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Unambiguous warming in the western tropical Pacific primarily caused by anthropogenic forcing

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ABSTRACT: Small Island Developing States in the tropical western Pacific are among the most vulnerable to climate change. While a great deal of information on the observed climate change trends and their cause is available for many other regions and for the globe as a whole, much less information has been available specifically for the Pacific. Here, we show that warming over the past 50 years in the western Pacific is evident in recently homogenized tropical station data, and in gridded surface temperature data sets for the region. The warming has already emerged from the background climate variability. The observational data and Coupled Model Intercomparison Project Phase 5 climate model output are used to show that the observed warming was primarily caused by human-forced changes to the earth's radiative balance. Further warming is projected to occur in the same models under all three Representative Concentration Pathways (RCPs) considered (RCP2.6, RCP4.5 and RCP8.5), with the magnitude far exceeding the warming to date under the two scenarios with higher emissions (RCP4.5 and RCP8.5).

KEY WORDS warming; surface temperature; Pacific Islands; CMIP5

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1. Introduction

Small Island Developing States including those in the western Pacific Ocean are among the most vulnerable to climate change (Nurse *et al.*, 2014). During this century, these islands will face increasing threats to sustainable development from the impacts of climate change. Sectors that are likely to be most affected include human health, infrastructure, coastal resources, disaster management, water resources, agriculture, fisheries, forestry, marine ecosystems and tourism. It is important, therefore, that these nations have access to sound scientific information about the magnitude of any observed climatic changes, their possible causes and projections of future changes (ABoM-CSIRO, 2011, 2014; Power *et al.*, 2011).

The most recent Intergovernmental Panel on Climate Change (IPCC) Working Group 1 Assessment Report (IPCC, 2013) concluded that 'it is extremely likely that more than half of the observed increase in global average surface temperature (SAT) from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings', and that 'over every continental region except Antarctica, anthropogenic forcings have likely made a substantial contribution to SAT increases since the mid-20th century'. While this is very useful information, additional information specifically focused on the western Pacific will provide a clearer picture of how climate change affects nations in the region (ABoM-CSIRO, 2011; Power *et al.*, 2011). In this study, we will determine whether or not a similar statement can be made for the western Pacific region alone.

Using results from the Coupled Model Intercomparison Project Phase 3 (CMIP3, Meehl *et al.*, 2007) and Phase 5 (CMIP5, Taylor *et al.*, 2012) projects, several studies have been devoted to SAT detection and attribution (D&A) at regional scales (e.g. Sakaguchi *et al.*, 2012; Jones *et al.*, 2013b; Knutson *et al.*, 2013). Knutson *et al.* (2013) found an anthropogenic warming signal was detectable in the observed temperature records over large parts of the globe. However, there was no systematic detectable warming over the tropical Pacific region. Sakaguchi *et al.* (2012) found that the multimodel ensemble mean (MMEM) of three CMIP3 climate models reproduced robust signals in zonal mean SATs over the 20th century at 30° spatial scale. Jones *et al.* (2013b) found that the observed warming trend over the western tropical Pacific in HadCRUT4 over the period 1951–2010 is consistent with CMIP5 model simulations that incorporate both anthropogenic and natural factors. They also found, however, that the same trend was largely inconsistent with simulations incorporating natural factors over the same period.

Additional methods have been developed in recent years focusing on the time when mean temperature has deviated from the range of natural variability and stay outside that range permanently, a process recently referred to as *climatic expulsion* (Power, 2014). The time that climatic expulsion occurs is sometimes referred to as the time of emergence (ToE; Hawkins and Sutton, 2012).

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The concept of ToE is particularly useful for regional climate change detection as it takes into account of regional climate signal and noise (Kattsov and Sporyshev, 2006; Mahlstein *et al.*, 2011). Using an 11-year running mean of temperature against 1910–1959 baseline climate, Kattsov and Sporyshev (2006) find significant change has already occurred in the tropical Indian Ocean and the Western Pacific. Defining the temperature signal as its mean difference over the last 10 years of the 20th century and over the whole 20th century, and the noise as its interannual variability, Mahlstein *et al.* (2011) show that due to the small temperature variability from one year to another, the largest signal to noise ratio in surface air temperature occurs in low latitude countries, implying that the earliest emergence of significant warming might occur here. They pointed out, however, that the lack of high-quality observational data might preclude this in many tropical countries.

Fortunately, a new homogeneous data set for Pacific Island station temperatures has recently been developed through collaboration between scientists from the national meteorological services in the western Pacific region under the Pacific Climate Change Science Program (PCCSP, 2009–2011; Power *et al.*, 2011) and Pacific Australia Climate Change Science and Adaptation Planning program (PACCSAP, 2012–2013). The station observations have undergone systematic quality control and homogenization in which non-climatic step changes and other inconsistencies were removed. This improves both spatial and temporal consistencies among the data records for both variability and trends (Jones *et al.*, 2013a). This homogenization builds on earlier work by Manton *et al.* (2001), Page *et al.* (2004) and Griffiths *et al.* (2005). The availability of this new monthly scale data set is an important contribution to currently available SAT data, as only a fraction of these station data have been exchanged internationally and incorporated into global data sets such as the Global Historical Climatology Network (Menne *et al.*, 2012).

Jones *et al.* (2013a) show a larger than natural variability warming trend in a regional mean of Pacific island station temperature series in the new data set and find this regional mean station series compares well with a regional mean series extracted from a global gridded data set over 1961–2010. Here, we expand their study by using an updated Pacific island station data set and compare a regional mean of this newer station data set with several other global gridded data sets over 1953–2010. We also compare the observed warming in this region with simulated warming from CMIP5 climate models in order to examine the extent to which anthropogenic forcing causing the warming, and whether the warming signal has already emerged. We then examine the amount of additional warming that could occur over the western Pacific under different greenhouse gas emission scenarios for the remainder of the 21st century.

This work is part of the PCCSP/PACCSAP science programs, which sought to understand past climate trends and variability and provide regional and national climate projections to the partner countries in the programs and associated capacity building (ABoM-CSIRO, 2011, 2014; Power *et al.*, 2011).

2. Data and methods

2.1. Observational station and gridded data

The PACCSAP (formerly PCCSP) program includes the following 14 partner countries: Cook Islands, Federated States of Micronesia, Fiji, Kiribati, Marshall Islands, Nauru, Niue, Palau, Papua New Guinea, Samoa, Solomon, Tonga, Tuvalu and Vanuatu (ABoM-CSIRO, 2011, 2014) (refer to Figure 1). The observational station data that we use is limited to currently operational homogenized monthly mean surface air temperature (hereafter SAT) data for stations in 13 of the 14 partner countries where data is available (Jones *et al.*, 2013a). In order to define a representative annual mean temperature anomaly for the region, we first derive annual mean temperature anomalies for each station following the method outlined by Jones *et al.* (2013b) with modification. An annual mean anomaly is defined if there are nine or more monthly data values available in a given calendar year. The results are not sensitive to the choice of the minimum number of months of monthly data, from 2 months (as in Jones *et al.*, 2013b) to all 12 months. For example, the trends over 1953–2010 in the station temperature average index $T_{Station}$, defined below, are 0.77, 0.76 and 0.76 °C per 50 years for minimum monthly data of 2, 9 and 12 months, respectively. A 30-year period (1961–1990) is used to define a reference period from which anomalies are derived.

The maximum number of stations for which annual mean anomalies can be derived in any year using the above procedure is 37. However, there are missing data, particularly prior to 1950 as indicated by Figure 2. From these records, we use a common subset of stations which meet two criteria: (1) data are available in at least 20 of 30 years during the reference period and (2) data is available for at least 80% of the time during the entire analysis period 1953–2010. We use 1953 as the first year of the analysis period. This choice ensures that 20 or more stations meet these criteria. Details of these stations are given in Table S1, Supporting Information. From hereon, we refer to this subset as the station data.

To examine temperature changes at the regional scale, a time series of regional annual mean temperature was created by averaging the annual mean temperature anomalies of the station data. Different averaging methods were tested: (1) a plain average of the station data; (2) averaging station data within each Exclusive Economic Zone (EEZ) first (14 of 19 zones are defined, see Figure 1), and then a plain average of the values from the 14 zones; (3) same as (2) but a weighted average of the values from the 14 zones with weights being the area of the zones. The resulting indices of the average annual mean station temperature anomalies are not sensitive to the choice of averaging methods (figure not shown). We use the first method in this article and denote this as $T_{Station}$.

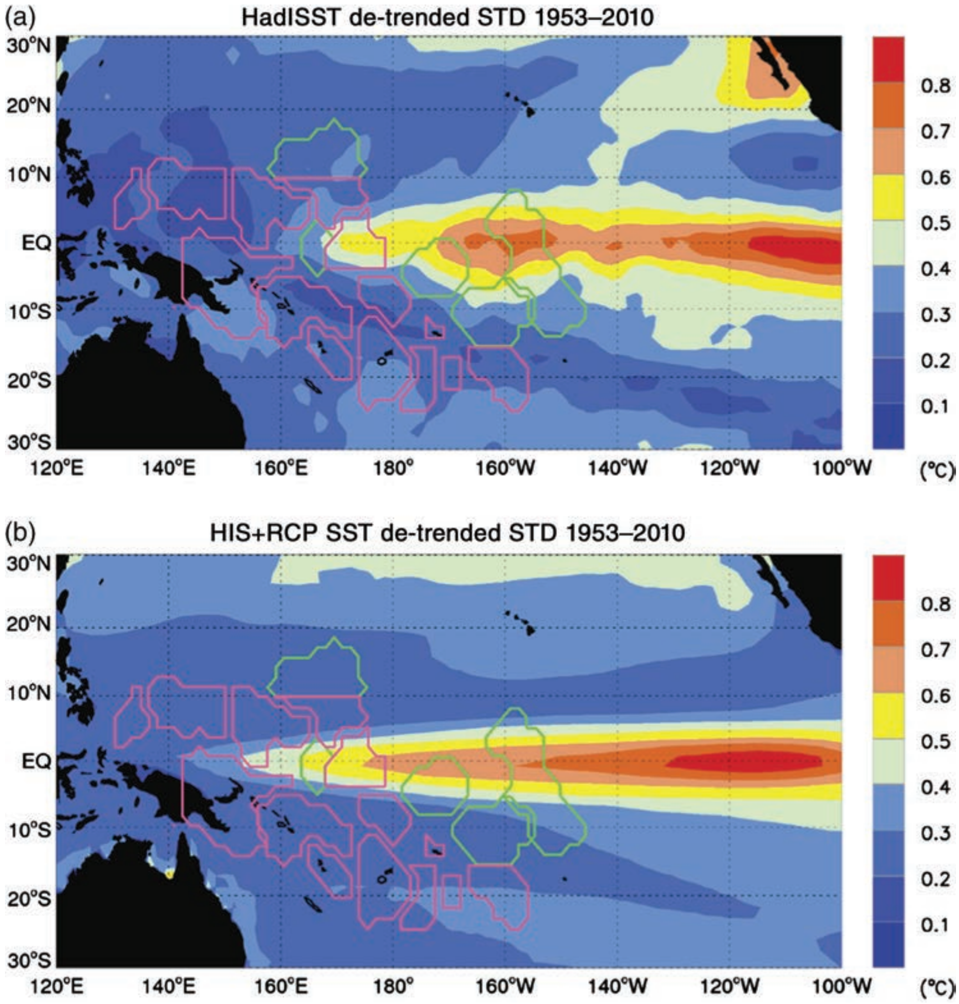

Figure 1. The standard deviation of detrended SST variability: (a) the observed (HadISST) and (b) the average of 14 CMIP5 models, with the EEZs and sub EEZs for the 14 partner countries superimposed (Source: Pacific Climate Futures, Clarke *et al.*, 2011, and Whetton *et al.*, 2012). The standard deviation is estimated using linearly detrended annual mean anomalies over the period 1953–2010. The model standard deviation presented is the multimodel mean of each model's standard deviation over the same period 1953–2010. SST variability in the Historical was used for 1953–2005, while RCP8.5 was used for 2006–2010. For the purposes of this article, we use 19 subregions based on EEZs of the 14 countries. We use the entire EEZ for ten countries, and we break up the large EEZs of the remaining four countries into two or three, to give a total of 19 subregions (for details see Pacific Climate Futures, Clarke *et al.*, 2011). Zone boundaries come from Flanders Marine Institute (Claus *et al.*, 2013). Zones encircled with green lines indicate there are no station data available for use in the article. The remaining 14 zones (in pink lines) are used in calculating the regional average temperature.

We compare $T_{Station}$ to other gridded climate data sets: HadCRUT4 (Morice *et al.*, 2012); NOAA Merged Land-Ocean Surface Temperature Analysis (MLOST) v3 (Smith *et al.*, 2008) and NASA GISS Surface Temperature Analysis (GISTEMP, Hansen *et al.*, 2010). The CRUTEM4 (Jones *et al.*, 2012), the land component of HadCRUT4, is also used as a separate data set in the comparison. Sea surface temperatures (SSTs) are closely related to SATs in the tropical Pacific (Whan *et al.*, 2014) and so we also make use of four gridded SST data sets: HadISST (Rayner *et al.*, 2003); Kaplan SST (Kaplan *et al.*, 1998); ERSSTv3b (Smith *et al.*, 2008) and COBE SST (Ishii *et al.*, 2005). All these data sets are largely drawn from the same sources, but differ in dealing with data quality control, measurement bias adjustments and data set gridding methodologies. Three gridded SAT data (HadCRUT4, MLOST and GISTEMP) are all a blend of land SAT and SST data sets. All these gridded data sets are subject to some degree of spatial interpolation except HadCRUT4 and CRUTEM4, neither of which employ any form of spatial infilling. In addition, the HadCRUT4 estimates we use here are the medians of 100 realizations of complex uncertainty and bias correction models (see Morice *et al.*, 2012 for more details) as the best estimate of the data set. We mainly use HadCRUT4 when comparing CMIP5 results with gridded observations for SAT.

The gridded data sets and the CMIP5 model output (see next section) are all re-gridded to a common $1.5° \times 1.5°$ grid before analysis. To be consistent with the $T_{Station}$, the same 14 EEZs are used as the study region over which the annual mean anomalies of the gridded data and the model outputs are averaged and weighted by grid cell size. These averages are denoted as T_{Grid} hereafter.

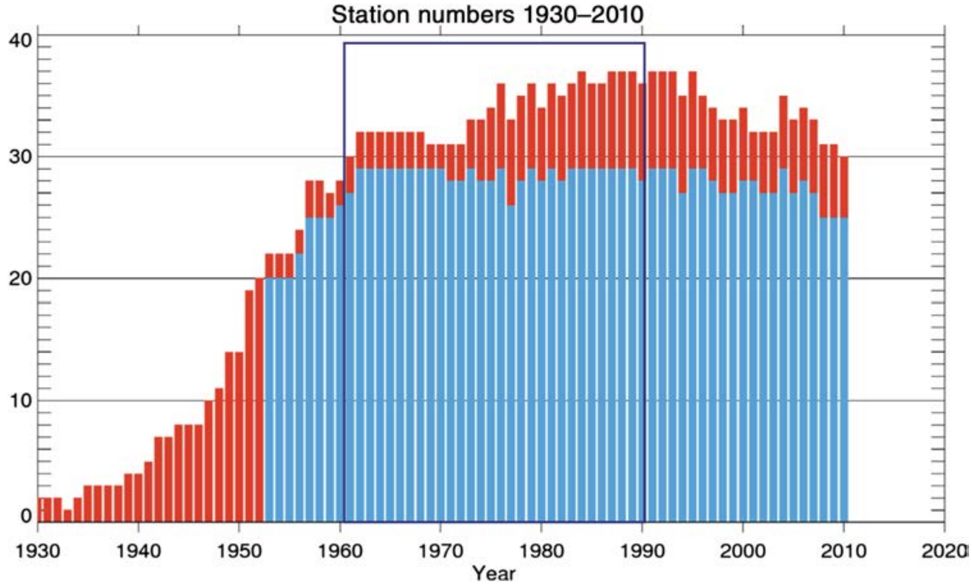

Figure 2. The number of stations that reported temperature observations with time in the study region. Dark grey (red in online): all available stations where annual mean temperature can be derived; light grey (light blue in online): the subset of all stations used in defining regional average temperature starting from 1953. The box indicates the climatological reference period 1961–1990.

2.2. CMIP5 model data

The CMIP5 results represent climate model experiments with different forcings referred to as piControl, Historical, HistoricalNatural and HistoricalGHG. The piControl experiment is a simulation with no variations in external forcings. The greenhouse gas concentrations applied in piControl experiment represent preindustrial concentrations. We use the piControl experiment to estimate variability that is generated internally by the models.

The other experiments can be considered as continuations of piControl simulations but with varying forcings. These forcings include combined natural and anthropogenic forcings (Historical), natural forcings such as solar variations and volcanic eruptions only (HistoricalNatural) and anthropogenic greenhouse forcings only (HistoricalGHG). The 21st century simulations begin by using initial conditions from the end of the equivalent Historical experiment, and then continue from 2006 to 2100 under different greenhouse gases ‘Representative Concentration Pathways’ (RCP). In this article, we consider three such experiments (RCP2.6, RCP4.5 and RCP8.5).

We use a subset of CMIP5 model data from 14 modelling groups whose models have required outputs from all of the piControl, Historical, HistoricalGHG (GHG), HistoricalNatural (Natural) and three RCP experiments (see Table 1 for details). For each model and each member the temperature anomalies from the Historical, GHG and Natural experiments as well as RCP projections are expressed as deviations relative to the respective model’s Historical experiment ensemble mean during the reference period (1961–1990). We use one member from each model in the D&A analysis. The MMEM of temperature anomalies of all models and members and its uncertainty are estimated according to the method outlined in the Appendix S1, Supporting Information. The method estimates the MMEM and uncertainty that are not biased to models with more members.

CMIP5 model performance has been evaluated extensively in the western Pacific (e.g. Brown *et al.*, 2015; Grose *et al.*, 2014). Grose *et al.* (2014) have assessed 27 CMIP5 models which include all models used here with one exception of FGOALS-g2. The FGOALS-g2 has been included in regional SAT D&A in Knutson *et al.* (2013). Both Brown *et al.* (2015) and Grose *et al.* (2014) indicate that SAT and SST simulations from CSIRO-Mk3-6-0 model have peculiar behaviour over the western Pacific region. We therefore excluded this model in our analysis.

As a further test of CMIP5 model performance, Figure 1 shows the spatial structure of the standard deviation of detrended SST variability in both the observations (HadISST) and in the models over 1953–2010. The latter is equal to the MMEM of the standard deviation in each model. The EEZs of the PACSSAP partner countries are superimposed. The observed and modelled standard deviation pattern exhibits similar characteristics to variability associated with ENSO, with maximum variability in the eastern equatorial Pacific. The 14 EEZs where station data are used (zones encircled by pink lines, which we will henceforth refer to as the study region) almost all lie in areas where SST variability is low. The study region also exhibited low variability on decadal time scales. Temperature variability here is therefore less susceptible to phase changes of the Interdecadal Pacific Oscillation (IPO; e.g. Power *et al.*, 1999; Christensen *et al.*, 2013) that is considered to have contributed to the recent global temperature hiatus (Meehl and Teng, 2012; Flato *et al.*, 2013; Kosaka and Xie, 2013; Meehl *et al.*, 2013; England *et al.*, 2014; Dai *et al.*, 2015).

Table 1. CMIP5 models and number of members used for SAT and SST. Number of members for SST is given in bracket if it differs from SAT. Numbers under piControl are simulation duration in years and (in bracket) number of samples used for estimate of internal variability in SAT trend. Model code names instead of full modelling group names are shown for brevity.

Model name	piControl years (samples)	Historical 1900–2005	Natural 1900–2005	GHG 1900–2005	RCP2.6 2006–2100	RCP4.5 2006–2100	RCP8.5 2006–2100
bcc-csm1-1	500 (18)	3	1	1	1	1	1
CanESM2	996 (38)	5	4 (5)	5	5	5	5
CCSM4	501 (18)	6	4	3 (4)	6	6	6
CNRM-CM5	850 (32)	10	5 (6)	6	1	1	5
FGOALS-g2	700 (26)	5	3	1 (3)	1	1	1
GFDL-CM3	500 (18)	5	3	3	1	1	1
GFDL-ESM2M	500 (18)	1	1	1	1	1	1
GISS-E2-H	480 (18)	6	5	5	1	5	1
GISS-E2-R	850 (32)	6	5	5	1	6	1
HadGEM2-ES	577 (21)	5	4	4	4	4	4
IPSL-CM5A-LR	1000 (38)	6	3	3	4	4	4
MIROC-ESM	630 (24)	3	3	3	1	1	1
MRI-CGCM3	500 (18)	3	1	1	1	1	1
NorESM1-M	501 (18)	3	1	1	1	1	1

2.3. Detection and attribution analysis

D&A seeks to determine whether climate is changing significantly (detection) and, if it is, to determine the likely causes of such changes (attribution). There exists a variety of D&A methods (see e.g. Hegerl *et al.*, 2007 and Bindoff *et al.*, 2013 for reviews). Here, we follow the framework proposed by Schneider and Held (2001), which has previously been applied in various regions of the world by, for instance, Drost and Karoly (2012) and Knutson *et al.* (2013). An observed measure of temperature change (e.g. trend) is 'detected' if it is inconsistent with simulated measure from the piControl (preindustrial) results and from the Natural (natural forcing only) results. The observed measure is 'attributable to anthropogenic forcing' if it is both detectable and consistent with Historical (all-forcing runs) results that contain both anthropogenic forcing (e.g. changes in greenhouse gases and aerosols) and natural forcings (e.g. changes in solar insolation or volcanic aerosol loading).

To facilitate a formal D&A assessment, we use the linear trend in temperature over the 53-year period (1953–2005) as a measure. The year 2005 is the last year of the CMIP5 Historical and Natural experiments. To examine whether the observed trend is 'detected', we need to estimate 'background noise' of internal or natural climate variability associated with the trend. We estimate the 'noise' by using climate control simulations, following the procedure used by Drost and Karoly (2012). First we calculate sample trends over a period of 53 years with a moving gap of 25 years taken from piControl simulations, for each of the models listed in Table 1, second column. A sample size of 53 years is used to match the sample size in the station data. The allowance of some overlapping in taking samples from the piControl simulations is employed in order to create more samples from the model simulations. Only those models with piControl runs of at least 480 years in duration are used. This ensures that at least 18 trend samples are available for estimating uncertainty ranges. The 2.5–97.5% confidence interval for a zero trend is then given by ±1.96 times the standard deviation of the trend samples, assuming that data are approximately normally distributed. This confidence interval is estimated for each model separately. The average of the confidence intervals of all models is used as a threshold for the detection of the observed trend.

For our ToE estimate, we adopt methods similar to those used by Kattsov and Sporyshev (2006) and Mahlstein *et al.* (2011). The method employed depends on testing whether two mean temperatures are significantly different between two time periods: a running 20-year window and a fixed baseline period. Here, we use the first 30 years of the analysis period for the station data (1953–1982) as the baseline period. The running windows start in 1953–1972 and end in 1991–2010 for the station data, 1993–2012 for the observed gridded data and 2081–2100 for the 21st century simulations under the RCP8.5 scenario. The ToE is defined as the last year in a 20 year window where the temperature mean in the window and all subsequent windows (1) deviates from the baseline mean, (2) retains its sign and (3) remains statistically significant at the 5% level. The results are not significantly different for using different lengths of the moving window (e.g. 10 or 30 years).

The significance test methods include the Student's difference of means test, the non-parametric Kolmogorov–Smirnov test (K–S test) and a simple test. The simple test detects a significant change when the difference of the mean temperature of the two time periods exceeds 1.96 times the standard deviation of the internal variability. The internal variability is estimated by the standard deviation of the detrended time series over 1953–2010 (58 years) for the station data and the observed gridded data. The standard deviation of internal variability for the models is estimated using samples of detrended 58-year time series of piControl simulations. The samples are taken in the same manner as described above for trends with a moving gap of 25 years. The average of the sample standard deviations for a particular

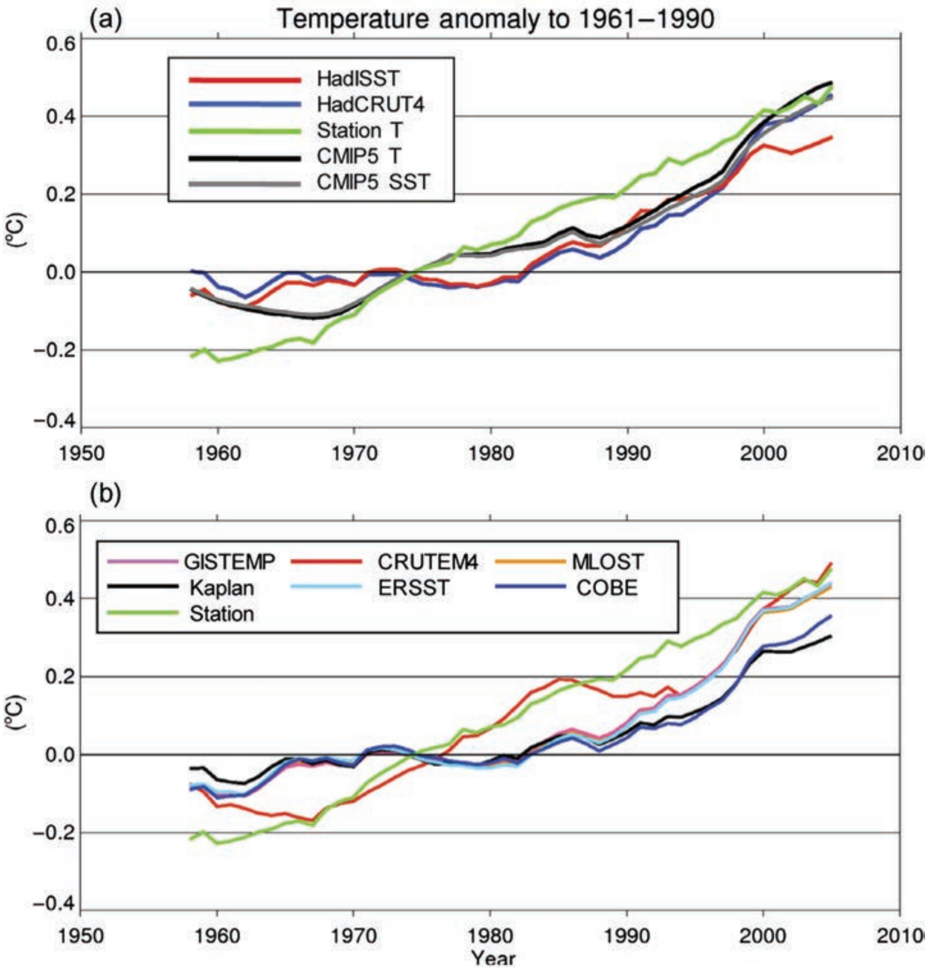

Figure 3. Time series of 11-year running mean of (a) station temperature $T_{Station}$ (green), gridded temperature T_{Grid} of the observed (HadCRUT4 in blue; HadISST in red) and MMEM of CMIP5 Historical (SAT in black; SST in grey) and (b) T_{Grid} from GISTEMP (pink), CRUTEP4 (red), MLOST (orange), Kaplan SST (black), ERSSTv3b (light blue) and COBE SST (blue). The station temperature $T_{Station}$ is repeated in (b) for reference.

model is taken as that model's standard deviation. This procedure is carried out for each model separately. The results show that the ToE values estimated using the Student's test are lower than those from the K–S test, and the K–S test estimates are lower than the ToE estimates from the simple test. Here, we present ToE results based on the K–S test and the simple test. Note that we do not address the possible influence of autocorrelation of the time series on the test. Here, we partially compensate the possible influence by use of interannual standard deviation σ instead of standard deviation of the mean difference $\sigma\sqrt{1/N + 1/M}$, where N, M are sample numbers of the two time periods, in the simple test. This results in later estimates for ToE. The true ToEs are unknown, but by using different test methods and incorporating multiple climate models we can better estimate them.

3. Results

3.1. Temperature change in the 20th century

In this section, we first examine whether the mean temperature evolution in the station data is consistent with the gridded data and CMIP5 model results for the same period. Then, we estimate ToEs in each of these data sets for the periods they allow.

The 11-year running mean temperature anomaly average over the western Pacific study region is shown in Figure 3(a). The $T_{Station}$ anomaly time series shows a steady upward trend from about −0.2 °C in the 1950s, to above +0.4 °C in the 2000s, relative to the reference period 1961–1990. The warming rate from our analysis is +0.15 °C decade^{-1}, which is close to that reported by Jones *et al.* (2013a), who found a long-term trend of +0.16 °C decade^{-1} based on a regional mean of Pacific island temperature series over the period 1961–2011.

The $T_{Station}$ time series also closely follows the trend derived from the HadCRUT4 T_{Grid}, which shows an approximately constant rate of warming since 1980. The main difference appears during the years prior to 1975 when T_{Grid} appears relatively warmer. A similar warming signal is also evident in the HadISST data, as can be expected given oceanic dominance in the region. The warming in both the station and gridded data is broadly similar to the range in the global average temperature

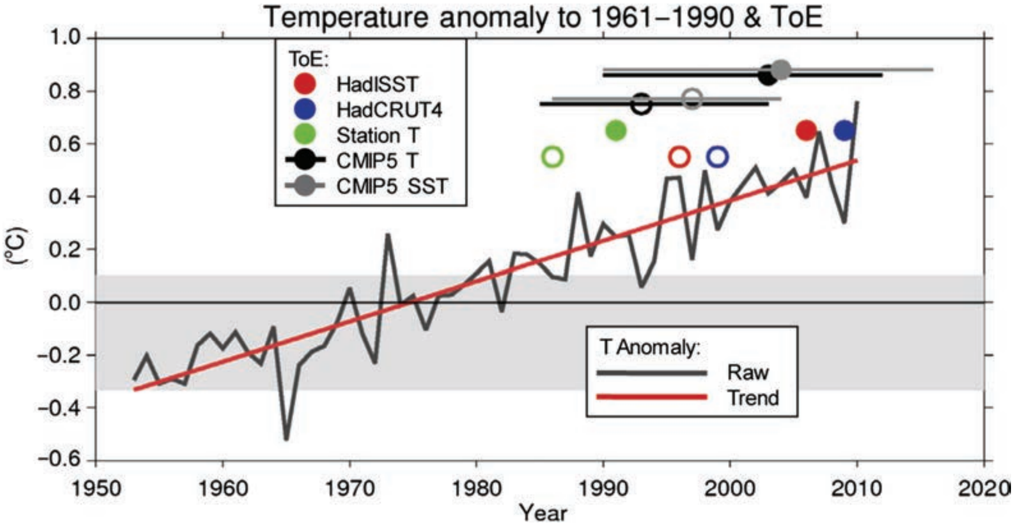

Figure 4. Time series of $T_{Station}$ (grey line) and its linear trend (red line) over 1953–2010. The shading is the 2.5–97.5% range of $T_{Station}$ interannual variability centred on its mean over the 1953–1982 baseline period. ToE estimates are provided based on the K–S test (open circles) and the simple test (solid circles) for $T_{Station}$ (green), T_{Grid} from HadCRUT4 (blue) and HadISST (red). ToE estimates based on the CMIP5 models are shown by the median values for SAT (black circles) and SST (grey circles), and the minimum to maximum ranges for SAT (black horizontal lines) and SST (grey horizontal lines). ToEs are displayed along the *x*-axis in unit of year and at arbitrary *y*-axis for presentation purpose only.

anomalies (Trenberth *et al.*, 2007; Drost and Karoly, 2012).

The difference between $T_{Station}$ and observed T_{Grid} appears related to SST. Figure 3(b) shows land-based CRUTEM4 T_{Grid} does follow $T_{Station}$ better than the blended land and SST data. Figure 3 shows that since 1980 temperature evolution in $T_{Station}$ and T_{Grid} are more or less consistent. This is not the case for period prior to 1980, when there are differences between the land-based temperature data and the blended land and SST data. We suspect the difference is due to fewer observations in the SST in the earlier part of the study period.

The MMEM results for SAT and SST in Historical (Figure 3(a)) show a similar evolution to the observed changes in the gridded data. Overall, both Historical and the observed record indicate a temperature rise since the late 1960s. Compared with the observations, the simulated changes are smoother and the warming in SST appears stronger than that was observed in recent decades. However, there are sizeable differences among the observed SST data sets in recent decades (Figure 3(b)).

The above comparison shows that there are consistent warming signals from the station data and from the gridded data sets, particularly after 1980. As mentioned earlier, the study region is characterized by relatively low temperature variability compared with other parts of the tropical Pacific Ocean. Thus, the warming signal may have already surpassed the noise level associated with natural variability (Jones *et al.*, 2013a). Indeed Figure 4 shows the ToE estimated from $T_{Station}$ is 1986 (green open circle) using K–S test and 1991 (green solid circle) using the simple test. Figure 4 also shows the time series of $T_{Station}$ (grey line) and its linear trend (red line). The shading indicates the 2.5–97.5% range of internal variability in $T_{Station}$ centred on its baseline mean. After 1994, the actual annual mean anomalies in $T_{Station}$ are all larger than the upper (97.5%) level of the internal variability range.

The data length in $T_{Station}$ may not be long enough to have a robust estimate of ToE. We address this by comparing ToEs from $T_{Station}$ with ToEs from other observed data sets and, more importantly, from models. For the observed gridded data sets, the records span 1953–2012, two more years than in $T_{Station}$. For models, we extend time series T_{Grid} by combining Historical and RCP8.5 and thus model ToEs can be estimated over 1953–2100. ToEs from T_{Grid} of HadCRUT4 and HadISST are in a range from 1999 to 2009 (blue and red circles in Figure 4). ToEs from the other observed gridded data occur on or before 2009 for SAT and 2012 for SST (see Table 2). ToEs from the 14 CMIP5 models are presented by their median and range of minimum to maximum. The median of ToEs for SAT(SST) are 1993 (1997) with K–S test and 2003 (2004) with the simple test (Figure 4 and Table 2). For SAT, the earliest ToE is 1985 with K–S test and the latest is 2012 with the simple test (Table 2). The ToE estimates from the CMIP5 models change little if other RCPs are used in extending the Historical time series T_{Grid}.

Our ToE estimates are consistent with previous studies (Kattsov and Sporyshev, 2006; Mahlstein *et al.*, 2011; Hawkins and Sutton, 2012) despite different data sets and different baseline periods and windows being used. For instance, using a 50-year period (1910–1959) baseline and 11-year windows Kattsov and Sporyshev (2006) obtain ToEs during the third quarter of the 20th century for temperature and SST in low latitudes, particularly, in the Indian Ocean and western Pacific, in both the observations and CMIP3 simulations. Using 30-year moving windows with 1900–1929 as a baseline, Mahlstein *et al.* (2011) conclude that a number of countries at low latitudes (e.g. Indonesia, parts of the Middle East and Central

Table 2. ToE values (in year) estimated with Kolmogorov–Smirnov test (K–S test) and the simple test from observations and models. The model results are presented by the median, minimum and maximum of 14 ToE values of the models listed in Table 1.

	SAT			SST		
	Data	K–S test	Simple test	Data	K–S test	Simple test
Observation	Station	1986	1991			
	HadCRUT4	1999	2009	HadISST	1996	2006
	MLOST	1998	2005	Kaplan	1997	2012
	CRUTEM4	1988	2002	ERSSTv3b	1998	2006
	GISTEMP	1998	2005	COBE SST	1999	2011
Models	Median	1993	2003	Median	1997	2004
	Min	1985	1990	Min	1986	1990
	Max	2003	2012	Max	2004	2016

America and large parts of Africa) are already experiencing significant warming based on CMIP3 models. These previous studies, together with the results presented in this article, using the newly updated station data, the gridded observational data and more recent CMIP5 model simulations, indicate that the surface warming is clear, and that the warming has emerged in the western Pacific unambiguously (i.e. climatic expulsion or emergence has taken place).

3.2. Temperature trend over 1953–2005

Figure 5 shows the observed trends from the station data and gridded data accompanied by estimates of the 2.5–97.5% confidence interval for zero trends based on piControl. The confidence interval is estimated for each model, and the average of the model values is used for the detection of the observed trends. The fact that the observed trends lie outside this interval suggests that they are unusual and cannot be explained by natural variability alone. For reference, the observed trend for SST is also displayed.

We now compare the observed trends with those simulated from CMIP5 experiments under different external forcings. The trends in T_{Grid} from each model in Historical are shown by grey circles (SAT) and grey diamonds (SST) in Figure 5. They are all located outside the 2.5–97.5% range of trends estimated from respective piControl runs. The trends from the GHG and Natural experiments are shown by red and green symbols, respectively. It is clear that the observed trends are consistent with trends from Historical (both anthropogenic and natural forcings), but obviously inconsistent with those in Natural (with natural forcings only). Trends from Natural are all within the uncertainty ranges, which mean they are not significantly different from zero. The one exception is bcc-csm1-1. However, it is negative in sign. We thus conclude that the

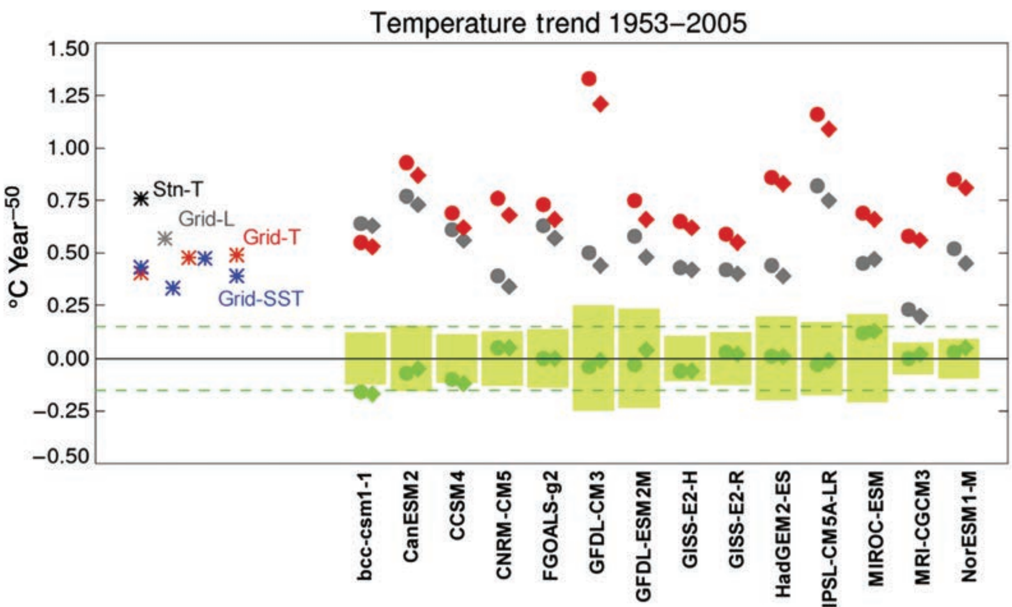

Figure 5. Trends over 1953–2005 of annual mean SAT and SST averaged over the study region. Observed trends (indicated by asterisks) are provided for station temperature (Stn-T), the gridded SAT over land (Grid-L), the other three gridded SATs (Grid-T) and four gridded SST (Grid-SST). Trends from CMIP5 models are displayed for each model, for both SAT (circle) and SST (diamond) from Historical (grey), GHG (red) and Natural (green). The 2.5–97.5% uncertainty ranges of trends in SAT estimated from piControl are provided for each model (green bars). The multimodel mean of uncertainty ranges are indicated by the two dashed horizontal lines.

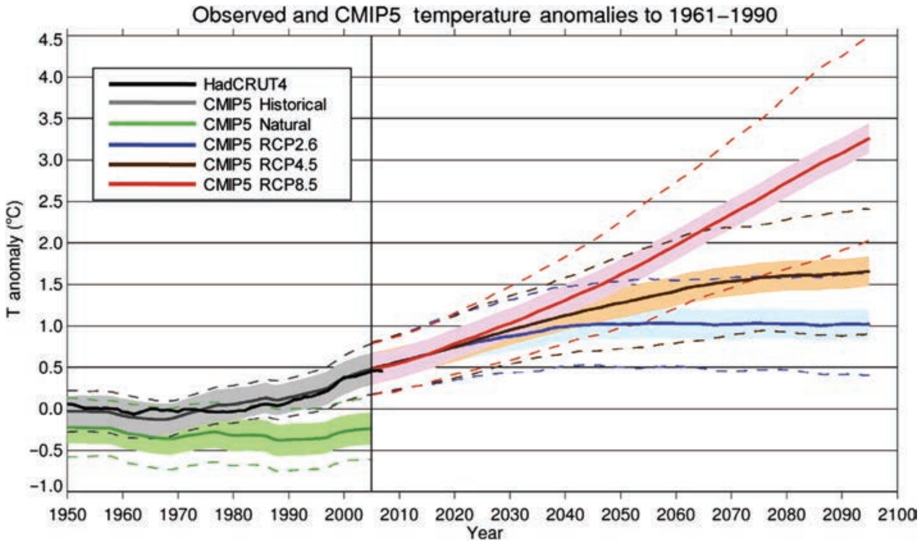

Figure 6. Time series of 11-year running mean of SAT, T_{Grid}, from observations and climate model simulations for the period 1950–2095. The observational time series is from HadCRUT4 during 1950–2007 (black line). MMEMs of CMIP5 Historical (forced with both anthropogenic and natural forcing, grey solid line) and Natural (natural forcings only, green solid line) are shown for the period 1950–2005. MMEMs of projections under three different future greenhouse gas and aerosols concentrations RCP2.6 (blue solid line), RCP4.5 (brown solid line) and RCP8.5 (red solid line) are shown during 2006–2095. The shading (dashed lines) is the 5–95% range of uncertainty associated with the internal variability (combined internal variability and model-to-model differences in model sensitivity). A reflective condition (Mann, 2004) has been used for Natural near the year 2005 for presentation purposes only. The uncertainty estimate method is given in the Appendix S1.

observed surface warming trend during 1953–2005 over the study region is largely attributable to anthropogenic forcing.

The trends in GHG tend to be larger than the observed trend and trends in Historical with one exception, again in the model bcc-csm1-1. The larger trends in GHG can be attributed to the cooling effect of anthropogenic aerosols in Historical, which is absent in GHG (see e.g. Stott *et al.*, 2006).

In summary, the results shown in Figure 5 indicate that the observed trends cannot be explained by natural forcings alone, and that a portion of the observed trends are *very likely* caused by combined anthropogenic greenhouse gas and aerosols forcing and natural forcings [indicating >90% probability as used in IPCC assessment reports (see Mastrandrea *et al.*, 2010)].

3.3. Temperature projections 2006–2100

Having detected and attributed the observed temperature changes for the past 50 years in the study region, we now turn to temperature projections for the 21st century for the same region. Figure 6 provides an 11-year running mean of T_{Grid} in the observations (1950–2007) and in climate model simulations from Historical and Natural (1950–2005) and projection experiments (2006–2095). Prior to 2006, the observed SAT from gridded data (black solid line) lies within the 5–95% ranges of internal (grey shade) and total (grey dashed line) uncertainty of the MMEM of the Historical experiment. In contrast, the MMEM of SAT in Natural (green solid line) has no statistically significant trend and is markedly cooler than both the observed and the simulated Historical values, particularly around 1985 (2005) onwards when the internal (total) uncertainty range of the MMEM time series in Natural separates from the Historical time series. The timing of the significant separation in MMEMs between Natural and Historical simulations is consistent with the ToE estimates above.

The simulated T_{Grid} during the 21st century increases at a similar rate among the scenarios in the near term (i.e. to approximately 2020s), then diverges depending on scenarios of future greenhouse gas concentrations. This behaviour is consistent with the behaviour of global temperature (Collins *et al.*, 2013; IPCC, 2013; Kirtman *et al.*, 2013). Two of the emission scenarios (RCP4.5 and RCP8.5) cause rate of temperature increases over the 21st century that are greater than the observed warming rate in the late 20th century. The third time series [RCP2.6, a strong mitigation scenario (IPCC, 2014)] also shows additional warming but this warming is milder than under the other two scenarios. The scenario with the greatest warming can be regarded a ‘business-as-usual’ scenario in which policies to reduce greenhouse gas emissions are not implemented (RCP8.5). The RCP2.6 scenario assumes that global emissions of greenhouse gases are drastically reduced over coming years and decades (IPCC, 2014). Current emissions are tracking close to the RCP8.5 business-as-usual scenario (Peters *et al.*, 2013).

4. Conclusion

We used recently homogenized Pacific island station temperature data and global gridded data sets to clearly establish that the western Pacific has warmed over the past 50 years. Furthermore, the analysis indicates the observed warming to date is so large that it has forced SAT in the region beyond historical limits, a process recently referred to as climatic expulsion. The observed temperature change and warming trend can only be reproduced by climate models (such as those in CMIP5 used in this study) if the models include forcing associated with anthropogenic increases in greenhouse gases and aerosols. The temperature trends in the observations and in the climate models with full forcings over the past 50 years are positive (warming trend) and exceed the 5% significance level. In contrast, the trends in models without anthropogenic forcing are not significantly different from zero.

The current warming as shown by the temperature anomaly multimodel mean is projected to increase by approximately 0.5–1.7 °C under the strong mitigation scenario RCP2.6, and by approximately 2.0–4.5 °C under the business-as-usual RCP8.5 scenario by the end of 21st century, relative to 1961–1990.

It needs to be borne in mind that 1961–1990 has been used as the climatological reference period. The global mean temperature had already warmed up by approximately 0.61 °C from the latter half of 19th century to 1986–2005 (IPCC, 2013; Kirtman *et al.*, 2013). The observed and projected warming anomalies therefore need to include an additional amount in order to estimate changes relative to the latter half of 19th Century. Further warming is also possible beyond 2100 (Collins *et al.*, 2013; IPCC, 2014).

In summary:

- Western Pacific mean surface air temperature has steadily increased during the last 50 years without a hiatus in recent years.
- The observed warming due to external forcings has emerged unambiguously from natural variability in the western Pacific where the relatively low natural variability assists the early emergence of the anthropogenic signal.
- Our results support the conclusion that humans have largely caused the observed warming of the western Pacific. In other words, the observed warming was not due to natural processes alone.
- Future warming rate over the remainder of the 21st century is projected to be greater than warming rate over the last 60 years under the two business-as-usual scenarios (RCP8.5 and RCP4.5).
- Future warming is greatest under RCP8.5 (2.0–4.5 °C relative to 1961–1990) and least under RCP2.6 (0.5–1.7 °C relative to 1961–1990) by the end of the 21st century. Future warming anomalies would be greater if warming that occurred prior to the reference period is included.
- The magnitude of projected warming is directly and strongly linked to future global emissions of greenhouse gases, with greater emissions leading to greater warming in the Pacific.

Figure 6, together with this supporting scientific information, is a valuable communication tool that can be used to address major questions relating to Pacific climate change for nations in the region that are among the most vulnerable to climate change.

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Supporting Information

The following supporting information is available as part of the online article:

Appendix S1. Estimate multimodel ensemble mean and its uncertainty.

Table S1. List of Pacific island stations with homogeneous annual mean temperature data used in this study, their locations, altitudes and period of record.

References

ABoM (Australian Bureau of Meteorology)-CSIRO. 2011. *Climate change in the Pacific: scientific assessment and new research. Volume 1 – regional overview*. http://www.pacificclimatechangescience.org (accessed 25 April 2015).

ABoM (Australian Bureau of Meteorology)-CSIRO. 2014. *Climate variability, extremes and change in the western tropical pacific: new science and updated country reports*. http://www.pacificclimatechangescience.org (accessed 25 April 2015).

Bindoff NL, Stott PA, AchutaRao KM, Allen MR, Gillett N, Gutzler D, Hansingo K, Hegerl G, Hu Y, Jain S, Mokhov II, Overland J, Perlwitz J, Sebbari R, Zhang X. 2013. Detection and attribution of climate change: from global to regional. In *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Stocker TF, Qin D, Plattner G-K, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, Midgley PM (eds). Cambridge University Press: Cambridge, UK and New York, NY, 867–952.

Brown JN, Clothilde L, Sen GA. 2015. Projected sea surface temperature changes in the equatorial Pacific relative to the Warm Pool edge. *Deep-Sea Res. II*, **113**: 47–58, doi: 10.1016/j.dsr2.2014.10.022.

Christensen JH, Kumar KK, Aldrian E, An S-I, Cavalcanti IFA, de Castro M, Dong W, Goswami P, Hall A, Kanyanga JK, Kitoh A, Kossin J, Lau N-C, Renwick J, Stephenson DB, Xie S-P, Zhou T. 2013. Climate phenomena and their relevance for future regional climate change. In *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Stocker TF, Qin D, Plattner G-K, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, Midgley PM (eds). Cambridge University Press: Cambridge, UK and New York, NY, 1217–1308.

Clarke JM, Whetton PH, Hennessy KJ. 2011. Providing application-specific climate projections datasets: CSIRO's climate futures framework. In *MODSIM2011, 19th International Congress on Modelling and Simulation*, Chan F, Marinova D, Anderssen RS (eds). Modelling and Simulation Society of Australia and New Zealand: Perth, Australia, 2683–2690. ISBN: 978-0-9872143-1-7.

Claus S, De Hauwere N, Vanhoorne B, Hernandez F, Mees J. 2013. *Marineregions.org*. http://www.marineregions.org (accessed 25 April 2015).

Collins M, Knutti R, Arblaster J, Dufresne J-L, Fichefet T, Friedlingstein P, Gao X, Gutowski WJ, Johns T, Krinner G, Shongwe M, Tebaldi C, Weaver AJ, Wehner M. 2013. Long-term climate change: projections, commitments and irreversibility. In *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Stocker TF, Qin D, Plattner G-K, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, Midgley PM (eds). Cambridge University Press: Cambridge, UK and New York, NY, 1029–1136.

Dai A, Fyfe JC, Xie S-P, Dai X. 2015. Decadal modulation of global surface temperature by internal climate variability. *Nat. Clim. Change* **5**: 555–559, doi: 10.1038/nclimate2605.

Drost F, Karoly D. 2012. Evaluating global climate responses to different forcings using simple indices. *Geophys. Res. Lett.* **39**: L16701, doi: 10.1029/2012GL052667.

England MH, McGregor S, Spence P, Meehl GA, Timmermann A, Cai W, Gupta AS, McPhaden MJ, Purich A, Santoso A. 2014: Recent intensification of wind-driven circulation in the Pacific and the ongoing warming hiatus. *Nat. Clim. Change* **4**: 222–227, doi: 10.1038/nclimate2106.

Flato G, Marotzke J, Abiodun B, Braconnot P, Chou SC, Collins W, Cox P, Driouech F, Emori S, Eyring V, Forest C, Gleckler P, Guilyardi E, Jakob C, Kattsov V, Reason C, Rummukainen M. 2013. Evaluation of climate models. In *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Stocker TF, Qin D, Plattner G-K, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, Midgley PM (eds). Cambridge University Press: Cambridge, UK and New York, NY, 741–866.

Griffiths GM, Chambers LE, Haylock MR, Manton MJ, Nicholls N, Baek HJ, Choi Y, Della-Marta PM, Gosai A, Iga N, Lata R, Laurent V, Maitrepierre L, Nakamigawa H, Ouprasitwong N, Solofa D, Tahani L, Thuy DT, Tibig L, Trewin B, Vediapan K, Zhai P. 2005. Change in mean temperature as a predictor of extreme temperature change in the Asia-Pacific region. *Int. J. Climatol.* **25**: 1301–1330, doi: 10.1002/joc.1194.

Grose MR, Brown JN, Narsey S, Brown JR, Murphy BF, Langlais C, Sen Gupta A, Moise AF, Irving DB. 2014. Assessment of the CMIP5 global climate model simulations of the western tropical Pacific climate system and comparison to CMIP3. *Int. J. Climatol.* **34**: 3382–3399, doi: 10.1002/joc.3916.

Hansen J, Ruedy R, Sato M, Lo K. 2010. Global surface temperature change. *Rev. Geophys.* **48**: RG4004, doi: 10.1029/2010RG000345.

Hawkins E, Sutton R. 2012. Time of emergence of climate signals. *Geophys. Res. Lett.* **39**: L01702, doi: 10.1029/2011GL050087.

Hegerl GC, Zwiers FW, Braconnot P, Gillett NP, Luo Y, Marengo Orsini JA, Nicholls N, Penner JE, Stott PA. 2007. Understanding and attributing climate change. In *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, Miller HL (eds). Cambridge University Press: Cambridge, UK, 663–745.

IPCC. 2013. Summary for policymakers. In *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Stocker TF, Qin D, Plattner G-K, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, Midgley PM (eds). Cambridge University Press: Cambridge, UK and New York, NY, 3–29.

IPCC. 2014. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Pachauri RK, Meyer LA (eds). IPCC: Geneva, Switzerland, 151 pp.

Ishii M, Shouji A, Sugimoto S, Matsumoto T. 2005. Objective analyses of sea-surface temperature and marine meteorological variables for the 20th century using ICOADS and the Kobe Collection. *Int. J. Climatol.* **25**: 865–879, doi: 10.1002/joc.1169.

Jones PD, Lister DH, Osborn TJ, Harpham C, Salmon M, Morice CP. 2012. Hemispheric and large-scale land surface air temperature variations: an extensive revision and an update to 2010. *J. Geophys. Res.* **117**: D05127, doi: 10.1029/2011JD017139.

Jones DA, Collins DA, McGree S, Trewin B, Skilling E, Diamond H, Fa'anunu O, Hiriasia D, Hugony S, Hutchinson R, Inape K, Jacklick L, Malsale P, Moniz T, Ngemaes M, Porteous A, Seuseu S, Tahani L, Teimitsi F, Toorua U, Vaiimene M, Vuniyayawa V, Vavae H. 2013a. An updated analysis of homogeneous temperature data at Pacific Island stations. *Aust. Meteorol. Mag.* **63**: 285–302.

Jones GS, Stott PA, Christidis N. 2013b. Attribution of observed historical near surface temperature variations to anthropogenic and natural causes using CMIP5 simulations. *J. Geophys. Res. Atmos.* **118**: 4001–4024, doi: 10.1002/jgrd.50239.

Kaplan A, Cane MA, Kushnir Y, Clement AC, Blumenthal MB, Rajagopalan B. 1998. Analyses of global sea surface temperature 1856–1991. *J. Geophys. Res.* **103**: 18567–18589, doi: 10.1029/97JC01736.

Kattsov VM, Sporyshev PV. 2006. Timing of global warming in IPCC AR4 AOGCM simulations. *Geophys. Res. Lett.* **33**(L23): 707, doi: 10.1029/2006GL027476.

Kirtman B, Power SB, Adedoyin JA, Boer GJ, Bojariu R, Camilloni I, Doblas-Reyes FJ, Fiore AM, Kimoto M, Meehl GA, Prather M, Sarr A, Schar C, Sutton R, van Oldenborgh GJ, Vecchi G, Wang HJ. 2013. Near-term climate change: projections and predictability. In *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Stocker TF, Qin D, Plattner G-K, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, Midgley PM (eds). Cambridge University Press: Cambridge, UK and New York, NY.

Knutson TR, Zeng F, Wittenberg AT. 2013. Multi-model assessment of regional surface temperature trends: CMIP3 and CMIP5 twentieth-century simulations. *J. Clim.* **26**: 8709–8743, doi: 10.1175/JCLI-D-12-00567.1.

Kosaka Y, Xie S-P. 2013. Recent global-warming hiatus tied to equatorial Pacific surface cooling. *Nature* **501**: 403–407, doi: 10.1038/nature12534.

Mahlstein I, Knutti R, Solomon S, Portmann R. 2011. Early onset of significant local warming in low latitude countries. *Environ. Res. Lett.* **6**: 034009, doi: 10.1088/1748-9326/6/3/034009.

Mann ME. 2004. On smoothing potentially nonstationary climate time series. *Geophys. Res. Lett.* **31**: L07214, doi: 10.1029/2004GL019569.

Manton MJ, Della-Marta PM, Haylock MR, Hennessy KJ, Nicholls N, Chambers LE, Collins DA, Daw G, Finet A, Gunawan D, Inape K, Isobe H, Kestin TS, Lefale P, Leyu CH, Lwin T, Maitrepierre L, Ouprasitwong N, Page CM, Pahalad J, Plummer N, Salinger MJ, Suppiah R, Tran VL, Trewin B, Tibig I, Yee D. 2001. Trends in extreme daily rainfall and temperature in Southeast Asia and the South Pacific: 1961–1998. *Int. J. Climatol.* **21**: 269–284, doi: 10.1002/joc.610.

Mastrandrea MD, Field CB, Stocker TF, Edenhofer O, Ebi KL, Frame DJ, Held H, Kriegler E, Mach KJ, Matschoss PR, Plattner G-K, Yohe GW, Zwiers FW. 2010. *Guidance note for lead authors of the IPCC Fifth Assessment Report on consistent treatment of uncertainties*. Intergovernmental Panel on Climate Change (IPCC). http://www.ipcc-wg2.gov/meetings/CGCs/index.html#UR (accessed 25 April 2015).

Meehl GA, Teng H. 2012. Case studies for initialized decadal hindcasts and predictions for the Pacific region. *Geophys. Res. Lett.* **39**: L22705.

Meehl GA, Covey C, Taylor KE, Delworth T, Stouffer RJ, Latif M, McAvaney B, Mitchell JFB. 2007. The WCRP CMIP3 multimodel dataset: a new era in climate change research. *Bull. Am. Meteorol. Soc.* **88**: 1383–1394.

Meehl GA, Hu A, Arblaster J, Fasullo J, Trenberth KE. 2013. Externally forced and internally generated decadal climate variability associated with the Interdecadal Pacific Oscillation. *J. Clim.* **26**: 7298–7310, doi: 10.1175/JCLI-D-12-00548.1.

Menne MJ, Durre I, Vose RS, Gleason BE, Houston TG. 2012. An overview of the Global Historical Climatology Network-daily database. *J. Atmos. Oceanic Technol.* **29**: 897–910.

Morice CP, Kennedy JJ, Rayner NA, Jones PD. 2012. Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: the HadCRUT4 data set. *J. Geophys. Res.* **117**: D08101, doi: 10.1029/2011JD017187.

Nurse LA, McLean RF, Agard J, Briguglio LP, Duvat-Magnan V, Pelesikoti N, Tompkins E, Webb A. 2014. Small islands. In *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Barros VR, Field CB, Dokken DJ, Mastrandrea MD, Mach

KJ, Bilir TE, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Girma B, Kissel ES, Levy AN, MacCracken S, Mastrandrea PR, White LL (eds). Cambridge University Press: Cambridge, UK and New York, NY, 1613–1654.

Page CM, Nicholls N, Plummer N, Trewin BC, Manton MJ, Alexander L, Chambers LE, Choi Y, Collins DA, Gosai A, Della-Marta P, Haylock MR, Inape K, Laurent V, Maitrepierre L, Makmur EEP, Nakamigawa H, Ouprasitwong N, McGree S, Pahalad J, Salinger MJ, Tibig L, Tran TD, Vediapan K, Zhai P. 2004. Data rescue in the South-east Asia and South Pacific region: challenges and opportunities. *Bull. Am. Meteorol. Soc.* **85**: 1483–1489.

Peters GP, Andrew RM, Boden T, Canadell JG, Ciais P, Le Quéré C, Marland G, Raupach MR, Wilson C. 2013. The challenge to keep global warming below 2°C. *Nat. Clim. Change* **3**: 4–6, doi: 10.1038/nclimate1783.

Power SB. 2014. Climate science: expulsion from history. *Nature* **511**: 38–39, doi: 10.1038/511038a.

Power SB, Folland C, Colman A, Mehta V. 1999. Inter-decadal modulation of the impact of ENSO on Australia. *Clim. Dyn.* **15**: 319–324.

Power SB, Schiller A, Cambers G, Jones D, Hennessy K. 2011. The Pacific climate change science program. *Bull. Am. Meteorol. Soc.* **92**: 1409–1411, doi: 10.1175/BAMS-D-10-05001.1.

Rayner NA, Parker DE, Horton EB, Folland CK, Alexander LV, Rowell DP, Kent EC, Kaplan A. 2003. Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *J. Geophys. Res.* **108**: 4407, doi: 10.1029/2002 JD002670.

Sakaguchi K, Zeng X, Brunke MA. 2012. Temporal- and spatial-scale dependence of three CMIP3 climate models in simulating the surface temperature trend in the twentieth century. *J. Clim.* **25**: 2456–2470, doi: 10.1175/JCLI-D-11-00106.1.

Schneider T, Held IM. 2001. Discriminants of twentieth-century changes in earth surface temperatures. *J. Clim.* **14**: 249–254.

Smith TM, Reynolds RW, Peterson TC, Lawrimore J. 2008. Improvements to NOAA's historical merged land–ocean surface temperature analysis (1880–2006). *J. Clim.* **21**: 2283–2296, doi: 10.1175/2007JCLI2100.1.

Stott PA, Mitchell JFB, Allen MR, Delworth TL, Gregory JM, Meehl GA, Santer BD. 2006. Observational constraints on past attributable warming and predictions of future global warming. *J. Clim.* **19**: 3055–3069.

Taylor KE, Stouffer RJ, Meehl GA. 2012. An overview of CMIP5 and the experiment design. *Bull. Am. Meteorol. Soc.* **93**: 485–498, doi: 10.1175/BAMS-D-11-00094.1.

Trenberth KE, Jones PD, Ambenje P, Bojariu R, Easterling D, Tank AK, Parker D, Rahimzadeh F, Renwick JA, Rusticucci M, Soden B, Zhai P. 2007. Observations: surface and atmospheric climate change. In *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, Miller HL (eds). Cambridge University Press: Cambridge, UK and New York, NY, 235–336.

Whan K, Alexander LV, Imielska A, McGree S, Jones D, Ene E, Finaulahi S, Inape K, Jacklick L, Kumar R, Laurent V, Malala H, Malsale P, Pulehetoa-Mitiepo R, Ngemaes M, Peltier A, Porteous A, Seuseu S, Skilling E, Tahani L, Toorua U, Vaiimene M. 2014. Trends and variability of temperature extremes in the tropical Western Pacific. *Int. J. Climatol.* **34**: 2585–2603, doi: 10.1002/joc.3861.

Whetton P, Hennessy K, Clarke J, McInnes K, Kent D. 2012. Use of representative climate futures in impact and adaptation assessment. *Clim. Change* **115**: 433–442, doi: 10.1007/s10584-012-0471-z.