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ABSTRACT

Seasonal and inter-annual climate variability is a major factor in determining the vulnerability of many Pacific Island countries and Timor Leste to climate change. A key goal of the Pacific Australia Climate Change Science and Adaptation Planning (PACCSAP) Program was to improve the understanding of existing and future climatic changes and impacts on countries in the Western Pacific region. The seasonal prediction component of the project was focused on development and delivery of seasonal prediction tools for extreme ocean temperature and sea level events.

Anomalously warm ocean temperatures are the primary cause of mass coral bleaching in the tropical oceans. Degraded coral reefs present many potential social and economic problems for Pacific Island countries, including long-term loss of tourism, potential loss or degradation of fisheries and reduction in coastal protection. Likewise the impacts of extreme sea level events can also be severe and include the loss of coastal amenities; the inhibition of primary production processes; loss of property; destruction of cultural resources and values; loss of tourism, recreation and transportation functionality; and increased risk of loss of life.

Real-time seasonal predictions of sea level anomalies (SLA) and sea surface temperatures (SST) are currently being created using the Australian Bureau of Meteorology's dynamical seasonal coupled ocean–atmosphere model forecasting system, POAMA (Predictive Ocean Atmosphere Model for Australia). These forecasts are made available, as experimental products, through a set of prototype seasonal prediction websites. This paper details the features and functionality of the SLA and SST websites that deliver forecasts, together with a summary of forecast methodology and skill assessment.

It is through natural variability that the early effects of climate change will be most acutely felt. Improving the accuracy and availability of long range forecasts of extreme natural variability can assist affected communities to prepare for the impacts.

1. INTRODUCTION

The Pacific Australia Climate Change Science and Adaptation Planning (PACCSAP) Program is an integral part of the International Climate Change Adaptation Initiative (ICCAI) - an Australian Government initiative to address high priority climate adaptation needs in vulnerable countries in the Asia-Pacific region.
(http://aid.dfat.gov.au/aidissues/climatechange/Pages/initiative-iccai.aspx)

The ICCAI recognises that seasonal and inter-annual climate variability is a major factor in determining the vulnerability of countries and communities to climate change impacts. An important aspect of climate variability is that it interacts with the changing background climate to produce many of the first noticeable impacts of climate change and expose regions of greatest vulnerability. Droughts, floods, tropical cyclones, and extreme ocean and air temperatures can all lead to social and economic stress within the Pacific region. Importantly, the character of such events is influenced by seasonal climate variability and will also change as a consequence of future climate change.

Climate change and climate extremes have a major impact on Pacific Island countries. The PACCSAP Program works with Western Pacific countries, both north and south of the equator, to deliver improved seasonal forecasting technologies and capacity. Subsequently referred to as the "Partner Countries", those involved are Timor Leste and 14 Pacific Island Countries: Papua New Guinea, Tuvalu, Kiribati, Fiji, Marshall Islands, Federated States of Micronesia, Palau, Nauru, Cook Islands, Samoa, Tonga, Niue, Solomon Islands, and Vanuatu (see Fig. 1).

Short term predictions of sea level due to tides, storm surge and waves can be made out to two weeks. Sea level due to tidal based harmonics, which are a result of the gravitational pull of the sun and moon, can be forecast years into the future. Projections of sea level rise at longer timescales due to climate change are also already well modelled. However, operational predictions of sea level contributions at seasonal timescales are scarce with only a few statistical models existing (Chowdhury et al., 2007). Climate processes such as ENSO, the Indian Ocean Dipole (IOD), Madden Julian Oscillation (MJO) and Southern Annular Mode (SAM) involve large spatial and temporal changes to winds and ocean temperatures. These can then create seasonal sea level signals of significant amplitudes (~30cm) at regional scales, which may persist for many months. When a spring tide (a high tide due to the full/new moon being aligned with the sun) and/or storm surge coincides with an extreme seasonal sea level event, there is increased potential for serious damage to occur. Prediction of sea level variability on a seasonal timescale is the next important step in capturing the major factors influencing regional sea level.

Fluctuations in sea surface temperature (SST) can have a significant impact on local and global climate. In the Pacific Ocean, seasonal variability of SST is closely linked with the inter-annual El Niño Southern Oscillation (ENSO) cycle. Droughts and floods, an increased risk of cyclones, and disease outbreaks have all been associated with ENSO events (Trenberth et al. 1998; White et al. 2013). SST fluctuations can also have serious implications for the coral reef marine ecosystems of the tropical Pacific. In particular, mass coral bleaching is largely a result of anomalously warm regional water temperatures (Goreau and Hayes, 1994). Degraded coral reefs present many potential social and economic problems for Partner Countries, including long-term loss of tourism, degradation of fisheries and reduction in coastal protection.

Two subprojects within the PACCSAP Program, *Seasonal Prediction of Sea Level Anomalies in the Western Pacific* and *Seasonal Prediction of Extreme Ocean Temperatures/Coral Bleaching*, focused on the prediction of seasonal variability of sea level and ocean temperatures across the Western Pacific region. These subprojects delivered seasonal prediction products, with associated skill assessments, for the Partner Countries through an online portal described in this report.

New seasonal outlooks for sea level and SST were developed for the Partner Countries based on the Predictive Ocean Atmosphere Model for Australia (POAMA; Griesser and Spillman, 2014; Miles et al., 2014). The POAMA forecast system consists of a data assimilation system for the initialisation of the ocean, land and atmosphere, a coupled ocean–atmosphere dynamical model and post-processing for bias correction (Hudson et al., 2010). The benefit of using a dynamical physics-based model is that it makes no assumption of climate stationarity, thus enabling the prediction of unprecedented events in a changing climate, unlike empirical forecasting methodologies. Previously, Kuleshov et al. (2012) developed seasonal outlooks for rainfall and temperature for Pacific Island countries based on the POAMA system.

POAMA has been shown to have high skill, particularly in the equatorial Pacific, in modelling the variability of global seasonal sea level anomalies (SLA) relative to altimeter and reanalyses (Miles et al., 2014) and tide-gauges within the Western Pacific (McIntosh et al., 2014). Coupled ocean-atmosphere model-based forecasting systems have been shown to produce skilful forecasts of SST in the equatorial Pacific at lead times up to several months (Barnston et al., 2012; Griesser and Spillman 2014). Operational POAMA forecast tools for SST-based coral bleaching risk have also been developed for the Australian Great Barrier Reef, with products shown to be skilful across the Pacific several months into the future (Griesser and Spillman, 2014; Spillman et al., 2011; Spillman, 2011).

We anticipate that advance warnings of extreme SLA and SST will be valuable tools for coastal communities, allowing the implementation of management policies and strategies to minimise loss of life and infrastructure damage. As climate change is likely to increase the frequency and severity of extreme SLA (Church et al. 2014) and SST events (Frieler et al. 2012) the development of such products is a crucial preparatory measure. The PACCSAP Program has developed web-based applications for delivering seasonal SLA and SST prediction products (http://poama.bom.gov.au/experimental/pasap/pacific/projects.shtml). Together with seasonal forecast tools, the applications provide information about expected forecast quality or skill, based on assessment of a retrospective forecast (hindcast) dataset.

This paper will provide details on POAMA and the methodology used to create these seasonal predictions, descriptions of the new SLA and SST forecast products, website access and an explanation of the associated skill scores.

2. POAMA-2 SYSTEM

The Predictive Ocean Atmosphere Model for Australia (POAMA) is a global coupled ocean–atmosphere ensemble seasonal prediction system, developed jointly by the Australian Bureau of Meteorology and the Commonwealth Scientific and Industrial Research Organisation (CSIRO)

Division of Marine and Atmospheric Research (CMAR). POAMA creates intra-seasonal (within the next two to four weeks) and seasonal (within the next one to nine months) climate forecasts and has been running operationally at the Bureau of Meteorology since October 2002 (Wang et al. 2008). The current version of POAMA (version 2; POAMA-2) has been operational since May 2013.

2.1 System overview

POAMA-2 consists of the Bureau of Meteorology's Atmospheric Model version 3.0 (BAM3.0; Colman et al. 2005; Wang et al. 2005; Zhong et al. 2006); the CMAR Australian Community Ocean Model version 2 (ACOM2; Schiller et al. 2002) and the Ocean Atmosphere Sea Ice Soil version 3 (OASIS3) coupling software (Valcke et al., 2000). The ocean model grid spacing is 2º in the zonal direction and in the meridional direction approximately 0.5º at the equator, gradually increasing to 1.5º at the poles. Initial conditions for the land surface and the atmosphere are created by the Atmosphere–Land Initialisation scheme (ALI; Hudson et al. 2010). Ocean initial conditions are generated daily by the POAMA Ensemble Data Assimilation System (PEODAS; Yin et al., 2011). PEODAS assimilates *in situ* temperature and salinity observations including those from expendable bathythermographs (XBTs), ARGO floats and the Tropical Atmosphere Ocean/Triangle Trans Ocean Buoy Network/Prediction and Research Moored Array in the Atlantic moorings, in addition to satellite SST (Reynolds et al., 2002).

POAMA-2 computes a 33 member ensemble, where the ensemble mean is the average of these 33 members. These members are generated by 3 sub models, each producing 11 members. The model is currently run operationally in real-time mode twice a week.

Further details on the model configuration of POAMA can be found in Hudson et al. (2013).

2.2 Seasonal forecasting timescales

Seasonal forecasts of the atmosphere and oceans aim to predict conditions in the upcoming months. Forecasts presented in the PACCSAP Program's seasonal prediction website show the monthly or three-monthly (seasonally) averaged values. For example, a February-March-April forecast is the average of the daily forecast conditions from 1 February up-to and including 30 April.

The definition of lead time is the number of months that have elapsed between the launch (initialisation) date of the model and the beginning of the forecasted period. In the above example, if the model start date is the 1st February, the forecast for the season February-March-April has a lead time of 0 months. The forecast for April-May-June, from the same model run, would be lead time 2 months, as two full months have elapsed between when the model was started (1 February) and the beginning of the forecast period (1 April).

2.3 Hindcasts

Retrospective forecasts, or hindcasts, are used to calculate the real-time anomaly forecasts and assess the skill or performance of the forecast system. The POAMA hindcast dataset consist of simulations including the full 33 member ensemble that has been initialised on the 1st, 11th and 21st of each month from 1981 to 2010.

3. FORECAST GENERATION

There are two dominant interpretation methods for ensemble forecasts, deterministic and probabilistic. Deterministic forecasts use the ensemble mean and can be interpreted as the average model state, or as the predictable signal. Probabilistic forecasts use the distribution of the ensemble to estimate the relative probabilities of different outcomes.

The spread of ensemble values should ideally represent the probability of occurrence in reality (reliability). By using the full ensemble, forecasts that indicate the likelihood of occurrence (as a percentage) of above average (upper tercile), near average (middle tercile), and below average (lower tercile) values can be generated. For each grid cell and month, the lowest 10 years from the 30 years of 1981-2010 define the lower tercile, the highest 10 years define the above upper tercile, and the remaining 10 years define the middle tercile. The tercile bounds, and the years which define these bounds, are different for each variable and location. Each year was cross validated by removing the year of interest from the timeseries.

An entirely random “forecast” (i.e. not using any model), would assign an equal probability of occurrence of 33.3% to each tercile. Using POAMA forecasts, however, it is possible to identify areas where the probability of occurrence is greater than 33.3% (corresponding to an increased likelihood of occurrence of this tercile). At any location on the map, the probabilities for each of the three tercile categories will add up to 100%.

The primary steps involved in generating forecasts from the model outputs are as follows:

1. Calculate monthly anomalies for each ensemble member by removing the appropriate monthly hindcast climatology (1981-2010), selected by start data and sub model.
2. Calculate the ensemble mean, i.e. calculate the arithmetic mean of all ensemble members.
3. For SST forecasts, the total field is calculated by adding the observed monthly climatology to the model ensemble mean SST anomaly (SSTA).
4. Calculate the 3-month sequential seasonal means (e.g. January-February-March, February-March-April etc.) for the ensemble mean and each ensemble member at each lead time.
5. Calculate the tercile probability by determining the percentage of ensemble members in the upper and lower tercile ranges, using upper and lower tercile thresholds computed from the model hindcast dataset. Forecasts are presented in the following formats:
   a. *Upper tercile probability*: These forecasts show for each grid point the percentage of ensemble members that predict an anomaly equal to or above the upper tercile limit.
   b. *Lower tercile probability*: These forecasts show for each grid point the percentage of ensemble members that predict an anomaly equal to or less than the lower tercile limit.

c. *Composite tercile map*: These forecasts combine the upper, lower and middle tercile forecasts into one concise map. The colours represent the most likely tercile (lower, middle, or upper), whilst the shading indicates the probability level (the percentage of forecasts in agreement).The forecast is labelled "Indeterminate" where all terciles have a probability of occurrence of less than 40%, e.g. upper tercile: 34%, middle tercile: 36% and lower tercile: 30%. The forecast is termed "Ambiguous" where two terciles have the same probability of occurrence; i.e. upper tercile: 45%, middle tercile: 45% and lower tercile: 10%.

d. *Chance of exceedance*: The 25%, 50%, and 75% chance-of-exceedance forecasts correspond to the 75th, 50th, and 25th percentiles of the ensemble, respectively. For example, if the 25% chance-of-exceedance SST value is 27°C, three quarters of the ensemble members were cooler than this, and one quarter were this warm or warmer, i.e., there is a one-in-four chance that the water will be warmer than 27°C according to this forecast. The 50% chance of exceeding forecast corresponds to the ensemble median value, rather than the mean.

6. Calculate the mean anomaly value across grid cells within each Partner Countries' Exclusive Economic Zone (EEZ) for both the ensemble mean and each of the 33 ensemble members.

Note that real-time POAMA forecasts are created weekly every Thursday and Sunday at 00Z. As the initialisation dates of the real-time simulations do not always correspond exactly with the initialisation dates used in the hindcast set (1st, 11th or 21st of each month), the nearest available model climatology is used for calculating anomaly values.

3.1 Skill scores

Forecast products presented on the website are accompanied by appropriate skill scores for that forecast season and lead time. The skill scores for each forecast are determined by assessing the ability of POAMA hindcasts to predict observed historical events using observational datasets and/or reanalyses. These scores are described in the following sections. Correlation and root mean square error are scores used for continuous variables (such as SLA value or SST value), while the other scores listed below are categorical skill scores, used to assess Yes/No forecasts such as "will the SSTA values be in the lower tercile"?

Further information on both forecast verification in general and specifically for POAMA can be found in Griesser & Spillman (2012), Hudson et al. (2013), Miles et al., (2014) and Wilks (1995). Generally, forecast accuracy is highest for lead time 0 months and decreases further into the future (i.e. increasing lead time).

3.1.1 Correlation

This score measures how well forecast values (F) correspond to observed values (O). Correlation measures the strength of the linear relationship between forecast values and observed values. This score does not consider forecast bias, i.e. it is possible for a forecast with large errors to still have a good correlation with the observations. The correlation for each variable (e.g. SLA or SSTA) is determined by comparing the POAMA hindcast time series to the observed time series at each location.

$$r = \frac{\sum(F - \bar{F})(O - \bar{O})}{\sqrt{\sum(F - \bar{F})^2}\sqrt{\sum(O - \bar{O})^2}}$$

Range: -1 to 1, No Skill: 0, Perfect score: -1 or 1.

3.1.2 Root mean square error

The root mean square error (RMSE) measures the average difference between values predicted by a model (F) and the values actually observed (O). A lower RMSE value indicates a better precision and a smaller difference between predicted and observed values.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(F_i - O_i)^2}$$

Range: 0 to ∞, Perfect score: 0.

3.1.3 Contingency tables

The following scores for tercile forecasts rely upon values found in a contingency table (Table 1). Chi-squared values are not calculated as this contingency table is being used to assess the skill of the seasonal forecasts and not attempting to model predictors.

Table 1. The contingency table.

		Observed	
		Yes	**No**
Forecast	**Yes**	Hit	False Alarm
	No	Miss	Correct Negative

The four combinations of forecasts (yes or no) and observations (yes or no) are:

- *Hit*: Event forecast to occur, and did occur.
- *Miss*: Event forecast not to occur, but did occur.
- *False Alarm*: Event forecast to occur, but did not occur.
- *Correct Negative*: Event forecast not to occur, and did not occur.

3.1.4 Accuracy

Accuracy is the fraction of forecasts that correctly predicted the tercile category. This score can be sensitive to the frequency of the event; e.g. for very rare events, a high score may be achieved by always forecasting "No" (i.e. correct negatives). However such forecasts would have very little value if the events are never forecasted.

$$Accuracy = \frac{Hits + Correct\ Negatives}{Total\ number\ of\ forecasts}$$

Range: 0 to 100%, Perfect score: 100%.

3.1.5 Hit rate

The number of correctly predicted occurrences of the event, divided by the total number of occasions when the event was forecast (whether or not it subsequently happened).

$$Hit\ rate = \frac{Hits}{Hits + Misses}$$

Range: 0 to 1, Perfect score: 1.

3.1.6 False alarm rate

The number of false positives divided by the total number of occasions when the event did not happen.

$$False\ alarm\ rate = \frac{False\ Alarms}{Correct\ Negatives + False\ Alarms}$$

Range: 0 to 1, Perfect score: 0.

3.1.7 Frequency bias

Ratio of the number of forecast events to the number of observed events.

$$BIAS = \frac{Hits + False\ Alarms}{Hits + Misses}$$

Range: 0 to infinity, Perfect score: 1.

3.1.8 Peirce skill score

An equitable skill score which is not influenced by the frequency of events. This is calculated by subtracting the false alarm rate from the hit rate;

$$Peirce\ Skill\ Score = Hit\ Rate - False\ Alarm\ Rate$$

Range: -1 to 1, Perfect score: 1.

3.1.9 Relative operating characteristic score

The relative operating characteristic (ROC) is a measure of the ability of a forecast system to discriminate between events and non-events i.e. do forecasts of a high event probability tend to be followed by events?

The ROC score is not sensitive to bias in the forecast or to overconfidence in the forecast probabilities. A biased forecast may still have good resolution and produce a good ROC curve, in which case it may be possible to improve other aspects of forecast quality through calibration. The ROC can thus be considered as a measure of potential usefulness.

It is calculated by plotting the False Alarm Rate against the Hit Rate using a set of increasing probability thresholds. The area beneath this curve is used to evaluate the performance of the model.

Range: 0 to 1, No skill: < 0.5, Perfect score: 1.

4. WEB SITES

The PACCSAP and PASAP websites are built using the software framework described by Charles et al. (2011). Documentation for navigating the PACCSAP Program websites is contained within the PASAP Portal User Manual: Part 1 (see http://poama.bom.gov.au/experimental/pasap/docs/website_guide.pdf). This guide provides details about using the website, featuring examples of how to select, display and download the various forms of seasonal forecasts. Technical information about the websites is also available online at http://poama.bom.gov.au/experimental/pasap/website_technical_information.shtml.

4.1 Accessing the websites

The project websites and data portals for the two PACCSAP subprojects, *Seasonal Prediction of Sea Level Anomalies in the Western Pacific* and *Seasonal Prediction of Extreme Ocean Temperatures/Coral Bleaching*, are publically available (see Table 2).

Table 2. Details for accessing the SLA and SST websites.

Supported browsers	Firefox, Chrome. Limited support for Internet Explorer.
Seasonal Prediction of Sea Level Anomalies in the Western Pacific	http://poama.bom.gov.au/experimental/pasap/sla.shtml
Seasonal Prediction of Extreme Ocean Temperatures/Coral Bleaching	http://poama.bom.gov.au/experimental/pasap/sst.shtml

4.2 Outlook types

The websites present forecasts in two formats: as maps, and as line graphs of spatially averaged values over each EEZ of every Partner Country.

4.2.1 Gridded outlooks

Gridded outlooks are global forecast maps showing the predicted conditions for a particular start date and lead time.

The rectangular grid (model resolution) is visible when the “Gridded” render style option is selected (“Gridded” style is the default; see Fig.1). When viewing gridded data, data at individual grid point should be interpreted with caution. Emphasis should be placed on broad scale features and patterns that encompass several or many grid points; POAMA cannot model geographic features smaller than the grid resolution, i.e. features that have scales less than 2° or ~200 km.

4.2.2 EEZ averages

Additional to the gridded forecasts, the areal average of most forecast quantities is calculated for each EEZ of every Partner Country (note Kiribati has been divided into three regions: Kiribati, Kanton and Kiritimati; Fig.1). The areal average is calculated for each ensemble member as well as for the overall deterministic forecast. The areal average forecast for every ensemble member and the overall mean deterministic forecast are plotted together and are known as a “plume plot” (see Fig. 2(a) for an example). These plume plots show the areal average forecast value for all available lead times of each ensemble member, along with the overall ensemble mean, illustrating the spread of values within the forecast system. Model climatology is also shown for SST reference.

The plume plots must be interpreted carefully and in conjunction with the gridded outlooks and their associated skill scores. As with any averaging process, looking solely at the mean value can hide local fluctuations and extremes; i.e. the forecast value could be high in some parts of an EEZ and low in others, having the effect of bringing the average value close to zero. However, for many forecast quantities, the mean value over an area comprising many grid cells is often more skilfully predicted than the value at any one of the included grid cells.

4.3 Sea level forecasts

This section outlines the model representation of sea level, the verification dataset used, and summaries of sea level forecast quantities and their corresponding skill scores. All forecast values are corrected for model bias and are presented as seasonal averages.

4.3.1 Sea level in POAMA

It should be noted that ACOM2, the ocean model used by both POAMA and PEODAS, does not explicitly represent sea level. Instead it returns a model diagnostic described as diagnostic surface height (Pacanowski 1996). ACOM2 uses a rigid-lid approximation which conserves volume (Bryan 1969), and the surface height variations for each grid cell are determined by using the hydrostatic equations to calculate the perpendicular forcing to this surface generated by water being shifted into different grid columns due to horizontal temperature, salinity and wind gradients. Altimeter observations are not currently assimilated in POAMA. The surface height reflects sea level contributions due to dynamic height, barotropic circulation, advection and dissipation processes. The following contributors to sea level variations are not simulated: changes in ocean mass from ice-sheet mass loss of other contributions, tectonic uplift, self-attraction and loading, glacial isostatic adjustment (GIA), land water storage, astronomical tides, surface waves, mesoscale eddies or atmospheric pressure effects within the ocean model. For further details please see Miles et al., (2014).

4.3.2 Verification dataset

PEODAS is used as a verification dataset to assess the performance of POAMA forecasts over the period of 1981-2010. Note that whilst both POAMA and PEODAS calculate sea surface height (SSH) using the same calculations, they are each launched with different start dates. POAMA is run continuously from the initialisation date out to 270 days before calculating the mean seasonal state whilst PEODAS runs the calculation daily before calculating the mean seasonal state.

Reports on POAMA's performance in predicting seasonal SLA relative to global reanalyses (Miles et al. 2014) and to tide gauges located in the Western Pacific (McIntosh et al. 2014) have been prepared.

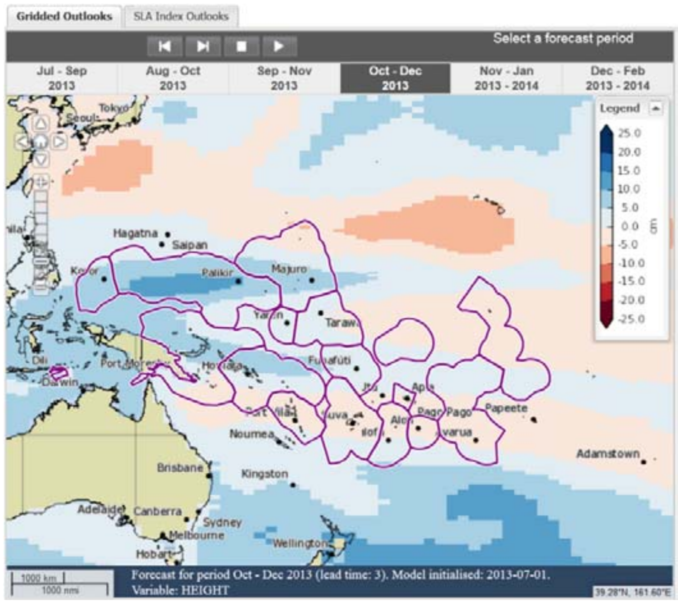
4.3.3 Available SLA forecasts

Details on the real-time SLA gridded outlooks available are provided in Table 3.

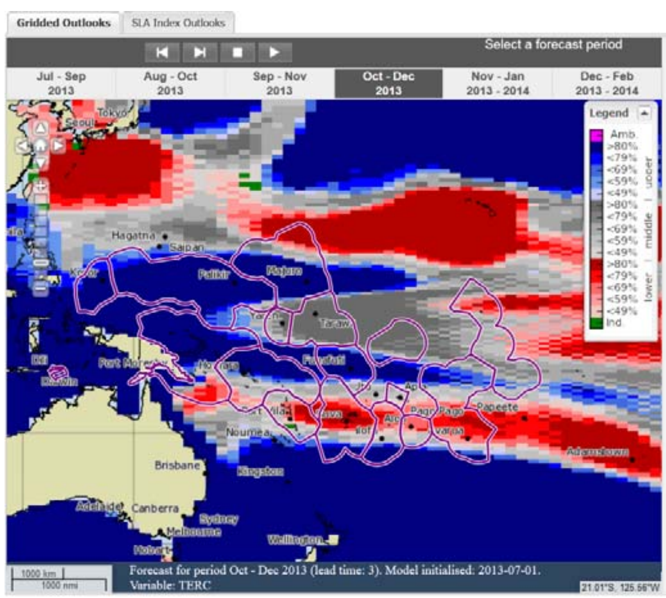
Table 3. Available SLA gridded outlook forecast products.

Quantity	**Units**	**Description**	**Skill scores available**
Sea Level Anomaly (SLA)	cm	Difference between the forecast SSH and the 1981-2010 monthly average	Correlation, RMSE
Upper Tercile	Percentage	The probability that the sea level will be in the upper climatological tercile, representing likely higher-than-usual sea levels.	Accuracy, ROC
Lower Tercile	Percentage	The probability that the sea level will be in the lowest climatological tercile, representing likely lower-than-usual sea levels.	Accuracy, ROC
Composite Tercile Map	Percentage	A combined upper, middle and lower tercile probability map showing the probability of only the most-likely tercile.	N/A
EEZ Sea Level Anomaly	cm	Areal average contained within EEZ of the difference between the forecast SSH and the 1981-2010 monthly average	Correlation, RMSE

Two example forecasts from the SLA website are shown in Figure 1. They have been initialised on the 1st of July 2013 and show the October-November-December 2013 (lead time 4 months) ensemble mean and composite tercile forecast.



(a)



(b)

Fig. 1 Example of an SLA forecast for October-November-December 2013, issued 1st July 2013 (based on 33 monthly ensembles). a) POAMA ensemble mean forecast of monthly SLA and b) probability of tercile events.

Plume plot forecasts, where each ensemble forecast is represented by a line, for EEZ of each Partner Country, and associated skill scores, are also available on the SLA website (http://poama.bom.gov.au/experimental/pasap/sla.shtml; Table 3). Figure 2 shows an example plume plot with relevant RMSE and correlation scores for the Federated States of Micronesia for October-November-December 2013, issued 1st July 2013.

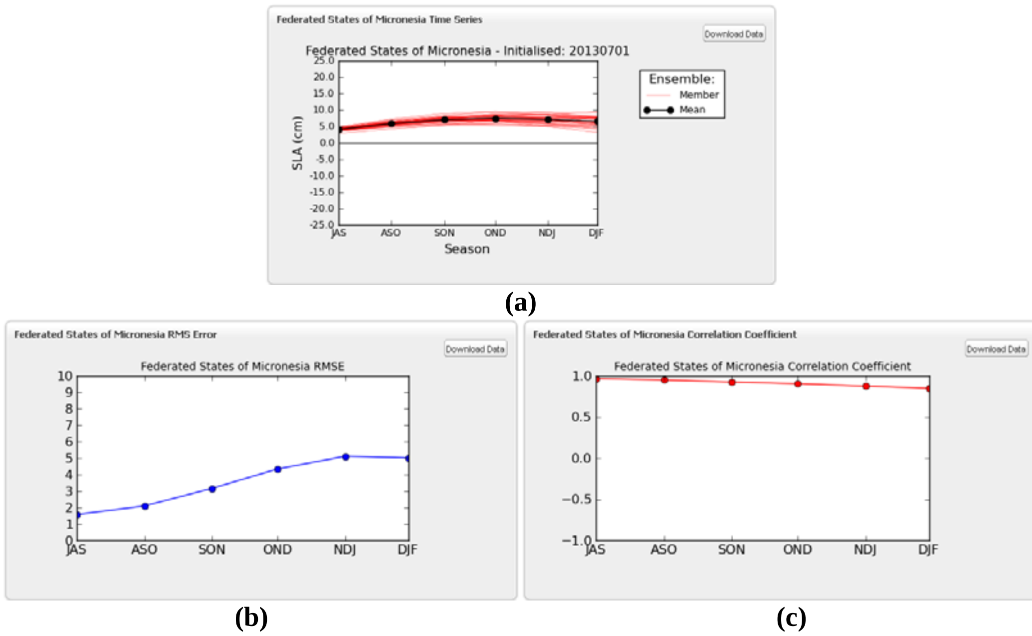


Fig. 2 a) Example monthly SLA plume plot forecast for the Federated States of Micronesia from July 2013 to February 2014, issued 1st July 2013 based on 33 member ensemble, together with b) the corresponding RMSE and c) correlation skill plots.

4.4 Sea surface temperature forecasts

This section outlines the forecast tools for monthly sea surface temperature and coral bleaching risk.

4.4.1 Coral bleaching risk metrics

Goreau and Hayes (1994) suggested that exposure to elevated temperatures (1°C above mean summer maxima) for a more than a month can induce mass coral bleaching. Where SSTA is defined as the difference between SST and the monthly climatology (calculated at each grid cell) and a HotSpot is defined as the difference between SST and the *warmest* month of the monthly climatology. The warmest month of the monthly climatology is referred to as the maximum monthly mean (MMM), and this quantity does not vary throughout the year as does the monthly climatology.

A Degree Heating Month (DHM) is defined as the integration of HotSpots over a period of time of one month (Glynn and D'croz 1990; Barton and Casey 2005; Donner et al. 2005; Spillman et al. 2011), and is indicative of thermal stress. A DHM value of approximately 1°C month is often assumed as the level above which a coral bleaching risk exists (Goreau and Hayes, 1994;

Teneva et al., 2011; Logan et al., 2012). Shown on the website is a three-month DHM accumulation, where HotSpots are integrated over a three-month period: this provides an indication as to the stress the corals can be expected to have experienced during that time period.

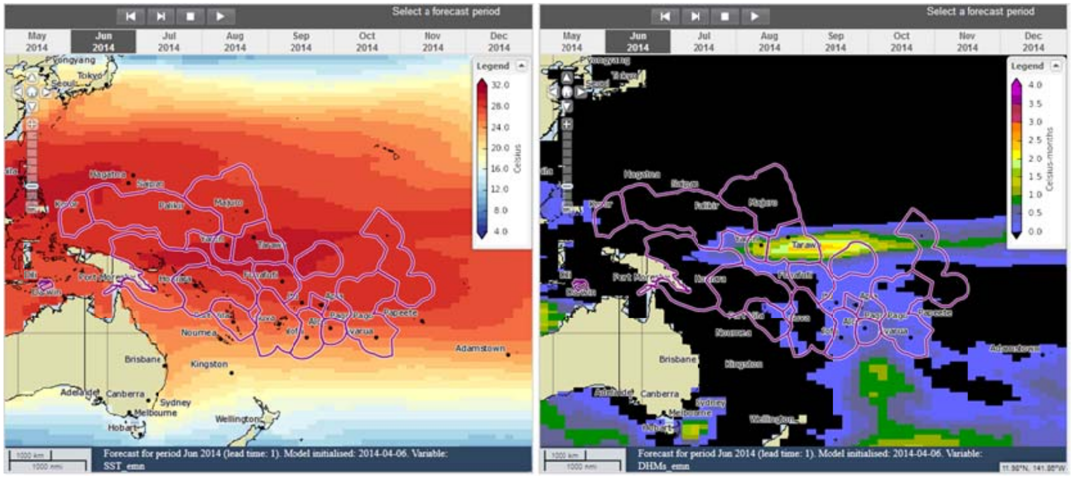
4.4.2 Verification dataset

The NOAA Optimum Interpolation (OI) Sea Surface Temperature (SST) V2 re-analysis is used as a verification dataset over the period 1982-2010 (Reynolds et al., 2002). Observed HotSpot and DHM values are calculated based on this dataset. The observed monthly SST climatology is the average SST in each month over the years 1982-2010. The maximum monthly mean climatology is the warmest month of the observed monthly climatology. SST-based forecast products are bias corrected by adding the model-predicted SSTA to the observed climatology.

4.4.3 Deterministic forecasts

Table 4. SST and thermal stress metrics.

Quantity	**Units**	**Description**
Sea Surface Temperature (SST)	Celsius	Bias-corrected ensemble-mean sea surface temperature.
Sea Surface Temperature Anomaly (SSTA)	Celsius	Difference between the forecast sea surface temperature and the long-term average (climatological value).
HotSpots (HS)	Celsius	Difference between the forecast sea surface temperature and the maximum monthly mean value (MMM)
Degree Heating Months (DHM)	Celsius Months	The accumulation of HotSpot values over the prior *three* months; i.e. to calculate the DHM value for April, HotSpots are accumulated over January, February, and March.



(a) (b)

Fig. 3 Examples of a) an SST forecast, and b) a DHM forecast, for June 2014, issued in April.

4.4.4 Probabilistic forecasts

Probabilistic forecast maps for ocean temperatures are presented in two formats: maps showing values which have a certain chance of being exceeded, and maps showing tercile probabilities.

The chance-of-exceedance maps are available for the four quantities listed in Table 4. Tercile probabilities are available for SST, as listed below in Table 5.

Table 5. SST probability metrics.

Quantity	**Description**
SST prob. lower tercile	The probability that the SST will be in the lower climatological tercile, representing likely cooler than usual conditions.
SST prob. upper tercile	The probability that the sea surface temperature will be in the upper climatological tercile, representing likely warmer than usual conditions.
SST most-likely tercile	A combined upper, middle and lower tercile probability map showing the probability of the most likely tercile. The red, grey, or blue colour groups correspond to the most likely tercile: upper, middle, and lower terciles corresponding to warmer, neutral, and cooler conditions, respectively. The intensity of the colouring indicates the probability level. Bright shading indicates a higher probability.

5. SUMMARY

Seasonal POAMA SST and SLA forecast products were developed under the PACCSAP Program subprojects *Seasonal Prediction of Sea Level Anomalies in the Western Pacific* and *Seasonal Prediction of Extreme Ocean Temperatures/Coral Bleaching*, and are made available to Partner Countries as experimental products. This paper has described the forecast tools, skill metrics and the websites used to deliver them.

There are a number of Partner Countries in the Western Pacific that are currently using, or interested in using, seasonal forecast products in their management plans to increase resilience under climate change. Education in the use of these tools is very important so that stakeholders can understand both the strengths and limitations of seasonal forecast products and the best way to interpret forecasts. Adoption of products over a period of time is more likely to result in long term benefit than adoption for a single season (McIntosh et al. 2014). Probabilistic forecasts are important for management by enabling the analysis of the risk or cost/benefit of implementing a particular strategy such as monitoring mid-range and short-term forecasts closely, updating contingency plans and educating communities. Appropriate skill scores can also add value to a risk-based cost/benefit analysis.

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REFERENCES

Barnston, A.G., Tippett, M.K. and L'Heureux, M.L. et al. (2012) Skill of Real-Time Seasonal ENSO Model Predictions during 2002–11: Is Our Capability Increasing? Bull Am Meteorol Soc 93:631–651. doi: 10.1175/BAMS-D-11-00111.1

Barton, A.D. and Casey, K.S. (2005) Climatological context for large-scale coral bleaching. Coral Reefs 24:536–554. doi: 10.1007/s00338-005-0017-1

Bryan, K. (1969) A numerical method for the study of the circulation of the world ocean. J Comput Phys 4:347–376. doi: 10.1016/0021-9991(69)90004-7

Charles, A., McClymont, D., de Wit, R. and Jones, D. (2011) A software architecture for seasonal climate forecasts in the tropical Pacific. 19th Int. Congr. Model. Simul. pp 1188–1194

Chowdhury, M.R., Chu, P., Schroeder, T. and Colasacco, N. (2007) Seasonal sea-level forecasts by canonical correlation analysis—an operational scheme for the U.S.-affiliated Pacific Islands. Int J Climatol 27:1389–1402. doi: 10.1002/joc.1474

Church, J.A., Clark, P.U. and Cazenave, A. et al. (2014) Sea Level Change. Climate Change: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. In: Stocker, T.F., Qin, D. and Plattner, G-K. et al. (eds)Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, in press., p 121pp

Colman, R., Deschamps, L. and Naughton, M. et al. (2005) BMRC Atmospheric Model (BAM) version 3.0: comparison with mean climatology. BMRC Res Rep 108:66pp.

Donner, S.D., Skirving, W.J. and Little, C.M. et al. (2005) Global assessment of coral bleaching and required rates of adaptation under climate change. Glob Chang Biol 11:2251–2265. doi: 10.1111/j.1365-2486.2005.01073.x

Frieler, K., Meinshausen, M. and Golly, A. et al. (2012) Limiting global warming to 2°C is unlikely to save most coral reefs. Nat Clim Chang 2:1–6. doi: 10.1038/nclimate1674

Glynn, P.W. and D'Croz, L. (1990) Experimental evidence for high temperature stress as the cause of El Nino-coincident coral mortality. Coral Reefs 8:181–191. doi: 10.1007/BF00265009

Goreau, T.J. and Hayes, R.L. (1994) Coral Bleaching and Ocean "Hot Spots."Ambio-Journal Hum Environ 23:176–180.

Griesser, A.G. and Spillman, C.M. (2014) The skill of seasonal coral bleaching risk forecasts at monthly timescales. In prep.

Griesser A,G. and Spillman, C.M. (2012) SST forecast skill of the new intra-seasonal configuration of POAMA-2. CAWCR Res Lett 8:10–16.

Hudson, D., Alves, O., Hendon, H.H. and Wang, G. (2010) The impact of atmospheric initialisation on seasonal prediction of tropical Pacific SST. Clim Dyn 36:1155–1171. doi: 10.1007/s00382-010-0763-9

Hudson, D., Marshall, A.G. and Yin, Y. et al. (2013) Improving Intraseasonal Prediction with a New Ensemble Generation Strategy. Mon Weather Rev 141:4429–4449. doi: 10.1175/MWR-D-13-00059.1

Kuleshov, Y., Jones, D. and Hendon, H.H. et al. (2012) Pacific Adaptation Strategy Assistance Program: Strengthening the Capacity for Seasonal Prediction Services in Pacific Countries. Bull Aust Meteorol Oceanogr Soc 25:7–12.

Logan, C.A., Dunne, J.P., Eakin, C.M. and Donner, S.D. (2012) A framework for comparing coral bleaching thresholds. Proc. 12th Int. Coral Reef Symp.

McIntosh, P.C., Church, J.A. and Miles, E. et al. (2014) Seasonal Prediction of Western Pacific Sea-level using a Coupled Ocean-Atmosphere Dynamical Model. In prep.

Miles, E.R., Spillman, C.M., Church, J.A. and McIntosh, P.C. (2014) Seasonal prediction of global sea level anomalies using an ocean–atmosphere dynamical model. Clim Dyn. doi: 10.1007/s00382-013-2039-7

Pacanowski, R.C. (1996) MOM2: Documentation, User’s Guide and Reference Manual. GFDL Ocean Tech Rep 3.2:329pp.

Reynolds, R.W., Rayner, N.A. and Smith, T.M. et al. (2002) An Improved In Situ and Satellite SST Analysis for Climate. J Clim 15:1609–1625. doi: 10.1175/1520-0442(2002)015<1609:AIISAS>2.0.CO;2

Schiller, A., Godfrey, J.S. and McIntosh, P.C. et al. (2002) A New Version of the Australian Community Ocean Model for Seasonal Climate Prediction. CSIRO Mar Lab Rep Ser 240:79pp.

Spillman, C.M. (2011) Operational real-time seasonal forecasts for coral reef management. J Oper Oceanogr 4:13–22.

Spillman, C.M., Alves, O. and Hudson, D.A. (2011) Seasonal Prediction of Thermal Stress Accumulation for Coral Bleaching in the Tropical Oceans. Mon Weather Rev 139:317–331. doi: 10.1175/2010MWR3526.1

Teneva, L., Karnauskas, M. and Logan, C.A. et al. (2011) Predicting coral bleaching hotspots: the role of regional variability in thermal stress and potential adaptation rates. Coral Reefs 31:1–12. doi: 10.1007/s00338-011-0812-9

Trenberth, K.E., Branstator, G.W. and Karoly, D. et al. (1998) Progress during TOGA in understanding and modeling global teleconnections associated with tropical sea surface temperatures. J Geophys Res 103:14291. doi: 10.1029/97JC01444

Valcke, S., Terray, L. and Piacentini, A. (2000) Oasis 2.4, Ocean atmosphere sea ice soil: user's guide. CERFACS TR/CMGC/00-10 85 pp.

Wang, G., Alves, O. and Hudson, D. et al. (2008) SST skill assessment from the new POAMA-1.5 system. BMRC Res. Lett. 8:

Wang, G., Alves, O. and Smith, N.R. (2005) BAM3.0 tropical surface flux simulation and its impact on SST drift in a coupled model. BMRC Res Rep 107:30pp.

White, C.J., Hudson, D. and Alves, O. (2013) ENSO, the IOD and the intraseasonal prediction of heat extremes across Australia using POAMA-2. Clim Dyn. doi: 10.1007/s00382-013-2007-2

Wilks, D.S. (1995) Statistical Methods in the Atmospheric Sciences, 1st ed. Academic Press, London

Yin, Y., Alves, O. and Oke, P.R. (2011) An Ensemble Ocean Data Assimilation System for Seasonal Prediction. Mon Weather Rev 139:786–808. doi: 10.1175/2010MWR3419.1

Zhong, A., Alves, O., Hendon, H.H. and Rikus, L. (2006) On aspects of the mean climatology and tropical interannual variability in the BMRC Atmospheric Model (BAM 3.0). BMRC Res Rep 121:34pp.

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