Focus Article

Climate model biases in the eastern tropical oceans: causes, impacts and ways forward

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The eastern boundaries of the tropical and subtropical oceans are regions of high biological productivity that support some of the world's largest fisheries. They also feature extensive stratocumulus cloud decks that play a pivotal role in the response of the climate system to greenhouse gas forcing. Global climate models experience great difficulties simulating eastern boundary regions, with one of the most notable shortcomings being warm sea-surface temperature biases that often exceed 5 K. These model biases are due to several reasons. (1) Weaker than observed alongshore winds lead to an underrepresentation of upwelling and alongshore currents and the cooling associated with them. (2) Stratocumulus decks and their effects on shortwave radiation are underpredicted in the models. (3) The offshore transport of cool waters by mesoscale eddies is not adequately represented by global models due to insufficient resolution. (4) The sharp vertical temperature gradient separating the warm upper ocean layer from the deep ocean is too diffuse in the models. More work will be required to assess the relative importance of these error sources and to find ways of mitigating them. Coordinated multi-model experiments are vital to achieve this goal, as are enhanced ocean and atmosphere observations of the eastern boundary regions. To what extent eastern ocean biases compromise the models' ability to produce accurate seasonal predictions, and climate change projections should be another focus of research efforts. © 2015 John Wiley & Sons, Ltd.

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INTRODUCTION

The eastern subtropical oceans are unique in several respects. Located under the descending branch of the Hadley circulation, these regions are characterized by large-scale subsidence that warms the free troposphere and generates divergence as the sinking air spreads out horizontally. The associated subtropical highs feature equatorward flow on their eastern flanks that can generate intense coastal upwelling. The cold upwelled water is transported by oceanic processes toward the ocean interior, leading to cool sea-surface temperatures (SSTs) that extend several thousand kilometers offshore (Figure 1(a)). The combination of warm atmospheric temperatures aloft and cool temperatures at the surface generates stable atmospheric conditions that confine convection to the lower troposphere. These conditions favor the development of extensive shallow stratocumulus decks that shield the underlying ocean from shortwave radiation and help to maintain cool SSTs. These stratocumulus decks cover approximately 23% of the world's oceans.[12] Meanwhile, the coastal upwelling carries not only cold water to the upper ocean but also nutrients that sustain biological productivity and some of the world's largest fisheries.[13]

Global climate models (also called general circulation models or GCMs) struggle to realistically simulate the eastern tropical oceans. The most obvious deficiency is the warm SST bias that virtually all

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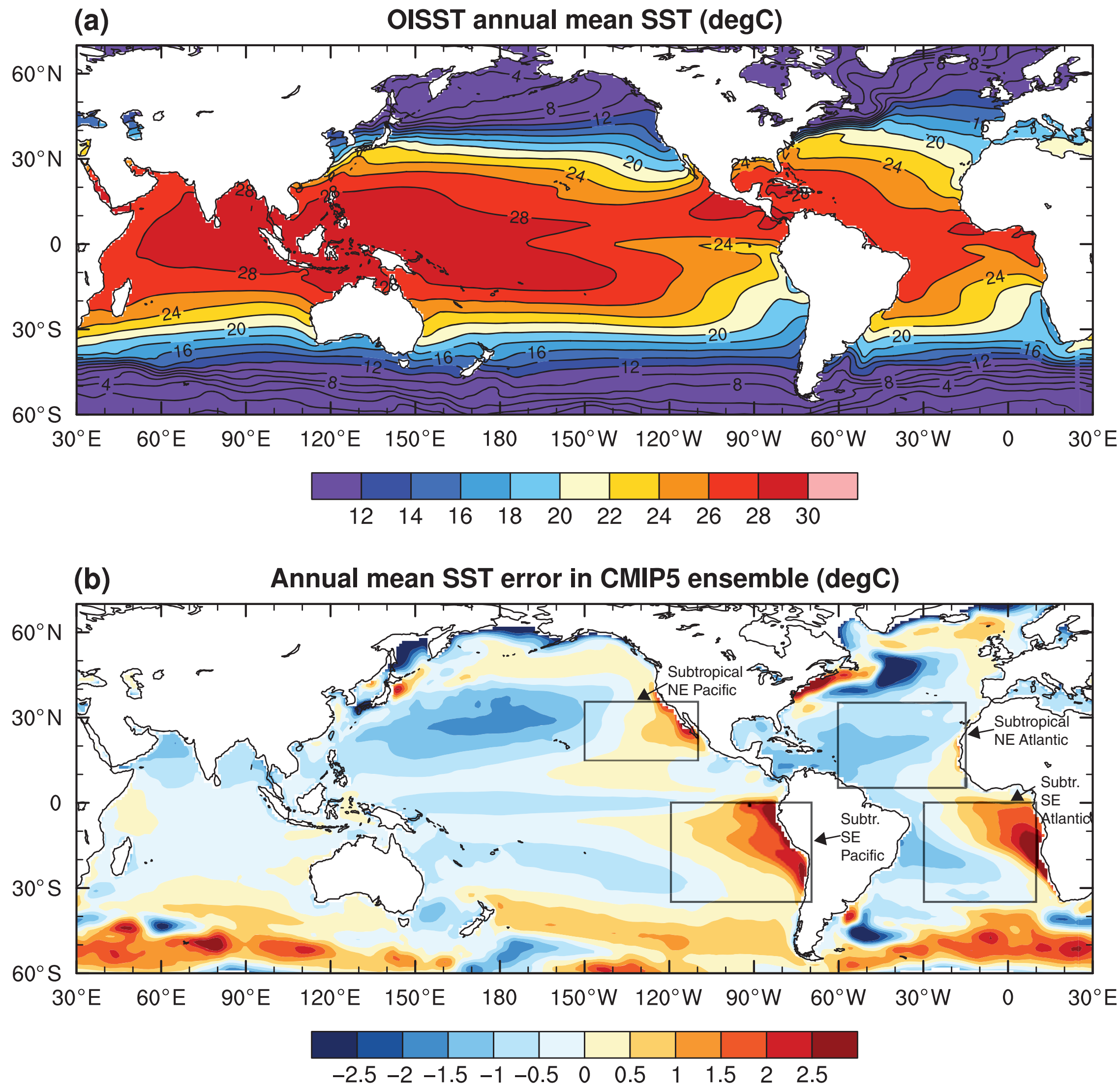

FIGURE 1 | (a) Observed annual mean sea-surface temperature (SST) from the optimally interpolated (OI) SST data set.[1] (b) Annual mean bias of the CMIP5[2] ensemble relative to OISST. See Table 1 for a list of models. The gray boxes denote the regions discussed in this article and their longitudinal and latitudinal extents correspond to the ranges plotted in Figures 2 and 3, respectively. The text labels refer to the naming used in Figure 2.

GCMs produce in vicinity to the eastern boundaries (Figure 1(b); see Table 1 for a list of the models used to generate the ensemble mean).[14–16] This is usually accompanied by an underrepresentation of the stratocumulus decks that leads to excessive shortwave radiation reaching the ocean surface (Figure 2(a) and (b)).[17–19] The poor GCM performance in reproducing SST and cloud cover is troubling because it undermines the credibility of climate change projections for the region. The response of stratocumulus clouds in these projections varies widely among models, with some models projecting increasing cloud cover (negative feedback) and others predicting decreasing cloud cover (positive feedback).[20–23] This disagreement adds substantially to the uncertainty of global temperature projections under greenhouse gas forcing.[24–26] Moreover, eastern boundary regions are also subject to pronounced year-to-year variability in upwelling strength and SST. This variability can have severe impacts on fisheries and also affect weather over the adjacent continents.[27–30] GCMs form the basis of many seasonal prediction systems and thus eastern ocean biases may hamper skillful predictions of climate anomalies around coastal upwelling regions.

Given the importance of tropical eastern boundaries to the climate system, it is crucial to alleviate the persistent GCM biases in the region. The present article aims to contribute to this goal by summarizing

TABLE 1 | List of Models Included in the CMIP5 Ensemble Mean

Model	Atm. Horiz. Grid	No. Atm. Lev.	Ocn. Horiz. Grid	No. Ocn. Lev.
ACCESS1-0	1.875° × 1.25°	38 (8)	~1°	50 (5)
ACCESS1-3	1.875° × 1.25°	38 (8)	~1°	50 (5)
bcc-csm1-1	T42 (2.8°)	26 (4)	~1°	40 (5)
CanESM2	T63 (1.8°)	35 (10)	1.4° × 0.94°	40 (5)
CCSM4	1.25° × 0.9°	26 (4)	1.125° × 0.27–0.64°	60 (5)
FGOALS-g2	2.8125° × 2.8125°	26 (4)	~1°	30 (5)
FGOALS-s2	R42 (2.81° × 1.66°)	26 (4)	1° × 0.5–1°	30 (5)
GFDL-CM3	200 km or 2°	48 (9)	~1°	50 (5)
GISS-E2-R	2° × 2.5°	29 (6)	1.25 × 1	32 (3)
HadGEM2-CC	1.875° × 1.25°	60 (8)	1.875° × 1.25°	40 (5)
HadGEM2-ES	1.875° × 1.25°	38 (8)	1° × 0.33–1°	40 (5)
inmcm4	2° × 1.5°	21 (5)	1° × 0.5°	40 (8)
IPSL-CM5B-LR	3.75° × 1.9°	39 (7)	2° × 0.5–2°	31 (5)
MIROC5	T85 (1.4°)	40 (10)	1.4° × 0.5–1.4°	50 (8)
MPI-ESM-LR	T63 (1.8°)	47 (6)	~1.5°	40 (5)
MPI-ESM-MR	T63 (1.8°)	95 (6)	~0.4°	40 (5)
MRI-CGCM3	T159 (1.125°)	35 (7)	1° × 0.5°	51 (6)
NorESM1-M	2.5° × 2.9°	26 (4)	~1°	70 (9)

All output is taken from the experiment 'Historical' with greenhouse gas and aerosol forcing prescribed from observations. The second and fourth columns from the left list horizontal model resolution in the atmospheric and oceanic components, respectively, with grid cell size given in longitude by latitude format. For spectral atmospheric models the equivalent grid cell size is given in parentheses. The horizontal resolution of OGCMs typically increases toward the equator. The third and firth column show the number of vertical model levels for the atmospheric and oceanic components, respectively. For the atmosphere, the typical number of levels below 850 hPa in marine subtropical regions is given in parenthesis, while for the ocean, the number of levels above 50 m is included in parentheses. These parenthetical numbers are meant to give a rough idea of the number of vertical levels available to resolve in the atmospheric and oceanic boundary layers. The actual number may vary considerably due to temporal and spatial variability.

our current understanding of GCM biases and their causes, and by pointing toward ways to mitigate these problems. In the following I will first describe the GCMs biases, then review our current understanding of the underlying causes and their relative importance, discuss the potential impacts on seasonal prediction and climate change projections, and close by pointing out ways of addressing the bias problem. While the format of this article does not allow for a comprehensive review, I hope to give a fairly broad overview of the topic. In this article, I will focus on four eastern boundary regions: the Peruvian-Chilean, the Namibian-Angolan, the Californian, and the Canarian upwelling systems. A fifth region off the west coast of Australia does not feature the consistent SST biases seen in the other four regions and is not considered here although examining the reasons for the general absence of large SST errors there may be worthwhile in its own right.

The article presupposes knowledge of some fundamental concepts in ocean–atmosphere dynamics, such as 'Kelvin waves', 'Ekman transport,' and 'intertropical convergence zone'. For explanation of these concepts, please refer to the literature cited in the 'Further Reading' section at the end of this article.

PERVASIVE GCM BIASES IN COASTAL UPWELLING REGIONS

The most obvious shortcoming of coupled GCMs in the eastern boundary regions is the warm SST bias (Figure 1(b)). In many models, this bias exceeds 2°C, with the Nambian and Peruvian regions featuring the most severe errors, followed by the Californian and Canarian regions. Several GCM errors may contribute to the warm SST biases. One of them is insufficient stratocumulus incidence, which leads to excessive shortwave radiation flux into the ocean (Figure 2(a) and (b)).[16–19,31–33] Another one is weaker than observed alongshore winds (Figures 2(d) and 3(b)). As these winds drive both equatorward alongshore currents and upwelling (Figure 3(c) and (e)), the associated cooling is underestimated in the models.[14,16,33,34] Note that the alongshore wind bias is small in the Canarian region, consistent with the small warm bias there.

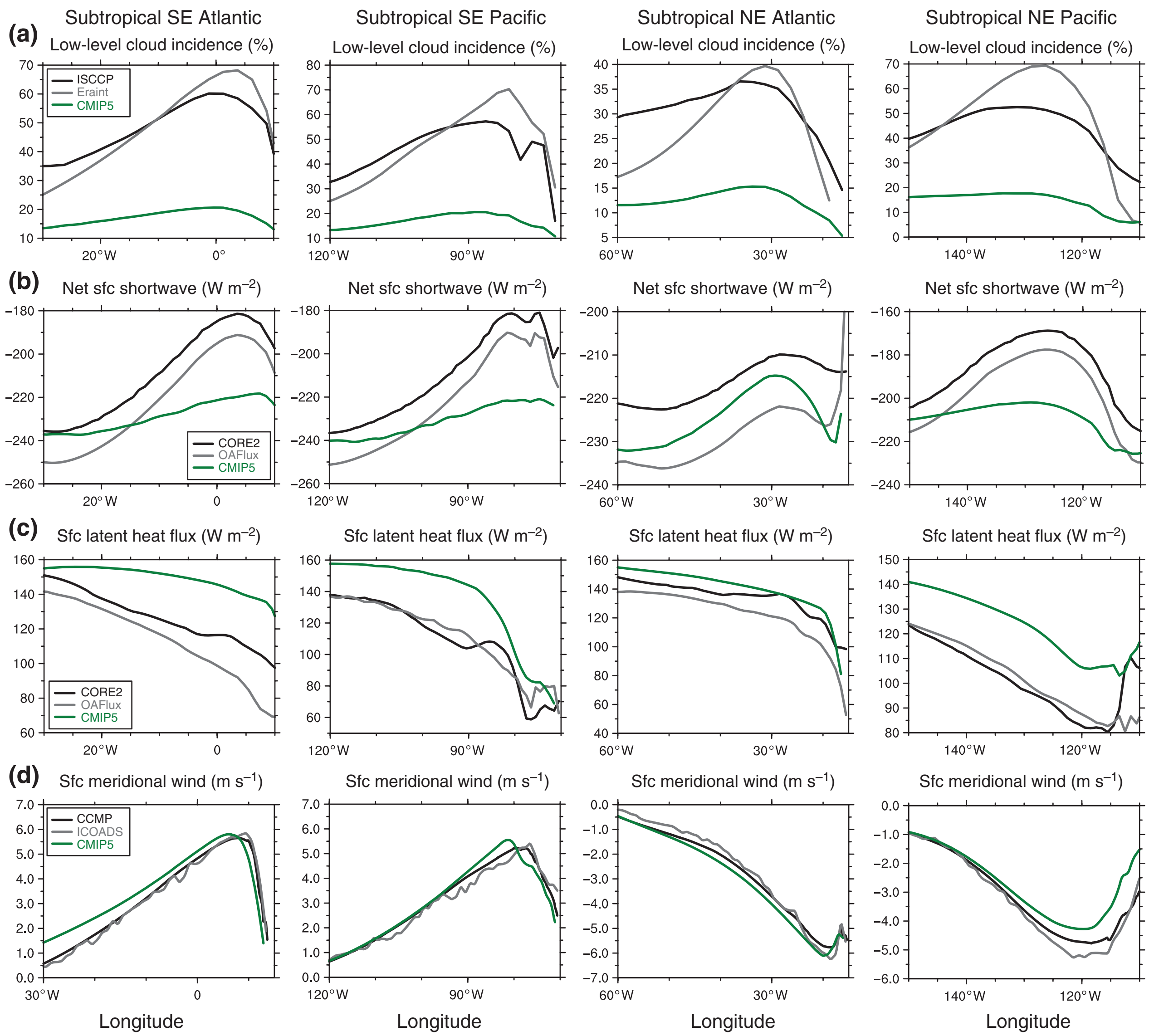

FIGURE 2 | Meridionally averaged fields from the CMIP5 ensemble mean (green line) and observations (gray and black lines) for the subtropical Southeast Atlantic (first column from the left; averaged 20–10°S), subtropical Southeast Pacific (second column; averaged 20–10°S), subtropical Northeast Atlantic (third column; averaged 15–25°N), and subtropical Northeast Pacific (fourth column; 20–30°N). Land points are masked out. The four averaging areas encompass the Namibian, Peruvian, Canarian, and Californian stratus regions in that order. All data are averaged from 1984 to 2005. (a) Low-level cloud incidence (%) from the International Satellite Cloud Climatology Project (ISCCP)[3] (black line) and ERA-Interim reanalysis[4] (gray line). (b) Net surface shortwave radiation ($W\,m^{-2}$; upward positive) from the CORE2[5] (black line) and OAFlux[6] (gray line) observationally derived products. (c) Surface latent data set heat flux ($W\,m^{-2}$; upward positive) from CORE2 (black line) and OAFlux (gray line). (d) Surface meridional wind ($m\,s^{-1}$) from the Cross-Calibrated Multi-Platform Ocean Surface Wind Vector (CCMP)[7] data set (black line) and the International Comprehensive Ocean-Atmosphere Data Set (ICOADS)[8] (gray line).

One shortcoming specific to the Namibian region concerns its complex current system. While in the other regions the alongshore currents are consistently equatorward, the Namibian region is marked by a poleward current, the Angola current, which originates from the equator and flows poleward (Figure 3(c)).[35] At about 18°S the Angola current encounters the equatorward Benguela current, which forces it to flow below the surface.[36] The Benguela current, on the other hand, veers offshore into the interior ocean. The confluence region around 18°S (usually referred to as the Angola-Benguela frontal zone or ABFZ) is marked by sharp meridional SST gradients due to the collision of tropical and midlatitude water masses. GCMs experience great difficulties simulating this complex current system. Typically, the

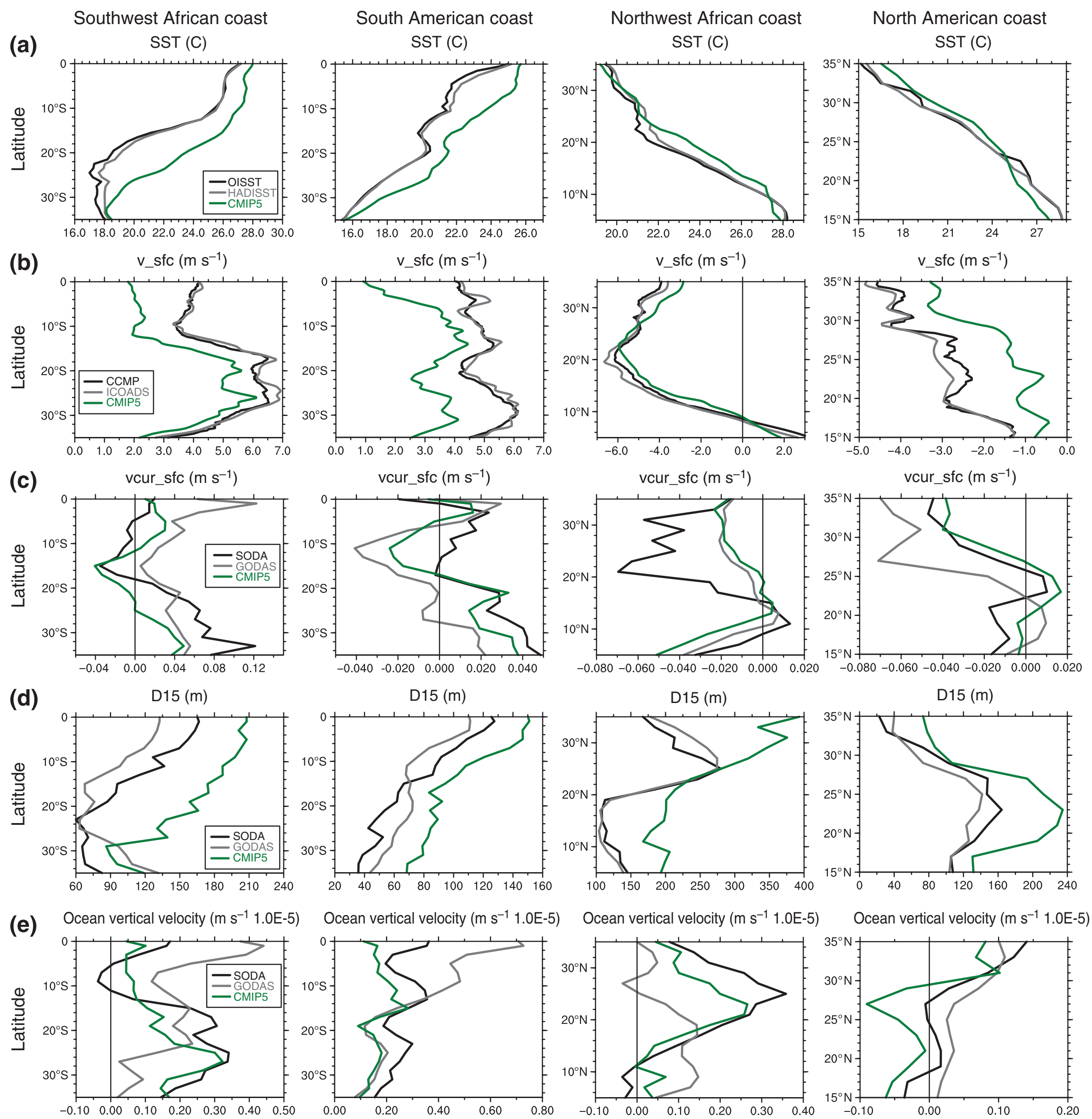

FIGURE 3 | Fields from the CMIP5 ensemble mean (green line) and observations (black and gray lines) zonally averaged from the coast to 5° offshore for the Southwest African coast (first column from the left), the South American coast (second column), the Northwest African coast (third column), and the North American coast (fourth column). The four averaging areas encompass the Namibian, Peruvian, Canarian, and Californian stratus regions in that order. All data are averaged from 1984 to 2005. (a) Sea-surface temperature (SST) (°C) from OISST (black line) and the Hadley Centre Sea Ice and Sea Surface Temperature (HADISST)[9] (gray line). (b) Meridional surface winds ($m\,s^{-1}$) from CCMP (black line) and ICOADS (gray line). (c) Meridional surface currents ($m\,s^{-1}$) from the Simple Ocean Data Assimilation (SODA)[10] (black line) and the Global Ocean Data Assimilation System (GODAS)[11] (gray line) reanalyses. (d) Depth of the 15°C isotherm from SODA (black line) and GODAS (gray line). (e) Ocean vertical velocity ($m\,s^{-1} \times 10^{-5}$) from SODA (black line) and GODAS (gray line).

simulated Angola current is too strong and penetrates farther poleward than observed (Figure 3(c)), leading to an erroneous southward displacement of the ABFZ, which adds to the severe SST biases along the Namibian coast.[16]

The simulated interannual variability is also subject to model errors though these are less consistent across regions (not shown). In the Peruvian and Namibian upwelling regions, SST variability tends to be too weak in the models. Peak variability typically occurs too late in the model, with the Peruvian and Namibian regions lagging observations by 1 and 3 months, respectively. For other upwelling regions, the simulated variability shows no consistent error with some models overestimating and some models underestimating the observed amplitude. Seasonality errors are also less pronounced in these regions.

CAUSES OF EASTERN OCEAN SST BIASES

Underestimation of Stratocumulus Cloud

It has long been recognized that GCMs face great difficulties in reproducing observed stratocumulus cloud fraction and optical depth over the eastern subtropical oceans.[37–39] While there may be many reasons for this shortcoming, an obvious hurdle is representing the sharp vertical temperature gradient in the thin layer that separates the cloud top from free troposphere. Over a few tens of meters, temperature increases by several degrees Celsius,[40,41] providing stability that inhibits vertical motion and thereby confines the cloud decks to the planetary boundary layer. The vertical resolution of current GCMs is typically several hundred meters (see Table 1 for vertical resolution used in some state-of-the-art GCMs), leaving them unable to resolve the sharp gradients of temperature and moisture across the cloud top. Furthermore, the vertical mixing that lifts surface moisture to the stratocumulus level is driven by small-scale turbulence (relevant eddy sizes ranging from about 10 to 1000 m in both the horizontal and vertical directions) that cannot be represented explicitly in GCMs. That resolution issues are a major factor in this problem is documented by the success of small-domain models that do resolve the relevant eddies (so called Large Eddy Simulation or LES models; e.g., Ref 42). These models usually have a horizontal domain size of a few kilometers and a resolution of about 10 m both in the horizontal and vertical. Boundary conditions for LES simulations are usually idealized, with, e.g., a constant subsidence rate prescribed at the model top. As the resolution of LES models is several orders of magnitude higher than what is feasible for current GCMs, the only way of representing stratocumulus in large-scale models is through parameterizations.

While stratocumulus decks can be seen as a product of the favorable large-scale environment, they themselves help to shape this environment. Reduction of downward surface radiation by stratocumulus cools SST and increases lower tropospheric stability, which creates a favorable environment for the clouds. SST biases and deficient stratocumulus decks are therefore often seen as two elements of a feedback loop: an error in cloud cover leads to excessive shortwave radiation reaching the sea surface. SSTs rise and thereby decrease the lower tropospheric stability, which makes conditions less favorable for stratocumulus persistence. Thus cloud cover decreases further, closing the feedback loop.[43] This has led to the idea that eastern boundary SST biases are to a large extent attributable to the inability of the models to reproduce realistic cloud cover in the region.[17,39,44–46] There are, however, some indications to the contrary. First, the SST biases have a strong coastal signature (Figure 1(b)), while stratocumulus biases do not (Figure 2(a)), indicating that a significant source of the bias lies in the insufficient coastal upwelling.[34] Furthermore, recent studies show that, on average, downward surface shortwave radiation biases in the stratocumulus regions are overcompensated for by excessive upward latent heat and longwave radiation fluxes.[16,32,33,47,48] Thus, on its own, the simulated surface net energy balance in the models should produce cooler than observed SST. The excessive upward fluxes are already present in atmospheric GCMs forced with observed SST and can therefore not be attributed solely to warm SST biases.[16] Regarding the stratocumulus–SST feedback, it has been shown for the Namibian stratocumulus region that the warm SST bias in Coupled Model Intercomparison Phase 5 (CMIP5) models increases net surface shortwave radiation by only $2\,\mathrm{W\,m^{-1}}$.[13,16] Thus the persistent SST bias in the fully coupled models has a relatively small influence on the surface energy balance, which suggests that the stratocumulus feedback is weak, at least in this particular region.

Errors in Surface Wind Stress

Coastal upwelling is to a large extent controlled by the strength of alongshore winds and their curl. The alongshore winds form the eastern flank of the subtropical anticyclones, which are controlled by large-scale subsidence associated with the Hadley cell, land–sea contrast, and orography.[49] GCMs simulate alongshore winds that are too weak (Figure 3(b)), which contributes to their insufficient upwelling.[16,33,34] Several eastern boundary regions feature significant coastal orography (particularly the Peruvian and Namibian regions) that cannot be fully resolved by GCMs. Some studies indicate that this failure to resolve coastal orography is a major contribution to the weak alongshore winds in the models.[14,34]

The strength of upwelling along the eastern boundaries depends on two properties of the winds:

the mean strength of their alongshore component, which leads to offshore transport with compensating upwelling at the coast; and their curl, which induces Ekman divergence and upward velocities a little distance offshore. Both the maximum wind speed and the maximum wind stress curl are displaced offshore in GCMs, often by several hundreds of kilometers (Figure 2(d)).[34,50] This contributes to comparatively weak alongshore winds and also places the area of maximum Ekman pumping too far offshore. Both factors contribute to the weak upwelling close to the coast in the GCMs. The reason for the offshore displacement of wind stress curl may again be attributed to orography issues but also to the representation of land–sea contrasts.

Conditions in the eastern boundary upwelling regions depend on not only local but also remote wind forcing. This is due to oceanic Kelvin waves that can be excited by wind stress changes over the equatorial oceans. Kelvin waves travel eastward along the equatorial waveguide and, upon reaching the eastern boundary, are transmitted into coastal Kelvin waves that propagate poleward along the coast in either hemisphere. Through these waves, winds over the equatorial oceans can influence coastal upwelling regions, and this has been suggested as the dominant influence on interannual variability in those regions,[51–53] though the importance of remote effects relative to those of local wind stress anomalies remains under debate.[54–56] In terms of GCM biases, it has been suggested that weaker than observed wind stress over the equatorial Atlantic contributes to the insufficient vertical temperature stratification and warm SST biases in the Namibian upwelling region.[50,57,58] Westerly wind biases over the equatorial Atlantic are a well-documented shortcoming of most GCMs during March–April–May (MAM) and exist even when the atmospheric components are forced with observed SSTs, indicating that this error originates in the atmosphere.[59] Model experiments indicate that, for the GFDL CM 2.1 model, the westerly wind biases may contribute about 25% to the warm SST bias in Namibian upwelling region.[57] Other studies suggest that the contribution could be even higher, but more work needs to be done to quantify this influence with confidence. The reason for the equatorial westerly wind bias remains under debate, but the erroneous southward shift of the simulated Atlantic intertropical convergence zone (ITCZ) and precipitation biases over the Amazon and Congo regions have been proposed.[57,60] Westerly wind biases on the equator may also be partly responsible for the overshooting of the poleward Angola current in GCMs because they lead to higher than observed sea level at the eastern boundary, which contributes to the strength of the current.

Westerly wind biases in the equatorial Atlantic not only influence the Namibian upwelling region but also lead to reduced upwelling on the equator. This inhibits cold tongue development and contributes to the warm eastern equatorial SST biases that characterize most GCMs.[59] Due to the vicinity of the eastern equatorial Atlantic to the Namibia/Angola upwelling region, maps of the SST biases show a contiguous area of warm biases stretching from the equator to about 30°S (Figure 1(b)), but this may actually obscure the fact that the two biases are, at least partly, of different origin.

In the equatorial Pacific, GCM wind biases are typically easterly rather than westerly, and therefore cannot explain the warm biases in the Peruvian upwelling region.[47] Conversely, the influence of equatorial easterly wind biases may compensate for other model errors.

Unresolved Offshore Transport by Ocean Eddies

Eastern boundary regions, like many other oceanic regions, feature mesoscale eddies that contribute to the transport of momentum and tracers (such as temperature and salinity) and have spatial scales from ~20 to 100 km. The mean currents in the eastern boundary regions are comparatively weak (~10 cm s^{-1}), and thus eddy activity may contribute substantially to oceanic transport.[61] The small spatial scale of mesoscale eddies prohibits their simulation in current GCMs that typically feature horizontal resolution of 50 km or higher (Table 1). Observations suggest that these eddies transport cold water from the coast toward the ocean interior,[62] thereby making a significant contribution toward balancing heating by downward shortwave radiation in the region.[63] A regional model study with 9 km horizontal resolution demonstrates that the eddies are indeed an important contribution to the heat budget of the subtropical southeastern Pacific, with cooling comparable to that provided by the large-scale offshore transport.[34] This is a strong indication that the failure of GCMs to resolve mesoscale eddies contributes significantly to the warm SST biases. Similar results were obtained with a different GCM at 1/3° (~30 km) horizontal resolution.[64] There are, however, conflicting studies. A GCM study using 1/12° (~8 km) resolution found no significant contribution from the mesoscale eddies to eastern boundary cooling.[65] Similarly, a few regional modeling studies found that resolving mesoscale eddies does not necessarily guard against the type of severe biases typically found in CGCMs.[50,58] Also note that the CMIP5 model with the highest resolution in the ocean (MIROC4h at ~1/4° or ~25 km) shows more severe SST biases in the eastern boundary regions than the multi-model average.

DISCUSSION OF ERROR SOURCES

Various explanations have been put forth for the consistent warm SST bias in the eastern boundary regions. While some of the explanations and associated mechanisms may be complementary, others are in direct conflict. Here I point out some of the discrepancies and attempt to reconcile them.

The first problem regards the universality of the SST biases. While all CMIP5 GCMs suffer from warm SST biases in the boundary regions, this does not hold true for regional climate models (RCMs). In fact, the *cold* bias of RCMs in the Peruvian and Namibian upwelling regions is a well-known problem.[66] Both GCMs and RCMs rely on the parameterization of processes such as vertical and horizontal ocean mixing and atmospheric convection. The fact that RCM and GCM biases are of opposite sign therefore challenges the universality of the problem and suggests that warm coastal biases are not an inevitable outcome of model simulations in the region.

So what are the reasons for the opposite biases in RCMs and GCMs? One factor that usually distinguishes RCMs is their higher resolution relative to GCMs though both types of models come at a variety of resolutions. Typically, however, RCMs are able to resolve oceanic mesoscale eddies, which should enable them to simulate more realistically offshore transport from the upwelling regions.[34] Thus the cold bias in RCMs could be seen as supporting the importance of resolving mesoscale eddies. Xu et al. (Ref 50) provide a different explanation. In their regional ocean model experiments of the tropical Atlantic with varying domain sizes, the warm bias along the Benguela coast turns into a cold bias once the western equatorial region is excluded. Noting that subsurface temperature biases associated with a diffuse thermocline are most pronounced in the western equatorial Atlantic, Xu et al. suggest that errors there propagate toward the Benguela region via advection or equatorial and coastal Kelvin waves. As Xu et al. used observed surface fluxes to force their ocean model, the results also imply that the biases in the southeastern Atlantic have a large component that is rooted in the ocean.

While the results of Xu et al. make a convincing case for remote oceanic influences in the southeastern Atlantic biases, it is not clear to what extent this error source is model dependent. The equatorial subsurface temperature biases in their regional model are significantly more severe than those found in most CMIP5 GCMs. In fact, some CMIP5 models actually have a subsurface *cold* bias in the western and central equatorial Atlantic. It is also not clear why the thermocline should be particularly diffuse in the western equatorial Atlantic and why such a misrepresentation is necessarily associated with a warm bias (rather than cold and warm biases above and below the thermocline, respectively). An analogous experimental setup performed with different regional models could help ascertain the robustness of the proposed mechanism, while GCM experiments with subsurface restoring in the equatorial Atlantic could help clarifying whether it applies to global models as well.

Conflicting results exist regarding the benefits of increasing model resolution in the atmosphere and ocean, with some studies indicating significant improvements[34,67,68] and others indicating little change.[14,58,69,70] First it should be noted that few studies have investigated the impact of resolution in isolation; often resolution changes are accompanied by other modifications, e.g., in parameterizations, which makes assessing the resolution effect difficult. Moreover, the exact meaning of 'improvement' and the resolution ranges in question have to be taken into account to reconcile these differences. Two important error sources are the near-shore winds and mesoscale eddies in the eastern ocean boundaries. Adequately resolving either of these two aspects requires resolutions of 10 km or finer. Thus increasing GCM resolution within a certain range (say from 200 to 100 km) is likely to have little impact until a certain threshold is reached at which relevant motions start being resolved. Further improvements will probably occur when GCMs manage to explicitly resolve stratocumulus clouds but this is not a likely prospect for the foreseeable future.

While SST biases in the southeastern Pacific and Atlantic show very similar spatial patterns, it remains to be clarified whether the underlying causes are similar in the two basins. The poleward Angola current and the sharp temperature gradient of the ABFZ have no counterpart in the southeastern Pacific and thus are potential error sources unique to the Atlantic. Some studies indicate that surface shortwave radiation errors play a bigger role in the southeast Pacific because the stratocumulus decks there are optically thicker than their Atlantic counterpart.[71,72]

Several studies conclude that, while GCMs overestimate surface downward shortwave radiation in the eastern ocean boundaries, this erroneous heating is overcompensated by excessive cooling, mostly through latent heat flux (Figure 2(c)).[16,32,33,47,48]

Furthermore, there is evidence that the stratocumulus–SST feedback may be weaker than originally thought.[16] These findings are in contrast to earlier studies that found significant impacts from stratocumulus under-prediction.[17,39] It is important to note that the latter studies corrected shortwave fluxes in isolation without fixing the excessive latent heat and longwave fluxes common to most models. Doing so would likely act to exacerbate the warm SST bias slightly. Thus, stratocumulus-related shortwave flux biases in isolation are an important contribution to SST biases and have to be remedied; however, the compensation by other flux biases means that the SST errors currently seen in GCMs are mostly due to other sources.

IMPLICATIONS OF EASTERN OCEAN SST BIASES

While GCMs serve many purposes prime among them is their use in seasonal prediction and global change projection. A vital question regarding eastern ocean biases must therefore be to what extent these biases compromise the models' ability to serve the aforementioned purposes. Surprisingly few studies have attempted to address this issue. This is in stark contrast to the vast number of studies citing bias improvement and its alleged benefits to models as motivation; the underlying assumption being that improving mean state biases will inevitably lead to improved model prediction skills.

Before examining how mean state biases affect prediction skill and projections, one may ask how they affect the simulated interannual variability. One frequently cited study in this context is the work by Ma et al. (Ref 39). By prescribing 100% Peruvian stratocumulus cloud cover in a coupled GCM, they obtained profound changes that generally improved the simulated tropical Pacific climate. The increased cloud cover first reduced the local warm SST bias and increased sea-level pressure. This invigorated the Hadley cell and southeastern trades, leading to stronger upwelling, eastern Pacific cooling and an intensification of the Walker cell. It should be kept in mind, however, that the experiment was highly idealized and therefore likely overestimated the potential climatic impact of alleviating stratocumulus errors. Furthermore, while the coupled model suffered from a warm SST bias in the eastern equatorial Pacific[39] some current GCMs are struggling with a cold bias in the region and would therefore not benefit from additional cooling. A different study focusing on the tropical Atlantic found that increased stratocumulus cover over the southeastern tropical Atlantic did have mixed impacts on the regional climate, with SST biases on and north of the equator deteriorating.[91] This indicates that previous results[39] may partly be region and model dependent and thus warrant further verification.

Several studies have performed GCM experiments in which SSTs in the Peruvian or Namibian stratus region are restored to observations. One study found that restoring SST in both southeastern boundary regions simultaneously led to a decrease in SST that extended far west and equatorward of the restoring region and generally reduced the warm SST biases in those regions.[14] This also improved the south-equatorial ITCZ bias in both basins. A similar result for the Atlantic ITCZ was obtained by different authors who tested the impact of SST biases in the southeastern Atlantic only.[16] They found that the southeastern Atlantic SST biases not only shift the Atlantic ITCZ southward, but also cool the tropical western Atlantic and eastern Pacific, which contributes to the cold biases in those regions and hints at interbasin connections.

It has been shown that a southward shift of the Atlantic ITCZ weakens the equatorial trades and therefore contributes to the MAM westerly wind bias common to most GCMs.[60,73] This indicates a potential coupling of equatorial and southeast Atlantic SST biases,[32] in which an initial southeast Atlantic SST bias leads to an erroneous southward shift of the Atlantic ITCZ. This induces westerly wind biases on the equator that, through Kelvin waves and advection, exacerbate the original warm bias. Further work remains to be done to validate the importance of this mechanism to tropical Atlantic biases.

Whether mean state biases in GCMs affect their interannual variability and prediction skill has been addressed by few studies, none of which have targeted the eastern ocean biases specifically. Several studies show that applying flux corrections in the tropical oceans not only improves mean state SST but also ENSO-related variability.[74–77] Another study obtained similar results for flux correction in the equatorial Atlantic and its influence on Atlantic Niños.[78] There is also some suggestion that adjusting tropical SST can improve prediction skill in the tropical Pacific.[77] One study suggests that Peruvian stratocumulus cloud feedbacks influence Pacific decadal variability, which hints at the possibility that improved cloud representation may lead to better long-range predictions.[79] Obviously there remains much room for further study.

Observed temperature trends over the 20th century show some of the most robust warming in the southeast Pacific and Atlantic,[80] where most GCMs suffer from severe mean sate biases. Moreover, CMIP5 projections show a particularly large spread in this region and this is, at least partly, due to the inconsistent stratocumulus response among models.[23,26] An often-cited figure in this context is that a mere 4% increase in marine stratocumulus could offset the global temperature rise due to CO_2 doubling.[81] Obtaining robust projections for the stratocumulus regions is complicated by the two-way interaction between the large-scale circulation and the cloud scale. LES models with their O(10 m) resolution can represent stratocumulus relatively realistically but can only be run for very limited domain sizes (a few kilometers) and thus cannot simulate feedbacks from the large-scale circulation that may well turn out to be crucial to the response of stratocumulus under global warming.[23] LES simulations have been used to understand the response of stratocumulus to greenhouse gas forcing,[82] but such experiments necessarily rely on boundary conditions supplied by GCM projections and thus carry with them a lot of the uncertainty associated with the large-scale models. How eastern tropical ocean biases play into projection uncertainties remains largely unexplored. Recently, however, important steps in this direction have been taken. One study relates present state stratocumulus errors to their global warming response in a given model.[23] Another study suggests that GCM climate sensitivity (the magnitude of the temperature response to a given radiative forcing) is linked to the simulated strength of convective mixing between the lower and middle troposphere under present-day conditions, which is closely related to the incidence of low-cloud (though not necessarily of the subtropical stratocumulus variety).[83] This opens up the possibility of narrowing down GCM spread using present-day observations. More work along these lines will have to be performed.

WAYS FORWARD

Warm SST biases in the eastern tropical oceans are a long-standing problem in GCM simulations with only moderate improvement over the years. Several factors contribute to these biases. (1) The alongshore winds that are essential to coastal upwelling are misrepresented in GCMs, partially due to resolution issues. (2) Stratocumulus decks are underpredicted in the models, leading to excessive shortwave radiation at the ocean surface. (3) Mesoscale eddies and their contribution to offshore transport are not captured by the GCMs. (4) For the Atlantic, the equatorial westerly wind bias may contribute remotely to the coastal SST biases. (5) Oceanic components of GCMs fail to simulate the sharp thermocline that characterizes equatorial and coastal regions, leading to biases in the vertical temperature profile and upwelling-related cooling (Figure 3(d) and (e)).

The relative importance of these contributions awaits further quantitative assessment. Ideally this should be done in the context of a CMIP-style multi-model study, with all models performing a number of sensitivity tests according to the same protocol. Several useful approaches have been mentioned in this article[14,16,32,33,45,46,50,75,77] and could be combined to construct a comprehensive set of sensitivity tests. Experiments should include ocean-only and atmosphere-only simulations to evaluate the relative impacts of errors in the two components. Some specific suggestions are sets of atmosphere-only simulations with successively refined resolution to assess the impact on coastal winds, and corresponding ocean-only experiments that examine the upwelling generated by those coastal wind climatologies; ocean-only experiments with idealized wind stress fields to test the importance of alongshore winds and their offshore gradients; atmosphere-only experiments with SST errors specified in one particular upwelling region to investigate the far-field response to SST biases in upwelling regions; ocean-only experiments with varying zonal wind stress strengths on the equator to examine the role of remote impacts from the equatorial oceans (particularly for the southeast Atlantic region). These are just some examples to stimulate further ideas for experiment design.

An alternative way of assessing the error sources is to analyze the variable increments that data assimilation systems use to nudge GCMs toward observations.[84–86] This illuminates initial error development before coupled feedbacks can set in. As data assimilation systems are only available to few modeling groups, an alternative approach would be to take advantage of (or build on) already existing experiments, such as Transpose AMIP for the atmosphere[87] and decadal predictions in the CMIP5 archive for the ocean, which can help assessing initial error development. Indeed, some studies have already examined model biases from this angle.[32,33,88] For coupled error development, however, the data assimilation approach seems most promising.

A problem facing model developers regarding the eastern tropical oceans is that the target is insufficiently well known due to lack of observations. This is particularly true for the southeastern tropical Atlantic where subsurface data on temperature and currents are sparse. A recent European project, PREFACE,[89] may be able to reduce data gaps in the southeastern tropical Atlantic but continued measurements in both eastern tropical oceans and the overlying atmosphere will be needed to obtain reliable reference data.

While there is certainly hope that biases will gradually be reduced, it appears that we will have to continue to deal with them for the next decade or longer. It is thus vital to assess the impact of biases in the eastern tropical oceans on seasonal prediction skill. Little work has been done in this regard leaving plenty of room for new studies. An equally important question is whether GCM biases can be corrected for using statistical methods. This is an active area of research, particularly in the context of regional downscaling.[90] Another crucial issue that has to be addressed in the coming years is whether the eastern ocean warm biases and the shortcoming of stratocumulus representation have important impacts on global change projections. Research on this topic is still in its early stages,[23,79] but hopefully concerted efforts of the research community can deliver results before global change projections are rendered obsolete by observations.

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