

# Implications of CMIP3 model biases and uncertainties for climate projections in the western tropical Pacific

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**Abstract** Regional climate projections in the Pacific region are potentially sensitive to a range of existing model biases. This study examines the implications of coupled model biases on regional climate projections in the tropical western Pacific. Model biases appear in the simulation of the El Niño Southern Oscillation, the location and movement of the South Pacific Convergence Zone, rainfall patterns, and the mean state of the ocean–atmosphere system including the cold tongue bias and erroneous location of the edge of the Western Pacific warm pool. These biases are examined in the CMIP3 20th century climate models and used to provide some context to the uncertainty in interpretations of regional-scale climate projections for the 21st century. To demonstrate, we provide examples for two island nations that are located in different climate zones and so are affected by different biases: Nauru and Palau. We discuss some of the common approaches to analyze climate projections and whether they are effective in reducing the effect of model biases. These approaches include model selection, calculating multi model means, downscaling and bias correcting.

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## 1 Introduction

Climate model projections add to the many biophysical and socio-economic considerations that guide adaptation planning (e.g. Lehodey and Maury 2010). Many countries in the tropical Pacific region are comprised of low-lying atolls which are particularly vulnerable to sea level rise. Others are reliant on agriculture and fishing for their livelihoods and thus are vulnerable to changes to rainfall patterns, ocean temperatures, circulation and ocean chemistry. Despite this need, the Intergovernmental Panel on Climate Change, Fourth Assessment Report, Working Group I stated that “With a few exceptions, the spread in projections of hydrological changes is still too large to make strong statements about the future of tropical climates at regional scales” (IPCC, Christensen and Coauthors 2007 pg. 861).

To make climate projections of the future, global climate model use scenarios of future changes in greenhouse and other radiatively important gases to estimate physical changes in the ocean and atmosphere. In recent years, extensive analysis of climate projections have been conducted using models taking part in the World Climate Research Programme’s Coupled Model Intercomparison Project (WCRP CMIP3, Meehl et al. 2007). Climate simulations undertaken as part of CMIP3 were used in the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC) (Randall and Coauthors 2007) and further simulations will be conducted using the new generation of CMIP5 models (Hurrell et al. 2011) for the IPCC Fifth Assessment Report.

The climate in the western Pacific is associated with a complex set of processes and climatological features (Online resource S1). In particular, the position of the western Pacific Warm Pool and equatorial cold tongue influence large scale patterns of circulation and precipitation. On seasonal time scales, the western Pacific monsoon, Inter-tropical Convergence Zone (ITCZ) and South Pacific Convergence zone (SPCZ) vary in position and intensity. If models do not capture the extension of the SPCZ into the south-eastern extra-tropical Pacific, for example, the mean rainfall and variability over countries such as Fiji, Tonga, Niue and Cook Islands will not be correctly reproduced.

On interannual to decadal time scales, the climate responds to the El Niño Southern Oscillation (ENSO) and the Pacific Decadal Oscillation. Depending on location, El Niño and La Niña events alter temperature, rainfall, ocean nutrients (Lehodey et al. 1997), and tropical cyclones (Vincent et al. 2011) in different ways. As such, ENSO changes in the future could have major implications for the region.

For the tropical Pacific region, there is high confidence in certain large-scale projected changes. These include robust indications that large parts of the western Pacific sea surface should warm and become fresher as the warm pool extends eastward (Cravatte et al. 2009). In addition, the (near-equator) trade winds are likely to weaken (Vecchi and Soden 2007) with an increase in thermal stratification in the eastern Pacific (DiNezio et al. 2011, Ganachaud et al. 2012). Increased moisture transport in a warmer world is expected to lead to increased precipitation in the inter-tropical convergence zones on average (Christensen and Coauthors 2007), although the spatial patterns of rainfall change may be complex (e.g. Chou et al. 2009). To the south of the equator the south-easterly trades are expected to intensify (Timmermann et al. 2010).

While leading global climate models have progressed rapidly (Randall et al. 2007) they are not at the stage where we can simply read off future regional climate projections. One important reason for this is the existence of systematic biases or errors in these models. It is well recognized that model biases need to be considered when making climate projections (Christensen and Coauthors 2007). A thorough understanding of the model biases relevant to a region is required in order to provide climate projections that reflect the wealth of understanding we do have about the climate system (as well as indicating where further research, model development, higher model

resolution etc. are needed to reduce uncertainty). An example of acknowledging and discussing climate model biases when providing projections for the western tropical Pacific can be found in the Pacific Climate Change Science Program (PCCSP) report (Australian Bureau of Meteorology and CSIRO 2011) and accompanying Climate Futures Tool (see Whetton et al. 2012).

In this paper we provide a summary of those elements that are poorly simulated in historical (20th century climate) simulations for the western tropical Pacific and in particular those features that show systematic biases across the set of CMIP3 models. These same issues are relevant for projections derived from the CMIP5 models as the biases are largely still present (Guilyardi et al. 2012, WCRP Workshop on Coupled Model Intercomparison Project Phase 5 Model Analysis, Hawaii 5–9 March 2012). We then discuss why many systematic model biases cannot be removed with simple techniques and why more complex analysis is needed. We hope that this review will add value to applications that use localized information taken from the CMIP3 (and CMIP5) models particularly in the western tropical Pacific region.

## 2 Methods - details of models used in study

In this study we use output from global climate models (or general circulation models, GCMs) in the WCRP's CMIP3 multi-model dataset (Meehl et al. 2007). Details of which models were used in each analysis vary as the availability of model output changes between scenarios and variables and results have been incorporated from a number of different individual studies. All realizations are used to construct a model mean for an individual model, and all available model means are used to construct the multi-model mean. Details of the CMIP3 models are outlined in Ganachaud et al. 2012.

A variety of observational data sets are used to assess model performance:

### **Sea Surface Temperature (SST)**

Hadley Centre Sea Ice and SST dataset (HADISST) (Rayner et al. 2003)

Second Hadley Centre SST dataset (HADSST2) (Rayner et al. 2006)

Extended Reconstruction SST version 3 dataset (ERSSTv.3) (Smith et al. 2008)

Kaplan Extended SST V2 (Kaplan et al. 1998)

### **Precipitation**

Global Precipitation Climatology Project (GPCP, Adler et al. 2003)

Climate Prediction Centre Merged Analysis of Precipitation (CMAP, Xie and Arkin 1997)

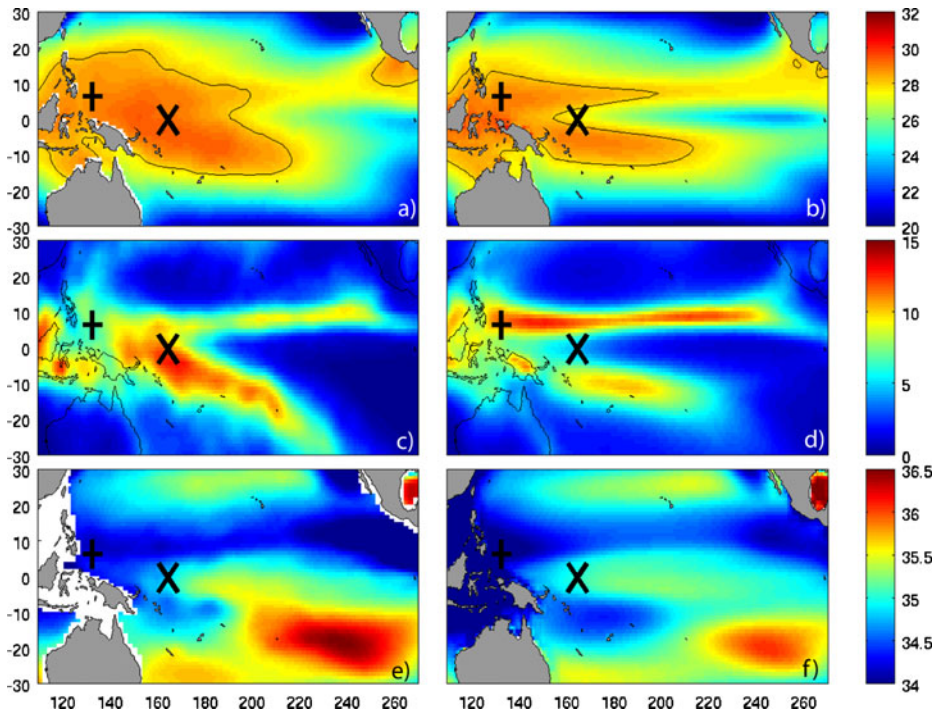
**Subsurface salinity and temperature** (Durack and Wijffels 2010)

We focus on the region of the western tropical Pacific (Online resource S1). In particular, as case studies for investigating the implications of model biases on national projections, we focus on the Exclusive Economic Zones (EEZs) of Nauru (regions surrounding approximately 0°31'S and 166°56'E) and Palau (7°21'N and 134°28'E). These two countries lie in different climate zones and are subject to different model simulation biases in the 20th Century.

## 3 Model biases and model discrepancies in the western tropical Pacific

### 3.1 Biases in the mean state and trends of the western Pacific

The western Pacific warm pool is characterized by fresh, warm water of temperatures greater than 28°C (Fig. 1a) and salinity less than 35 psu (Fig. 1c) (see Cravatte et al. 2009 for



**Fig. 1** *Top*: Annual mean SST ( $^{\circ}\text{C}$ ) (*top*), DJF precipitation ( $\text{mm day}^{-1}$ ) (*middle*) and sea surface salinity (*bottom*). Observations shown on left and multi-model mean on right. SST and SSS are averaged over 1950–2000 and precipitation over 1980–2000. SST observations are from HadISST, Precipitation observations are from CMAP, and Sea Surface Salinity from observations (Durack and Wijffels 2010). Models used are from the 20th century runs of the WCRP CMIP3 database over corresponding time periods. The  $28^{\circ}\text{C}$  isotherm is plotted in black on the SST panel. Nauru is denoted by X and Palau by +

review). A sharp salinity front demarcates the warm, fresh water from the surrounding cool, saltier water.

The cooler waters of the eastern equatorial Pacific are known to extend too far west in almost all CMIP3 models. Consequently, the western Pacific warm pool is contracted westward and the zonal winds are generally too strong in the west (Guilyardi et al. 2009). This is known as the *cold tongue bias* (e.g. Reichler and Kim 2008). This systematic bias cannot be eliminated by selecting the best performing models or taking a multi-model mean due to its presence in almost all models. Ocean heat flux adjustment applied to the models can reduce or remove these SST biases, and the associated rainfall biases. However, these are inherently undesirable because they are not physically based and can significantly alter the temporal evolution of climate simulations (Neelin and Dijkstra 1995).

Precipitation is notoriously difficult to simulate for a variety of reasons (Dai 2006). Biases in mean SST have flow-on effects on mean precipitation and contribute to associated biases observed. Biases simulated in precipitation further contribute to biases in surface salinity. Precipitation biases are most prominent in the tropical Pacific, where the largest disagreement with observations are evident in the South Pacific Convergence Zone (SPCZ) and Intertropical Convergence Zone (ITCZ), discussed in following section.

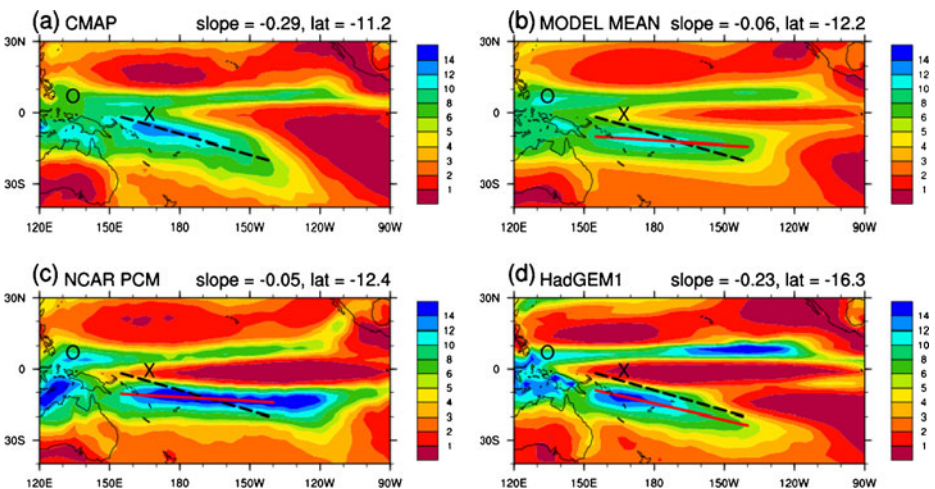
### 3.2 Intertropical convergence zone and south pacific convergence zone

Most state-of-the-art coupled models are able to simulate distinct bands of converging surface winds and convective rainfall forming the ITCZ and SPCZ (Fig. 2). However, models tend to simulate the extension of the equatorial dry zone between the ITCZ and SPCZ too far towards the west. This is associated with the SST and wind biases discussed above. The mean position and seasonal movement of the ITCZ is reasonably well simulated by most models although the ITCZ tends to be displaced too far north in the Northern Hemisphere summer in many models (further discussion in Australian Bureau of Meteorology and Commonwealth Scientific and Industrial Research Organisation 2011).

The majority of models also simulate an SPCZ rainfall band, although the simulated SPCZ tends to have an overly zonal (east–west) orientation rather than the observed northwest to southeast orientation (Fig. 2), particularly east of the dateline (Brown et al. 2011). In extreme cases, the model SPCZ has a purely zonal orientation, parallel to the ITCZ (Bellucci et al. 2010). Some models also have an extension of the Southern Hemisphere rainfall band into the far eastern Pacific. While there is an observed rainfall band in this region in March and April, many models simulate a permanent “double ITCZ”, or a rainfall band alternating between hemispheres over the seasonal cycle (de Szoeke and Xie 2008).

The SPCZ exhibits significant displacement associated with ENSO variability. Typically, the SPCZ moves north-east during El Niño and south-west during La Niña events (Vincent et al. 2011). Most models are able to capture some movement of the SPCZ in response to ENSO (Brown et al. 2011), but if the mean position of the SPCZ is not correct in a model, then the rainfall change associated with ENSO will be unrealistic, and in some locations of the wrong sign.

In the case of Nauru, in most CMIP3 models the western portion of the SPCZ is located too far south, with a dry zone between the SPCZ and ITCZ, resulting in a dry bias over Nauru. As this dry bias is associated with the persistence of overly cold SSTs on the equator

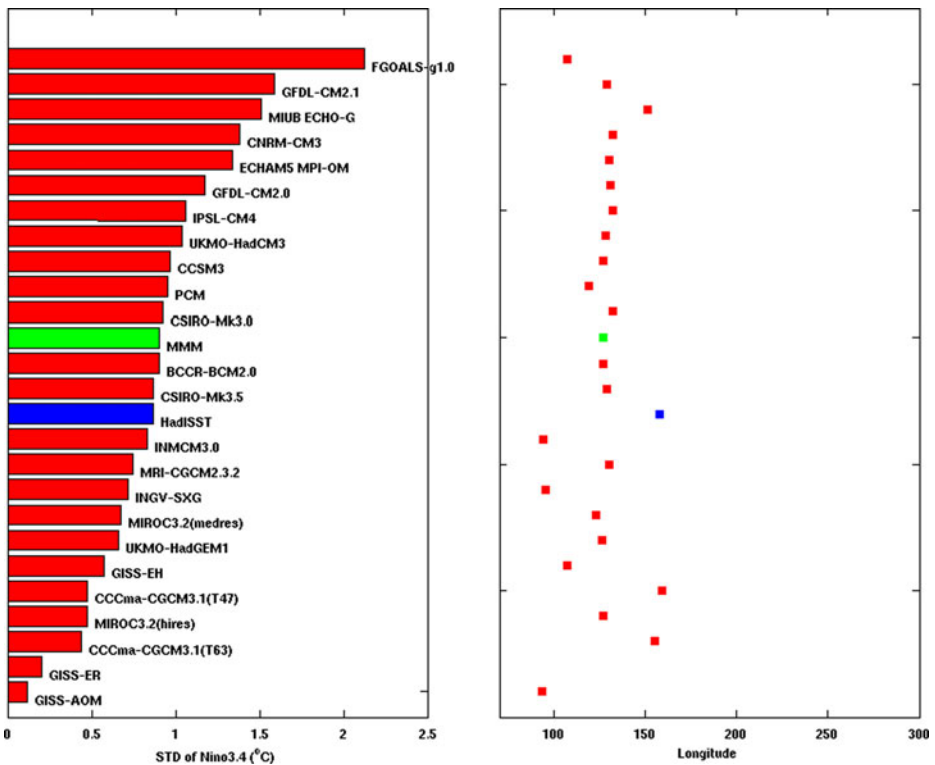


**Fig. 2** Location of the SPCZ determined from seasonal mean Dec-Feb precipitation (mm/day). (a) Observed precipitation from CMAP (1980–1999), (b) Multi-model mean from CMIP3 models (1980–1999), and example models (c) NCAR PCM and (d) HadGEM1. Red line shows mean position of SPCZ for models, compared with observed position (black dashed line). “O” is location of Palau, and “X” is location of Nauru. Figure adapted from (Brown et al. 2011)

in this region, some models do not simulate the northward shift of the SPCZ over Nauru during El Niño events. Models may also simulate unrealistically large percentage increases in rainfall over Nauru in future climates relative to the dry 20th century mean state. It is also expected from theory and models that to first order net precipitation should scale as the mean state precipitation multiplied by the temperature change (Held and Soden 2006). As a result, if the simulated precipitation distribution in the 20th Century mean state is significantly wrong then the spatial pattern of the precipitation projection is likely to be wrong.

### 3.3 El Niño Southern Oscillation

There is considerable variability in the simulation of ENSO in the CMIP3 models, as highlighted by the strength of the variability of the Nino3.4 index (Fig. 3a). Despite these differences, the multi-model mean of the Nino3.4 standard deviations (green bar in Fig. 3a) is very similar to the observations (shown in blue). In addition to Nino3.4 strength there are also considerable differences in the frequency, seasonal timing and spatial pattern in ENSO simulated in the models (Guilyardi et al. 2009) in CMIP3 and also in CMIP5 (Guilyardi et al. 2012).



**Fig. 3** Left: Standard Deviation of Nino3.4 (Sept-Nov) over the 1900–2000 period of the 20th Century CMIP3 runs, ranked smallest to largest. Observations (from HadISST) are shown in blue and the multi-model mean in green. Right: The longitude of the zero line of the ENSO response in SST. Location is found by correlating Nino3.4 with SST and identifying the location where the correlation changes from positive to negative. Nino3.4 is calculated as the average SST in the region 5°S to 5°N and 170°W to 120°W over the 20th Century

Despite these large differences in the simulation of ENSO, there are systematic biases that are common to nearly all global coupled models. The systematic mean state biases in SST, discussed above, are manifest in the spatial pattern associated with ENSO. As the mean position of the warm pool edge is too far west in the models, so too is the location of the maximum ENSO SST variability (Fig. 3b) and associated dynamics. These factors can lead to differences in the amplitude, period, and dynamics of the simulated ENSO (Picaut et al. 1997; Maes and Belmari 2011). Similarly, the spatial bias in ENSO SST manifests in the location of wind-stress and precipitation anomalies (Online resource S2 e-h).

At some locations in the Pacific, biases in simulations of ENSO can lead to year to year responses of opposite sign to what is observed. This has major implications for projected changes to regional climatic variability and potentially for projected changes to the mean climate. This problem is largest at along the boundary of the warm pool and cold tongue. As a result, countries to the west of 160°W and away from the equator (Fig. 4) have systematically weaker simulated correlations between SST and precipitation than observed. If climate change leads to changes in ENSO variability then this bias becomes a significant issue for understanding future climate.

In the case of Palau, if the future climate shifts towards an increased frequency of strong El Niños, instead of projecting a strong rainfall decrease, many models would simulate projected rainfall increases (Fig. 4). Nauru, because of its location on the boundary between cool and warm ENSO-related SST anomalies, is only moderately affected by ENSO variability. Yet, in all model simulations, the ENSO SST bias means that Nauru becomes located within a region of very strong positive ENSO SST correlation (Fig. 4). This bias again poses problems for investigating changes in the 21st century projections. For example, if there was a future increase in the amplitude of ENSO variability it might drive strong changes for Nauru's climate in the models when, in the real system, its effect would be more modest.

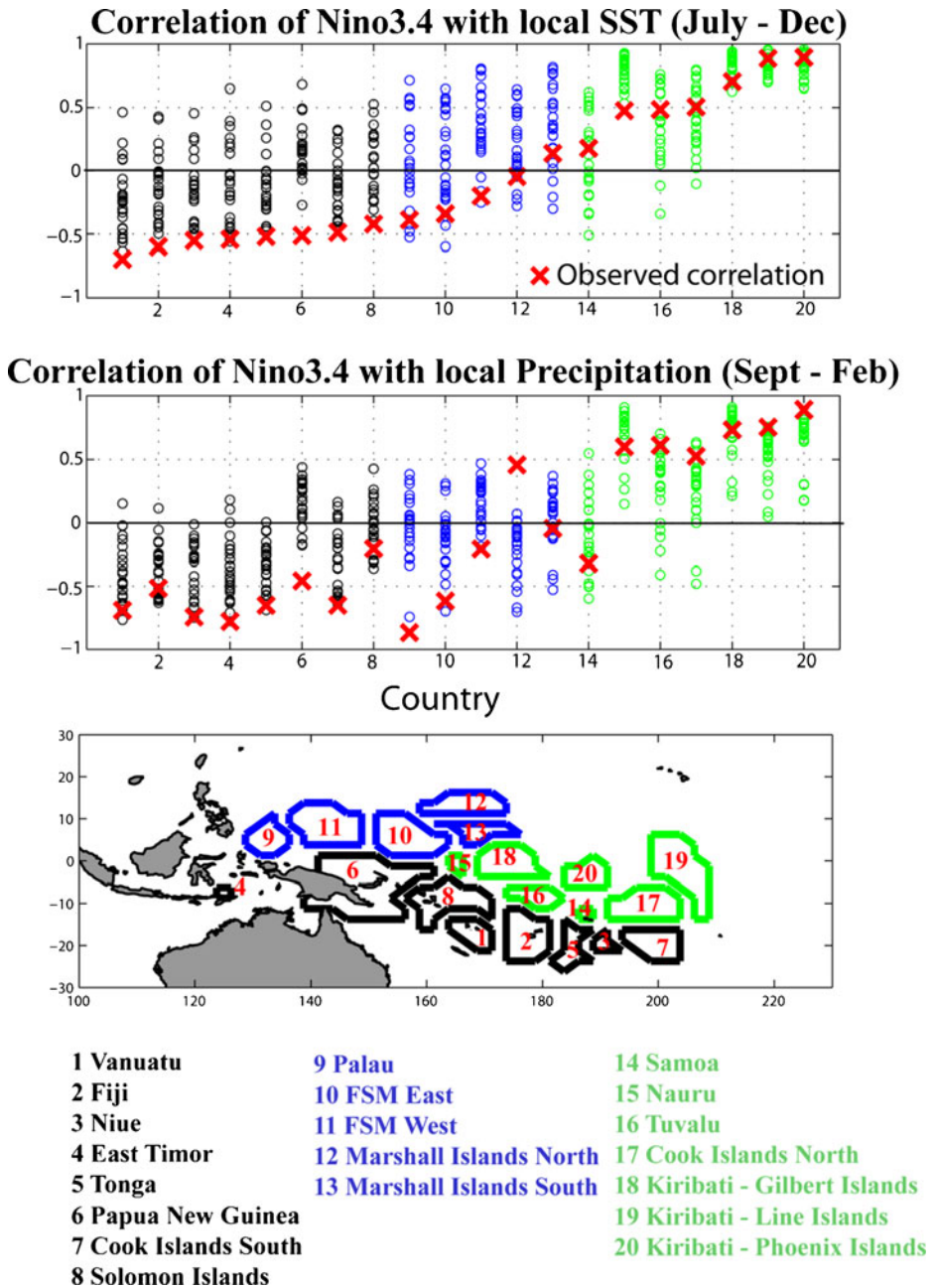
The CMIP3 models simulate ongoing interannual ENSO variability under greenhouse forcing, but no consistency regarding changes in projected ENSO characteristics, as some models simulate increased ENSO amplitude or frequency and others simulate a decrease in amplitude or frequency (Vecchi and Wittenberg 2010; Ganachaud et al. 2012).

### 3.4 Subsurface ocean

The subsurface tropical western Pacific ocean (Fig. 5a) is characterized by a surface warm pool extending to 100m or more, with strong stratification at its base defined as the thermocline. The thermocline domes upward in regions of Ekman pumping such as at the equator and in the vicinity of the ITCZ (around 8°N).

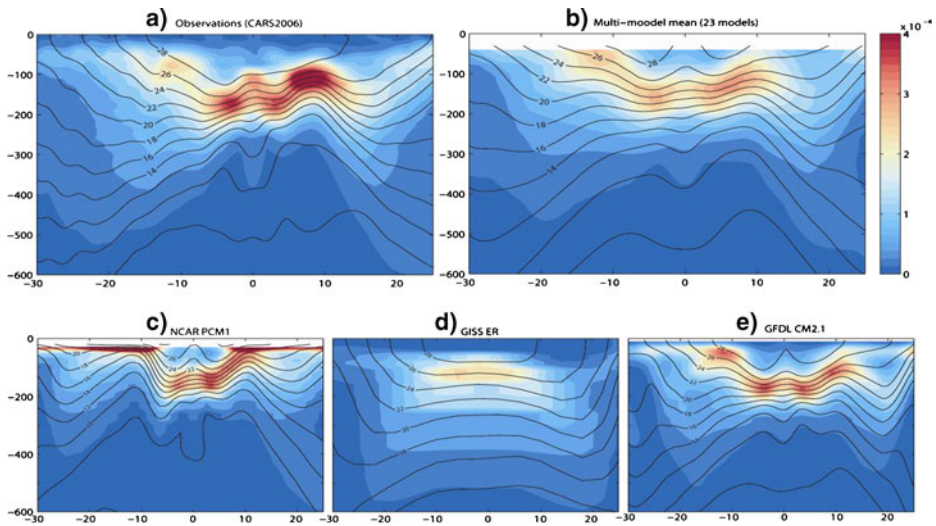
In general, most models are able to reproduce these features, although the warm pool tends to be less extensive and slightly cooler than observed (Fig. 5b, c, d). Many individual models also simulate a realistic subsurface structure, with the thermocline at approximately the correct depth, although the stratification is often underestimated. The double ITCZ bias introduces an erroneous upward doming in the southern hemisphere in many models (Zhang et al. 2007).

The vertical structure of temperature and density in the ocean are a defining feature for many oceanic processes. Biases that appear in the ocean subsurface temperature and salinity alter the ocean circulation and ocean current strength, upwelling, sea level and vertical mixing important for modeling marine biogeochemistry. In particular, biases in the thermocline structure affect the evolution of ENSO and the degree of coupling between ocean and atmosphere, important factors for reliable future climate projections. Sea level projections (discussed in the next section) are very sensitive to the correct simulation of the subsurface temperature and salinity profiles and any biases within.



**Fig. 4** Correlations of **a)** SST (July – December) and **b)** precipitation (September – February) with Nino3.4 for observations (*red cross*) and the CMIP3 models (*circles*) over regional EEZs. EEZs are outlined in **c)** and correspond to islands involved in the PCCSP. Regions bounded by green are situated in the Pacific cold tongue and tend to have a strong positive correlation with ENSO. The black and blue bounded regions represent the southern and northern branches around the cold tongue





**Fig. 5** Subsurface temperatures (*contours*) averaged between 160°E and 170°E. Calculations of the Brunt–Väisälä frequency  $N^2$  (representing the dynamical impact of stratification) are shown by the shading. **a**) observations from CARS 2006, **b**) Multi-model mean; and examples from individual models **c**) PCM **d**) GISS-ER and **e**) GFDL-CM2.1

### 3.5 Sea level trends

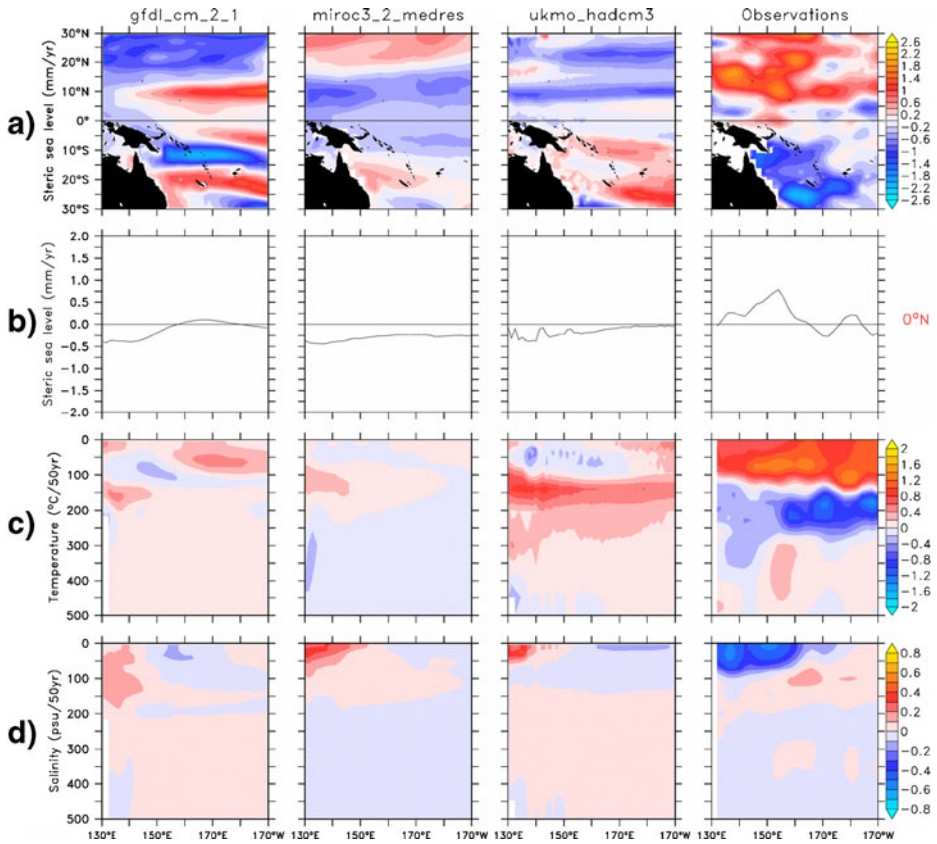
Trends in simulated sea level are influenced by model biases in the temperature and salinity at all time scales. In addition to such biases, ocean temperature and salinity often exhibit ‘model drift’ (Sen Gupta et al. 2012b). Differences in the way models reproduce interannual and low frequency variability also contribute to the projected sea level.

Western Pacific regional patterns of dynamic sea level change (mainly due to ocean density and circulation change) can be mostly explained by steric sea-level change calculated over the full ocean depth (Fig. 6). Over a period of 50 years for which reliable observations are available, the CMIP3 models show large discrepancies in the simulated sea level change compared to observations and large differences between models (Fig. 6a). The differences can be traced to the simulation of the temperature and salinity changes over the same period (Fig. 6c, d). Therefore, model biases in temperature and precipitation are likely to be important for sea level projections.

## 4 Accounting for model biases in climate projections

While it is not difficult to quantify the model biases in the western tropical Pacific, it is not clear how these biases might filter through to affect climate projections. Tuna for example are attracted to the ocean current convergence point near the dateline. In CMIP3 models this is simulated too far west or even right against Papua New Guinea. This convergence point is defined by a number of subtle features including windstress curl, upwelling rates of nutrients and gradients of salinity. When these are all poorly simulated for the 20th Century, projected changes for the 21st Century should be interpreted with caution.

Over the long-term, we can expect the simulation of the ocean–atmosphere system to improve, partly through better understanding of the key processes and partly through



**Fig. 6** Top row (a): Comparison between 1950–2000 sea level trends from 3 sample CMIP3 models and observations. Second row (b): Corresponding sea level trend along the equator. Third (c) and fourth (d) rows: Equatorial Depth sections of temperature and salinity trends. Model data have been de-drifted (Sen Gupta et al. 2012b) by removing the trend from the relevant control run. Observed steric sea level linear trend was derived from the linear trend of observed temperature and salinity dataset (Durack and Wijffels 2010)

inevitable advancements in computer power and model resolution (Risbey and O’Kane 2011). In the meantime, there are various techniques that are applied to global climate models to increase our confidence in future climate projections including model selection; use of multi-model means; downscaling; and bias-adjusting. While helpful in improving confidence in climate projections, they do not remove the effect of the systematic model biases and different techniques need to be employed.

#### 4.1 Model selection

A potential way to address model deficiencies in projecting future changes is to apply a model selection process based on performance of models compared to historical observations (e.g. Irving et al. 2011 for the western tropical Pacific) using a range of metrics. Deciding which are the most important criteria to assess models against is quite difficult. Different models tend to have strengths in different areas and at different spatial scales, performing relatively well in some metrics and not in others. For example, in the Nauru region, amongst a range of considerations, it would be important to have a model that

simulates the position of the SPCZ as well as possible. The variability of the SPCZ is however dependent on the simulation of ENSO, and the long term trend in the SPCZ may depend on the climate sensitivity of the model or the simulation of the Hadley Cell. It is not possible to determine which of these features is the most important as a selection criterion. Systematic model biases, such as the cold tongue bias and warm pool edge, occur in nearly all models and therefore can't be a criterion for model selection.

#### 4.2 Multi-model means

Use of a multi-model mean, in general, results in a more realistic depiction of the current climate than any individual model (Reichler and Kim 2008). It is also useful for summarizing results of model projections. Taking a multi-model mean removes non-systematic errors, reduces model drift (Sen Gupta, Ganachaud et al. 2012a) and reduces the aliasing of low frequency variability on the long term trend. However, systematic errors, such as the cold tongue bias, are not alleviated by multi-model means and must still be carefully considered. The multi-model mean can also 'smear out' climate features (due to averaging of slightly offset anomalies). The thermocline for example (Fig. 5) is much sharper in any individual model than in the average.

#### 4.3 Downscaling approaches

There is currently significant uncertainty in the ability of global climate models to represent small scale climate processes; particularly at sub-grid scales of less than 100 km. Use of dynamical downscaling approaches is one way to account for such processes whereby boundary conditions in the coupled global climate model are passed to a higher resolution atmospheric or ocean model. (e.g. CCAM, RegCM, PRECIS, WRF, MM5 – see Australian Bureau of Meteorology and Commonwealth Scientific and Industrial Research Organisation 2011, Ch. 4 for more information). This technique is useful as it allows the smaller scale features such as orographic rainfall or coastal upwelling to be explored in more detail. In terms of the systematic model biases discussed here, dynamical downscaling cannot eliminate the issue. If a bias is present in the boundary condition forcing, this will have an impact on the higher resolution model.

Statistical downscaling is another way to produce a less biased current climate simulation and regional projections that account for small scale forcing (Wilby et al. 2009). A variety of techniques can be applied, for example in empirical downscaling, a statistical relationship is developed between fine-scale historical observations and broad scale climatic conditions that can be simulated by climate models, and this same relationship applied in the future (e.g. Donner et al. 2005 for coral bleaching). While potentially removing the bias to some extent in the current climate, this approach will still be affected by any impact that the GCM biases have on the GCM projected fields used for downscaling. This method contains assumptions that the present day interactions of weather and climate systems will continue into the future (Pielke and Wilby 2012)

Finally, downscaled projections are often produced by simply adjusting a fine scale observed data base by the changes simulated by the GCM (the approach known as 'change factors', in Wilby et al. 2009). This approach, by definition, leads to no biases in the current climate case, but it too does not correct for any effect the GCM current climate biases have on the projected changes.

#### 4.4 Bias adjustment

A technique used (often within a dynamical downscaling framework) to account for spatial biases (including systematic biases) is bias adjustment (e.g. Australian Bureau of

Meteorology and Commonwealth Scientific and Industrial Research Organisation 2011, Ch. 4). In general, this involves ‘adjusting’ the projected forcing field by altering the current climate mean state to be the same as the observed mean state. This is often done to the SST to force an atmospheric model (Nguyen et al. 2011), or to the winds to force an ocean model (Chamberlain et al. 2012) The corrected fields are then used as boundary conditions for a subsequent higher-resolution simulation. The resulting output has a reduced (but not completely eradicated) current model bias in the mean and hence reduced biases in related variables such as precipitation. This method assumes that the mean climate state and other climate modes are independent, which is not the case for ENSO variability. As a consequence, the bias that remains in the interannual variability has the potential to feed back on the mean state, thus retaining aspects of the model bias that can remain significant for small-scale projections. Hence the methods of downscaling with bias adjustment cannot completely remove the influence of biases present in the climate model mean state and variability.

## 5 Conclusions

Some climate change due to increased anthropogenic greenhouse gases is now inevitable and action is being undertaken or planned to adapt to the regional impacts. Climate model output such as that from the CMIP3 and CMIP5 datasets, are being increasingly interrogated to provide regional and local climate projections at scales that are useful to inform adaptation decisions. While basin-scale projections for certain climate variables (e.g. temperature, sea level) can be made with a high level of confidence, uncertainty in climate projections becomes more prominent at smaller scales and for other climate variables such as precipitation.

At regional scales in the western tropical Pacific, systematic regional biases in global climate models can have significant impacts on projections. We have discussed the issues for Nauru and Palau regions for demonstration purposes, but they also apply to regions that lie around the observed and simulated edge of the cold tongue and warm pool via the same reasoning.

When using output from GCMs to create climate projections in the western tropical Pacific, the results should be interpreted with the model biases and uncertainties in mind. These considerations include, but are not limited to:

- The differing locations of each key climate feature, such as the SPCZ, in each model should be assessed in regard to whether it is situated in the correct place relative to the region of interest.
- Whether the region is affected by the mean state bias of the cold tongue and erroneously westward location of the edge of the warm pool. The mean state bias influences SST, salinity, wind -stress and precipitation.
- The mean state bias affects ENSO impacts. When interpreting changes to interannual variability it is important to determine whether the region has the correct climate response to ENSO in the historical simulations. Some regions have a response of the wrong sign and/or amplitude to ENSO.
- There is no consensus on the future behavior of ENSO. It can be misleading to only look at a few model projections without exploring the fuller range of possible ENSO futures, however this is often difficult due to limited resources.
- Those making projections of ocean biology should also be aware of the mean state subsurface biases. In addition, assessment should be made of how well the model

simulates the subsurface and particularly the thermocline. This can affect the simulation of nutrient upwelling.

- Sea level projections are highly sensitive to model biases that occur through the water column and require model drift correction for the relevant fields.

Our discussions have addressed only some of the model biases and issues in the region. Other biases relate to the simulation of the Hadley and Walker cells and the location and strength of ocean currents (Sen Gupta et al. 2012a), In addition climate change signals may be distorted by model drift (Sen Gupta et al. 2012b) or aliasing of low frequency natural variability like the Pacific Decadal Oscillation (Zhang and Church 2012)

Approaches to increase reliability of climate model projections were discussed including multi-model means, model selection, down-scaling and bias adjusting. While all methods are useful and may improve understanding, they cannot remove the effect that systematic biases have on regional projected changes. We can expect that in the future, models will improve and biases will reduce. In the meantime, other techniques are emerging that show promise for adjusting for the effect of model bias on projections. Examples include “pattern matching” of climate features (Moise and Delage 2011) and analyzing projected changes in particular climate features (e.g. the SPCZ) rather than changes at specific locations (Brown et al. 2012; Ganachaud et al. 2012)

In summary, the results from the climate models for regional climate projections should be used with caution by decision makers needing accurate and reliable information about local or regional trends or changes over coming decades. Our study has expanded upon this conclusion already drawn by the IPCC AR4 report (Christensen and Coauthors 2007, pg. 861). Information about the strengths and limitations of each model should be considered when interpreting climate model projections. The latest simulations as part of CMIP5 are now coming online and continue to show similar model biases (Guilyardi et al. 2012, WCRP Workshop on Coupled Model Intercomparison Project Phase 5 Model Analysis, Hawaii 5–9 March 2012) – though some of the more extreme biases seen in CMIP3 seem to have been reduced in CMIP5. We expect that the limitations discussed here will still remain relevant.

While the model results have varying levels of uncertainty, there is still a need for adaptation planning and implementation to occur. This must be done taking into account the systematic model biases where they have the potential to significantly affect projections (e.g. Wilby and Dessai 2010). Future work to reduce, manage and communicate the model biases is essential, as is the need to continue focusing on how we can develop techniques to provide higher confidence in our regional climate projections.

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