations between (a) equatorial Atlantic SST (5°S – 5°N , 50°W – 0°) and zonal wind anomalies at 850 hPa in the Indo-Pacific region (5°S – 5°N , 90°E – 150°E), (b) zonal wind anomalies at 850 hPa in the Indo-Pacific region and Nino 3.4 index (SST anomalies in 5°S – 5°N , 170°W – 120°W), and (c) equatorial Atlantic SST and Nino 3.4 index. Black and red lines are observations and multi-model ensemble of ATL runs, respectively. Green, blue solid and blue dashed lines correspond to the MIROC ATL anomaly, CESM ATL anomaly, and CESM ATL full runs, respectively. A 3-month running mean filter is applied to anomalies after detrending.

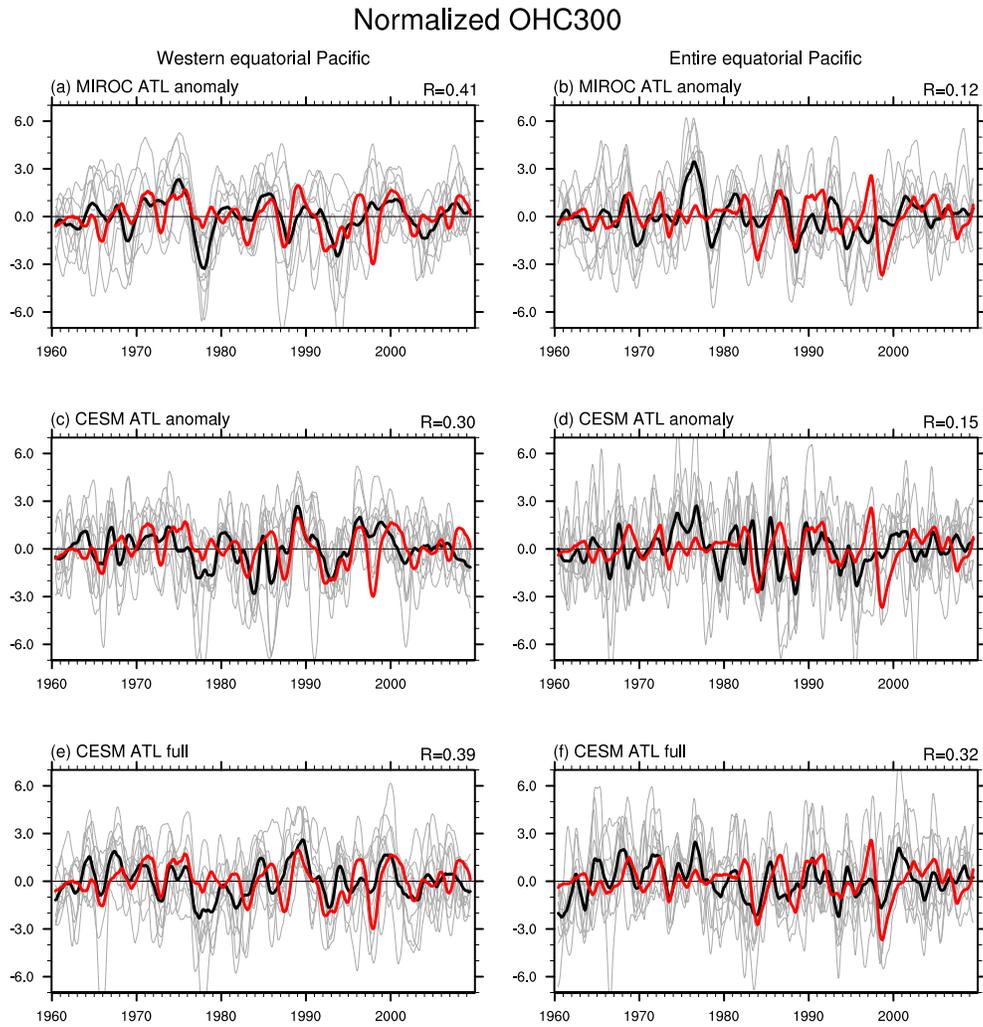


Figure S3. Timeseries of normalized upper ocean heat content at the western (left panels; 5°S – 5°N , 120°E – 165°E) and the entire equatorial Pacific (right panels; 5°S – 5°N , 120°E – 80°W) in (a, b) MIROC ATL anomaly, (c, d) CESM ATL anomaly, and (e, f) CESM ATL full runs. The upper ocean heat content is estimated by ocean heat content averaged from surface to 300 m depth. Red, black, and gray lines are the observations (ProjD), the ensemble mean, and each ensemble member, respectively. Anomalies are normalized by one standard deviations in the observation and the 10-ensemble mean. A correlation coefficient between the observation and the 10-ensemble mean is denoted at the upper-right corner.