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REPORT

Dynamical seasonal prediction of summer sea surface temperatures in the Great Barrier Reef

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Abstract Coral bleaching is a serious problem threatening the world coral reef systems, triggered by high sea surface temperatures (SST) which are becoming more prevalent as a result of global warming. Seasonal forecasts from coupled ocean–atmosphere models can be used to predict anomalous SST months in advance. In this study, we assess the ability of the Australian Bureau of Meteorology seasonal forecast model (POAMA) to forecast SST anomalies in the Great Barrier Reef, Australia, with particular focus on the major 1998 and 2002 bleaching events. Advance warning of potential bleaching events allows for the implementation of management strategies to minimise reef damage. This study represents the first attempt to apply a dynamical seasonal model to the problem of coral bleaching and predict SST over a reef system for up to 6 months lead-time, a potentially invaluable tool for reef managers.

Keywords Seasonal forecast · POAMA · Coral bleaching · SST · Coupled ocean–atmosphere model · Great Barrier Reef

Introduction

Coral reef systems around the world are subject to increasing pressure due to anthropogenic sources and climate change (Donner et al. 2005). Coral reefs such as the Great Barrier Reef (GBR), Australia, are ecosystems of enormous diversity, providing habitats for a huge variety of species, in addition to forming the basis of valuable tourism and fishing industries of great economic importance (Hoegh-Guldberg 1999; Marshall and Johnson 2007). Coral bleaching is a significant threat to the future of the world ocean's coral reefs, and steps must be taken to improve management tools to protect these resources of global significance (Hughes et al. 2003).

Sea surface temperature (SST) is recognised as the primary cause of mass coral bleaching events (Brown 1997; Hoegh-Guldberg 1999; Lesser 2004). Coral bleaching results from the loss of symbiotic algae, known as zooxantheallae, from coral tissues during times of stress, often due to temperatures higher than the coral colony's tolerance level (Glynn 1993). Coral bleaching has been observed sporadically on the GBR since 1982, with severe bleaching events occurring during the summers of 1998 and 2002, resulting in widespread damage (Done et al. 2003; Berkelmans et al. 2004). Major bleaching events in Southern Hemisphere reefs (Pacific and Indian Oceans) tend to occur in February–April (Hoegh-Guldberg 1999), with a lag of up to a month in the bleaching response of corals following thermal stress (Berkelmans and Willis 1999). Mortality appears to increase with the intensity of the bleaching event, which is determined by how much and for how long temperatures remain above the maximum mean summer temperatures (Hoegh-Guldberg 1999).

Global warming is a serious threat to the future of the Great Barrier Reef with predictions that bleaching will increase in both frequency and severity (Donner et al. 2005). Bleaching has occurred in locations both positively and negatively correlated with El Niño Southern Oscillation (ENSO) index, though strong links with ENSO are

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likely to weaken as global warming is predicted to drive temperatures above bleaching thresholds annually (Goreau and Hayes 2005). Frequency of bleaching events in the GBR region is predicted to increase by as much as 1.6–1.7 more events per decade until events occur annually by the year 2030 (Hoegh-Guldberg 1999). The recovery of the reef is dependent on the severity of the bleaching and the time between events, with increasing frequency of bleaching episodes severely limiting recovery capability (McCook 1999; Fabricius et al. 2007). Biological adaptation of coral to warmer ambient conditions is unlikely to keep pace with expected temperature increases due to climate change (Fabricius et al. 2007). The increasing frequency of events highlights the importance of gaining insight into the processes of coral bleaching and developing appropriate management strategies to minimise damage to the reef ecosystem during such events.

Current now-cast systems use satellite SST data and accumulate conditions over a 3-month period to predict the likelihood of coral bleaching, i.e. the National Oceanographic and Atmospheric Administration (NOAA) Coral Reef Watch (Strong et al. 2004; Goreau and Hayes 2005; McClanahan et al. 2007) and the Great Barrier Reef Marine Park Authority's ReefTemp program (Maynard et al. 2008). Global Climate Models (GCMs) have also been applied to coral reefs with predictions for coral bleaching events on both the decadal scale (Done et al. 2003; Donner et al. 2005) and the scale of long-term climate change (Done et al. 2003; Wooldridge et al. 2005; Donner et al. 2007; Hennessy et al. 2007). Donner et al. (2005) adapted the NOAA Coral Reef Watch bleaching prediction method to the output of a GCM and determined the frequency of coral bleaching under two emission scenarios. NOAA has also recently released a new experimental seasonal forecast product, CRW Experimental Bleaching Outlook, based on observed SST anomalies (SSTAs) and Empirical Orthogonal Functions (EOFs), for statistically based forecasts up to 3 months into the future (http://coralreefwatch.noaa.gov). However, currently there are no dynamical prediction systems for forecasting coral bleaching on a seasonal timescale, incorporating ocean data assimilation, atmospheric conditions and ocean–atmosphere coupling.

Seasonal forecasting models have the potential to revolutionise the way in which coral bleaching events are monitored and assessed in coral reefs such as the Great Barrier Reef. Advance warning of potential bleaching events allows for the implementation of management strategies to minimise reef damage months ahead of the event. Bleaching itself can not currently be prevented but by limiting access to areas of the reef under threat, recovery times can be improved by decreasing other stresses and increasing reef resilience to bleaching (West and Salm 2003; Marshall and Schuttenberg 2006). Natural disturbances are often exacerbated by anthropogenic stresses, such as pollution, sedimentation and overfishing, which can further weaken coral systems and compromise their ability to recover from disturbances (McCook 1999; Hughes et al. 2003). Timely indications of bleaching sites also enables the relocation of monitoring equipment and collection of data during the prelude to bleaching, increasing current knowledge of reef response and bleaching triggers.

The primary objective of this study is to assess the skill of the Australian Bureau of Meteorology's seasonal coupled ocean–atmosphere model (POAMA) in forecasting SST over the Great Barrier Reef up to 6 months in advance over a range of spatial scales. This study is believed to be the first attempt to quantitatively evaluate large scale dynamical sea surface temperatures forecasts on seasonal timescales in a reef system with the view for future application in coral bleaching management. The capacity for dynamical bleaching forecasts on a seasonal timescale addresses a current deficit in reef forecasts, complementing the observation-based high resolution now-cast and statistical seasonal forecast products currently available. Accurate seasonal SST forecasts for this region will be an invaluable tool for the future management and conservation of the reef.

Methods

Site description

The Great Barrier Reef (GBR) stretches for more than 2,300 km along the northeast coast of Australia and is the largest coral reef ecosystem and natural feature on earth (Fig. 1). The GBR Marine Park, established in 1975 and managed by the GBR Marine Park Authority (GBRMPA), covers an area of 348,700 km^2 and is the world's largest World Heritage Area. The GBR is the habitat for a richly diverse community of species as well as an extremely valuable economic resource.

Model description

The Predictive Ocean Atmosphere Model for Australia (POAMA; Alves et al. 2003) is a global coupled ocean–atmosphere seasonal forecast system developed jointly by the Australian Bureau of Meteorology and CSIRO Division of Marine and Atmospheric Research (CMAR). The forecast system consists of a coupled model and initialisation systems for the ocean, land and atmosphere.

The coupled model in POAMA (version 1.5; P1.5) consists of the Australian Bureau of Meteorology atmospheric model (BAM 3.0; Colman and McAvaney 1995; Colman 2002) and the CMAR Australian Community

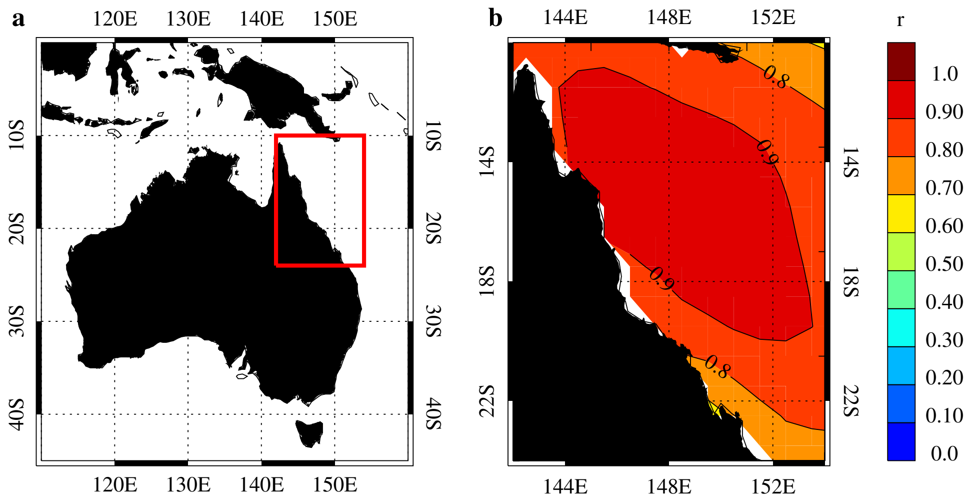


Fig. 1 (**a**) The Great Barrier Reef study area (10–24 S, 142–154 E). The GBR Index is the average SSTA in this region. (**b**) Spatial correlation of the Reynolds GBR Index with all Reynolds SSTA values in the GBR study region

Ocean Model V.2 (ACOM2; Schiller et al. 2002), the latter based on the Geophysical Fluid Dynamics Laboratory Modular Ocean Model Version 2.0 (MOM2; Pacanowski 1995). The atmospheric model component has a horizontal spectral resolution of T47 and 17 vertical levels. The ocean model grid spacing is 2° in the zonal direction and 0.5–1.5° in the meridional direction, with 25 vertical levels, of which 12 are in the upper 185 m. The coupling of the two models was achieved using the Ocean Atmosphere Sea Ice Soil (OASIS) coupling software (Valcke et al. 2000), with no correction applied to the exchanged fluxes between the models.

Atmosphere initial conditions are provided by an Atmosphere–Land Initialisation (ALI) scheme (Hudson and Alves 2007), where a BAM 3.0 atmosphere-only integration forced with observed weekly Reynolds OI.v1 SST (Reynolds and Smith 1994), commonly used for large scale seasonal forecasting, is nudged towards the ERA-40 reanalysis (Uppala et al. 2005). The ocean model is initialised using an ocean data assimilation scheme based on the optimum interpolation (OI) technique described by Smith et al. (1991).

A hind-cast is a retrospective forecast which can be used to gauge model performance by assessing the skill of the model in predicting past events. To generate a hind-cast set, the model is started on the 1st day of each month of a set period, initialised only with information available before the start date, and run forward in forecast mode for 9 months. Lead-time is defined as the time elapsed between the model start date and the forecast date, i.e. if the model start month is January and the forecast is for April, the forecast lead-time is 3 months. A hind-cast ensemble can then be created by running the model multiple times for each start month with slightly varying initial atmospheric conditions each time. An ensemble gives an indication of the potential spread in forecast skill by allowing the stochastic component of the model to evolve differently in each member and reduce the effects of uncertainties in model initial conditions. In this study, a 10-member ensemble set of hind-casts was generated each month for the period from 1980 to 2006, with the members then averaged to give the overall ensemble mean forecast.

Seasonal forecasts, in addition to monthly forecasts, are also presented in this study, particularly for the period January–February–March (JFM) when annual temperatures are warmest in the GBR region. To calculate a three monthly (seasonal) average forecast in the model, the forecasts are averaged according to lead-time. For example, the forecast for JFM at lead-time 0 months is the average of the forecasts starting in January for January, February and March. For a JFM forecast at a lead-time of 1 month, the forecasts starting in December for January, February and March are averaged (lead-times 1–3 months). Then for a forecast for JFM at a lead-time of 2 months, the forecasts starting in November for January, February and March are averaged and so forth.

Model skill

To evaluate the accuracy of model forecasts and provide a measure of the skill of the model, hind-casts of SSTAs are compared to observed SSTAs for the same period (Alves et al. 2003). SSTAs are calculated for both the model forecasts and observed values as the difference between SST values and the relevant climatology. The climatology is the monthly mean SST over the period 1980–2006, computed relative to start month and lead-time for the model, and removing this from SST values reduces the effects of any model bias (Stockdale 1997). Skill is calculated by correlating model anomalies with observed anomalies in both space and time. The correlation coefficient (r) is defined as the ratio of the covariance of the sample populations to the product of their standard deviations, with a skill value of 1.0 indicating a perfect fit between model and observed values.

Persistence is used as a minimum skill forecast to assess the predictive value of the model. A forecast of persistence simply uses current observed anomaly conditions as a predictor of future conditions e.g. for a forecast beginning on 1 March, the SSTA for February is used as the forecast and persisted for the duration of the forecast period. Persistence forecasts are then correlated with observed values with skill compared to that of the model.

GBR SST Index

The GBR Index is the areal average of monthly SSTAs within the Great Barrier Reef study region (Fig. 1a). The index is calculated for the ten individual model ensemble members and the ensemble mean as well as observed SST from the Reynolds OI.v2 daily 1° analysis (Reynolds and Smith 1994; Reynolds et al. 2002). It provides a useful summary of SSTAs for the GBR region, and a potential indicator as to the likelihood of coral bleaching occurring. The high spatial correlation of the observed GBR Index with all other observed values in the GBR region (Fig. 1b) indicates that the GBR Index is an adequate indicator of the overall SSTAs of the region.

Results

Forecast skill assessment

Figure 2 compares the seasonal (3-month mean) GBR Index calculated for both model ensemble mean forecasts and observed values at lead-times of 0–3 months for the years 1982–2006. At a lead-time of 0 months, there is good agreement between POAMA and observed GBR Indices, with a correlation coefficient of 0.73. The timing and magnitude of the majority of peaks is captured by the model. Exceptions include the SSTA minimums in 1991 and 1997 and maximum in 2004, all of which are underestimated by the model. As the lead-time of the forecast increases, the correlation between observed and modelled indices decreases, i.e. 0.61 at 1 month, 0.53 at 2 months and 0.49 at 3 months lead-time. POAMA captures the general variability exhibited in the observed GBR Index but tends to underestimate the extreme values, particularly the negative SSTAs. High SSTAs associated with the 1998 El Niño event are predicted up to 3 months ahead, though the magnitude is lower and the timing slightly delayed.

The correlations of the model and persistence to observed GBR Indices for 1982–2006 are shown in Fig. 3a for monthly forecasts starting all months, and in Fig. 3b for seasonal forecasts for the target season of January–February–March (JFM) starting at different lead-times. In both cases, the model skill exceeds that of persistence, indicating the model forecasts have useful value. As expected, the skill of model forecasts decreases with lead-time, with skill of JFM forecasts generally lower than that for all months. Model skill still exceeds 0.5 for lead-times of 0–2 months and is an improvement over persistence forecasts at greater lead-times. Note that the skill of both model and persistence forecasts actually increase at lead-time of 5 months for JFM. This may be simply a statistical artefact due to a small sample. Alternatively, it may be an increased skill due to remote forcing. For example, El Niño Southern Oscillation SSTAs which are mainly located in the central and eastern Pacific, influence the SST in the GBR region several months later (see Fig. 9). The lag relationship may lead to increased skill at longer leads.

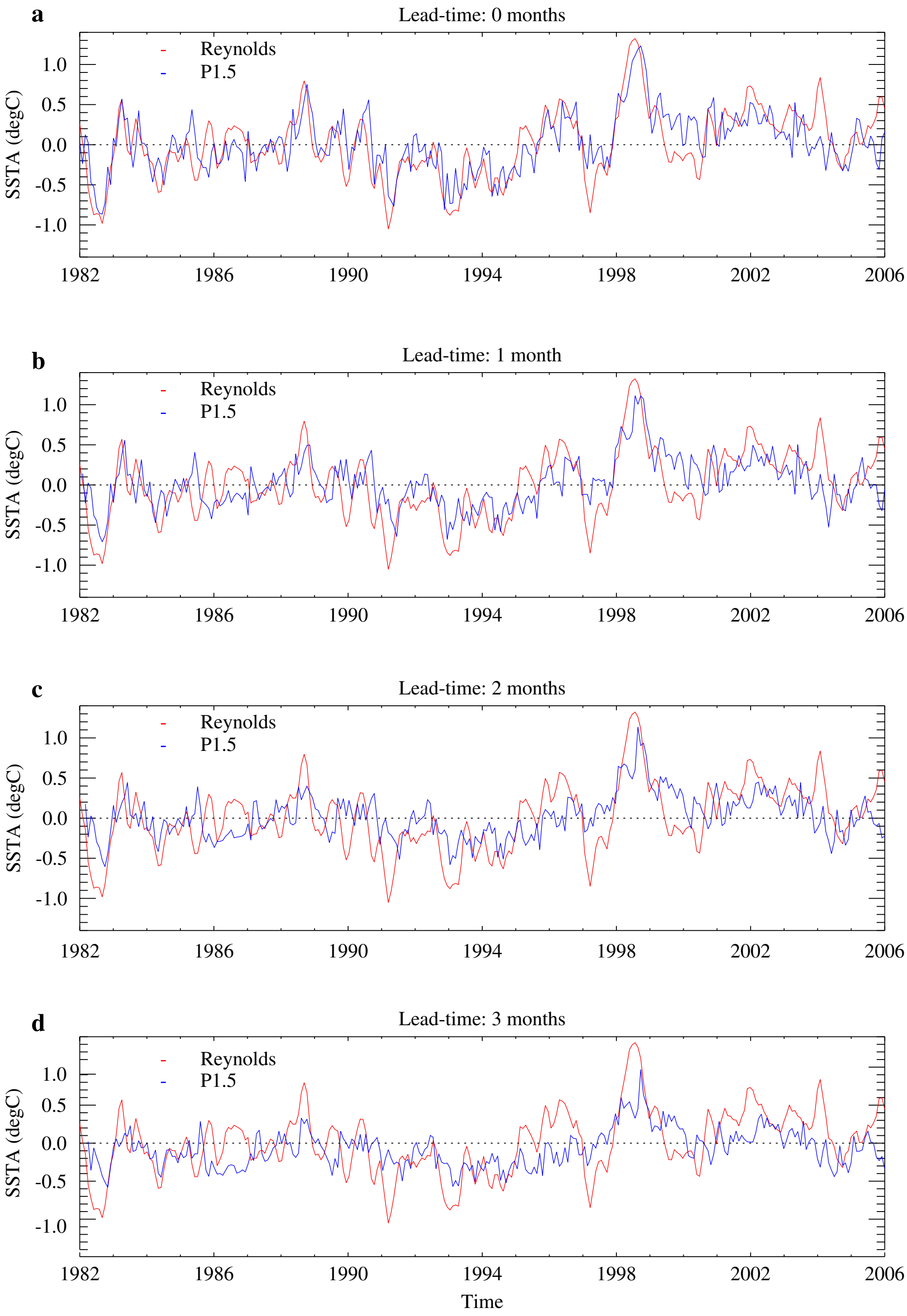
The spatial distribution of skill of POAMA SSTA forecasts across the GBR region is compared to that of persistence forecasts for the target season of JFM in Fig. 4. Whilst the GBR Index is a useful indicator for regional SST conditions, greater detail is also necessary to determine the location of high SSTAs and thus, potential bleaching sites. At almost all lead-times and locations, model skill exceeds that of persistence. Model skill appears to be higher in the northern reaches of the GBR region than in the south, with the exception of an area of lower skill along the northern coast at lead-time of 1 month. Conversely, persistence has greater skill in the southern extent of the region than in the north at lead-times of 0–1 month. Skill of both the model and persistence decrease significantly at lead-times of 2 months in the southeast quadrant of the region. The higher skill in the northern parts compared to the southern area is likely due to the larger influence of tropical variability, principally ENSO.

Case Studies: 1998 and 2002 bleaching events

1998 Bleaching event

The ten ensemble member forecasts and the ensemble mean forecast beginning in the months of September 1997 to February 1998 for the GBR Index are shown in Fig. 5. The ensemble mean is the best forecast estimate, with ensemble members providing an indication of forecast spread or uncertainty due to internal variability. The ensemble mean is generally comparable with the observed values at short lead-times but diverges at longer lead-times. Model forecasts starting in September 1997 capture the rising trend in the GBR Index. Forecasts started in October, November, December and January (Fig. 5b–e) for January and February agree well with the observed values, with the observations lying near the centre of the ensemble. For

Fig. 2 Seasonal Reynolds (red) and POAMA 1.5 (blue) GBR Indices for 1982–2006 for lead-times of (**a**) 0 months, (**b**) 1 month, (**c**) 2 months and (**d**) 3 months



autumn the forecasts tend to underestimate the amplitude of the warming, particularly at longer lead-times. Observed SSTAs are generally captured within the ensemble spread at short lead-times, though the ensemble members diverge from observations at longer lead-times, particularly in the summer months.

Observed and modelled SSTAs (ensemble mean) for different start dates for the GBR region for JFM 1998 are presented in Fig. 6. The model captures the general north–south SSTA gradient with higher anomalies in the southern reaches of the GBR. The model predicts the spatial patterns of observed anomalies reasonably well though some values are up to 0.4°C higher than those observed (Fig. 6c). Spatial correlations of SSTAs in the GBR region for JFM 1998 at lead-times of 0, 1 and 2 months are 0.59, 0.84 and 0.87, respectively. The model,

Fig. 3 Skill of ensemble mean GBR Index predicted by POAMA 1.5, persistence and potential predictability for all lead-times for (**a**) all months and (**b**) target season January–February–March

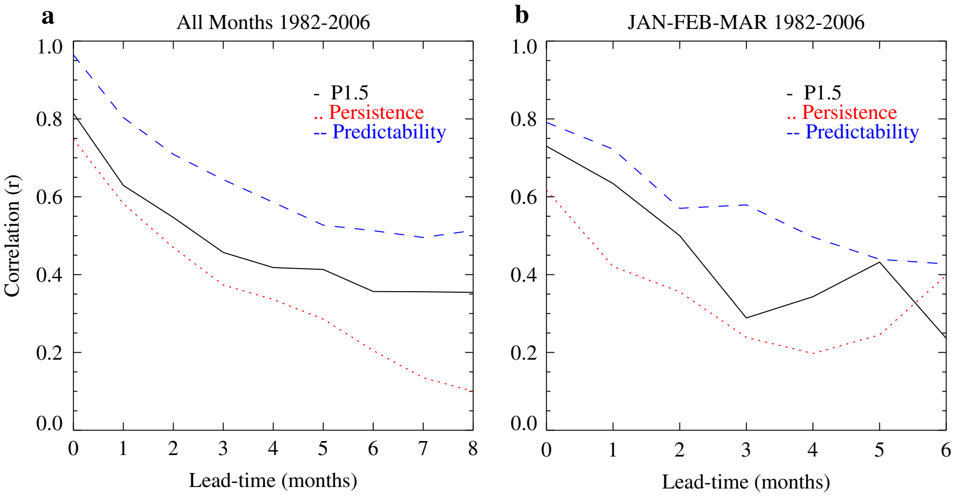
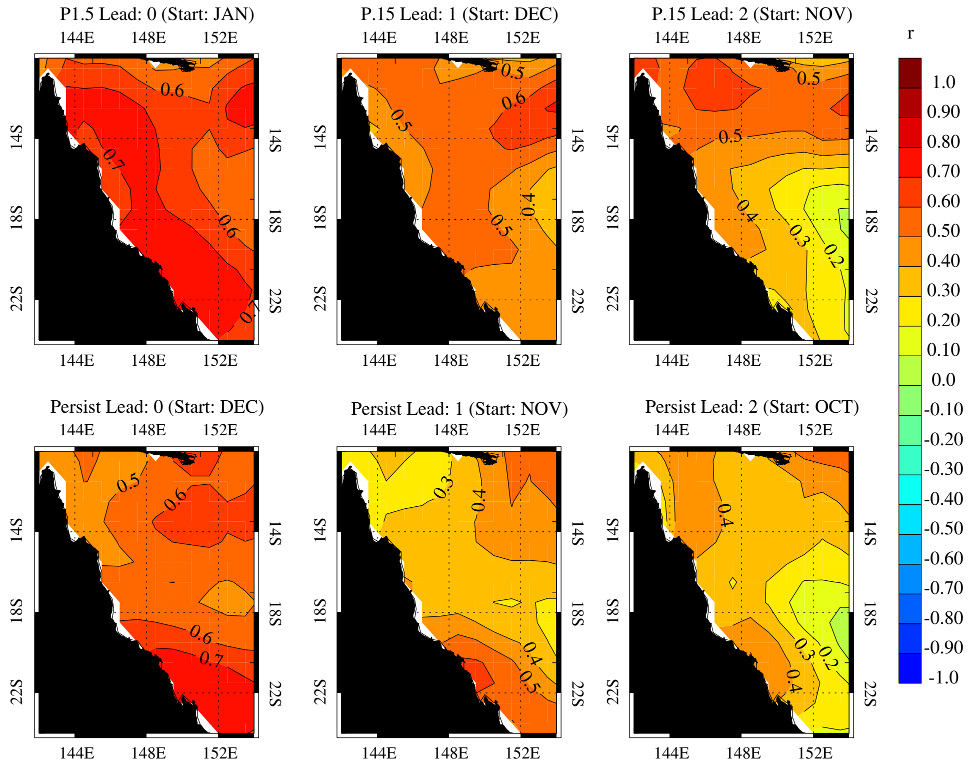


Fig. 4 Skill of POAMA 1.5 (ensemble mean) SSTA forecasts at lead-times of (**a**) 0 months, (**b**) 1 month and (**c**) 2 months, and skill of persistence SSTA forecasts at lead-times of (**d**) 0 months, (**e**) 1 month and (**f**) 2 months, for January–February–March 1983–2006 in the GBR study region



somewhat counter-intuitively, seems to produce better forecasts at longer lead-times in this case. However, in January 1998 the tropical cyclone Katrina occurred in the GBR region, with maximum wind speeds of 89 knots at 15.1 S and 149 E (Australian Bureau of Meteorology, http://www.bom.gov.au). The location of these high winds seems to correspond that of the cooler observed anomalies (Fig. 6a), which could not be captured by the model. However in general, the model tends to underestimate the magnitude of SSTAs with lead-time (e.g. Figs. 2 and 5), so this coupled with weaker observed anomalies could result in improved forecast at longer lead-times in this case.

2002 Bleaching event

The ten ensemble member forecasts and the ensemble mean forecast starting in the months of September 2001 to February 2002 for the GBR Index are shown in Fig. 7. For September, October and November forecast start dates, the model ensemble mean underpredicts the observed GBR Index by 0.2–0.3°C and exhibits little variability with lead-time (Fig. 7a–c). None of the ensemble members shows the observed warming. For December, January and February forecast start dates, some of the ensemble members do capture the observed warming, however, the model

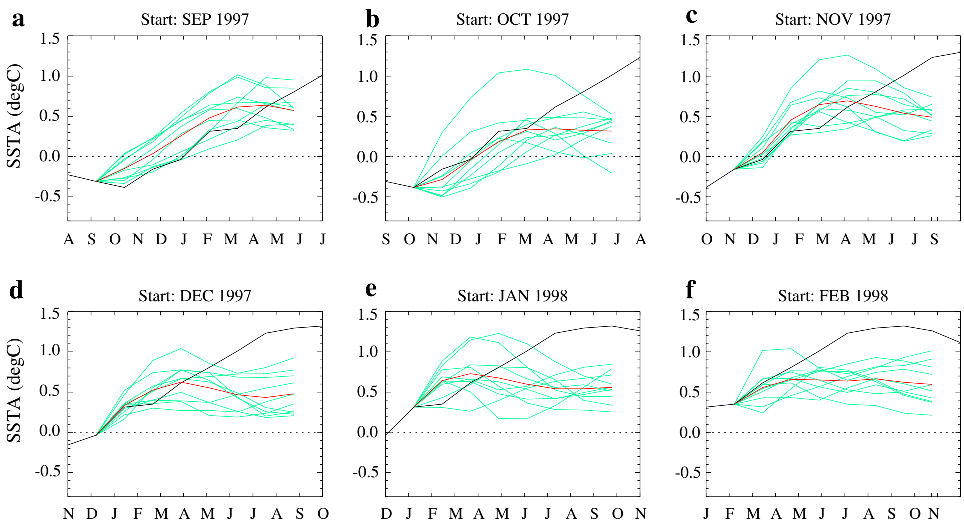


Fig. 5 Reynolds GBR Index (black) compared to individual POAMA 1.5 ensembles (green) and ensemble mean (red) seasonal forecasts of the GBR Index at lead-times of 0–6 months for forecasts starting in (**a**) September 1997, (**b**) October 1997, (**c**) November 1997, (**d**) December 1997, (**e**) January 1998 and (**f**) February 1998

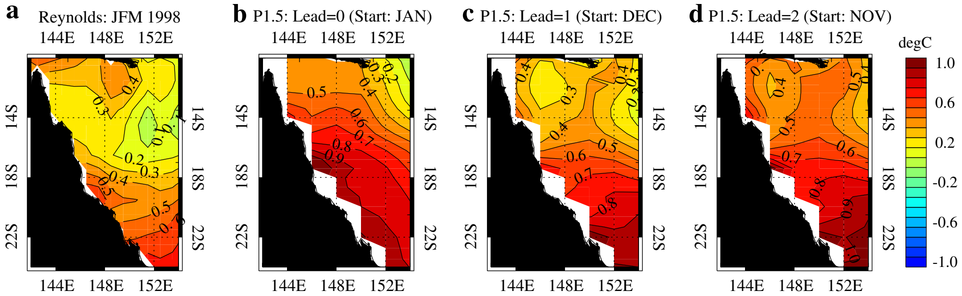


Fig. 6 (**a**) Observed (Reynolds) SSTAs and POAMA 1.5 SSTAs at lead-times of (**b**) 0 month, (**c**) 1 month and (**d**) 2 months for January–February–March 1998 in the GBR region

ensemble mean consistently underestimates the degree of warming observed even at short lead-times (Fig. 7d–f). In the summer of 2001–2002, observed SSTAs were considerably higher than those recorded in 1997–1998, i.e. 0.7°C in January 2002 compared with 0.3°C in January 1998 (Fig. 5). The model does not appear to capture these relatively high anomalies, which may be possibly due to local scale processes such as low wind conditions or high solar radiation.

Observed and modelled SSTAs (ensemble mean) for different start dates for the GBR region for JFM 2002 are presented in Fig. 8. Spatial correlation values for SSTAs in the GBR region for JFM 2002 at lead-times of 0, 1 and 2 months are 0.76, 0.71 and 0.60, respectively. The model

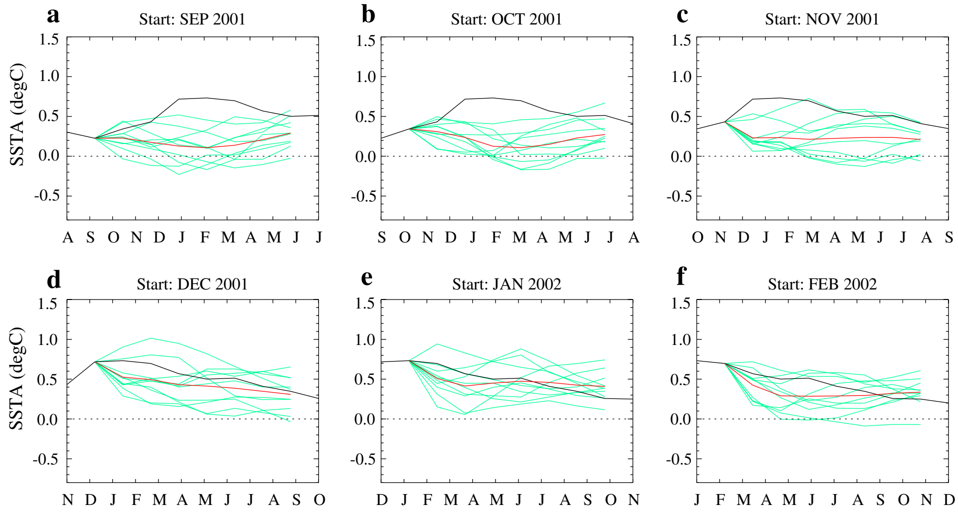


Fig. 7 Reynolds GBR Index (black) compared to individual POAMA 1.5 ensembles (green) and ensemble mean (red) seasonal forecasts of the GBR Index at lead-times of 0–6 months for forecasts starting in (**a**) September 2001, (**b**) October 2001, (**c**) November 2001, (**d**) December 2001, (**e**) January 2002 and (**f**) February 2002

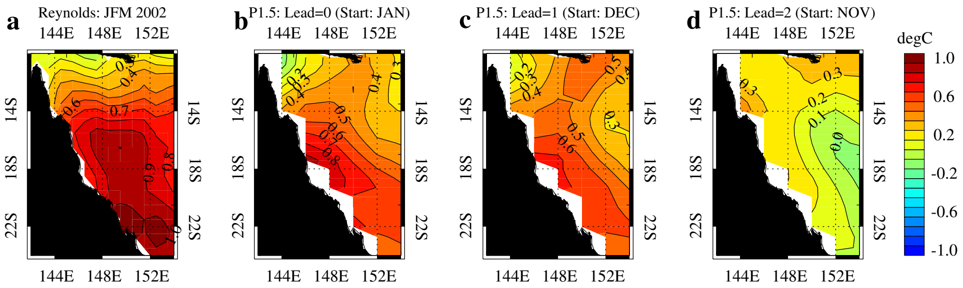


Fig. 8 (**a**) Observed (Reynolds) SSTAs and POAMA 1.5 SSTAs for at lead-times of (**b**) 0 month, (**c**) 1 month and (**d**) 2 months for January–February–March 2002 in the GBR region

appears to have reasonable skill though underestimates observed values for the period by up to 0.5°C even at short lead-times, and worsening with larger lead-times. Observed anomalies in the southern parts of the GBR were up to 1°C, 0.3–0.4°C higher than those in the same season in 1998, which resulted in widespread and severe coral bleaching (Berkelmans et al. 2004). The model fails to capture these high anomalies in 2002, compared to those in 1998. The annual variability of the influence of large scale patterns such as ENSO on the GBR region may contribute to the difference in model skill for these two cases.

Figure 9 shows the time series of observed NINO34 SSTAs and the observed GBR SST Index. NINO34 is defined as the areal average of monthly SSTAs in the tropical Pacific Ocean (5 S–5 N, 170–120 W) and is an index used to describe ENSO. There is an inverse relation between NINO34 and the GBR Index with a correlation of −0.32. However, there is also a phase shift of approximately 3 months. When this lag is taken into account, correlation between the two indexes is maximised at −0.43. Warm events in the GBR Index have been associated with the onset of a La Niña event e.g. in 1986 and 1998. The warming in GBR Index in 1998 is a relatively long-lived event lasting over a year and associated with the development of La Niña conditions following the decay of the 1997/1998 El Niño. In general, POAMA forecasts for large scale SST events such as ENSO have high skill (Wang et al. 2008). However, the 2002 GBR warming event is more short-lived and not associated with a large scale Pacific wide ENSO event, which is the likely reason why the model did not predict this event.

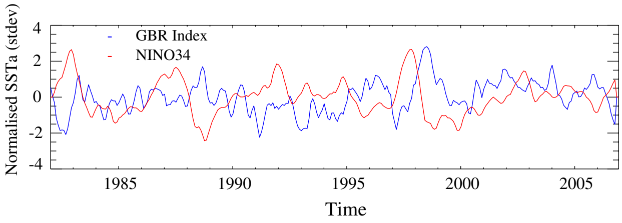


Fig. 9 Seasonal normalised Reynolds NINO34 (red) and Reynolds GBR (blue) indices for 1982–2006

Discussion

This study represents the first attempt to investigate the ability of a coupled ocean–atmosphere model to predict SSTAs for the purpose of anticipating coral bleaching events at the seasonal scale. The model reproduces monthly SSTAs in the Great Barrier Reef with predictive skill up to 2 months lead-time, a useful time frame for reef managers. Future improvements in model error may lead to more skilful forecasts at longer lead-times.

The model shows reasonable skill in predicting both the GBR Index and spatial SSTAs for the season JFM at lead-times of up to 2 months. POAMA also predicted the warm SSTAs in the summers of 1998 and 2002, which triggered mass coral bleaching (Berkelmans et al. 2004), with a degree of accuracy. The model however seems to exhibit less variability than is evident in the observed values, with fewer extremes predicted. At longer lead-times the SST skill decreases rapidly, most likely due to model systematic error. Model skill is nevertheless consistently greater than that of persistence, indicating these forecasts have useful skill and thus management applicability on a seasonal timescale. Forecasts of SSTAs alert reef managers of potential risk for warm conditions that can promote bleaching and form the basis for more bleaching-specific products such as Coral HotSpots and Degree Heating Weeks (NOAA). Seasonal forecasts of probabilities of SST exceeding specific bleaching thresholds with predictive skill would prove to be a valuable tool for reef managers.

Various local conditions, such as extreme ultraviolet radiation (Gleason and Wellington 1993), reduced salinity (Kerswell and Jones 2003) and low wind conditions, can all exacerbate coral bleaching. These factors also contribute to the heterogeneity of bleaching patterns across the GBR, as do the spatial extent of the reef and a range of species, communities and physical environments existing within the reef (Done et al. 2003). POAMA simulates solar radiation, winds and salinity, but as SST is recognised to be the primary contributor to coral bleaching (Hoegh-Guldberg 1999), we limit the model skill assessment to SST in this initial study. The GBR Index forms a useful indicator of SSTAs for the GBR region and has application in future work as a potential indicator of bleaching. Further, the spatial resolution of POAMA allows for the prediction of anomalous SST at a scale on the order of 150–300 km, providing more specific information as to the location of coral bleaching as well as its likelihood. It is worth noting though, that skill of POAMA forecasts is generally higher for large scale SST events such as ENSO, and so skill of forecasts in the GBR can be low if local conditions are relatively unaffected by larger patterns, as seems to be the case in 2002 (Fig. 8). Whilst the strength of the model lies in the prediction of large scale SSTAs that can lead to bleaching in the GBR region, it is also necessary to note the potential masking of reef areas close to land by the coarse resolution model grid. Regional downscaling of model forecasts to sub-grid scales has potential applicability for increasing the value of the model as a reef management tool and is the subject for future study.

Potential predictability is the upper level of skill that can be achieved for a model forecast given a perfect model and initial conditions (Griffies and Bryan 1997). It is calculated by using one ensemble member as a reference and calculating the skill of the mean of the remaining ensemble members in predicting it. This is repeated using different ensemble members as the reference ensemble member. Skill is never perfect as the chaotic component in the system leads to ensemble spread, which in turn limits predictability. Predictability values indicate that POAMA has the potential to improve the anomaly correlation skill of model forecasts by 2–4 months (Fig. 3), e.g. current skill at 2 months lead-time could potentially be reached at 4 months lead-time if the model and initial conditions were improved. Increased resolution in the atmospheric model, assimilation of both salinity and temperature data and bias corrections are all planned improvements for future versions of POAMA.

However, these first results look promising and indicate POAMA could be a very effective tool in the management of coral reefs. Development of operational management type tools based on the GBR Index and spatial forecasts, in conjunction with statistical downscaling to enhance model forecasts, is the next step in this work and will be of great benefit for reef management on seasonal timescales. Daily 30-member ensemble forecasts of SSTAs are now available online in real time as an experimental product, with plans to include more bleaching-specific products in the future (http://poama.bom.gov.au). The use of a multi-member ensemble has the potential for use in probabilistic forecast generation for coral bleaching, in providing associated probabilities or risk factors to allow for more informed management decisions. There is great potential for application to other reef systems around the world to improve management of these fragile ecosystems in the face of global warming. Global warming is likely to increase the frequency and severity of bleaching (Hoegh-Guldberg 1999), and thus development of such tools is crucial to combat problems due to climate change in the near future.

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