Decadal-Scale Forecasting of Climate Drivers for Marine Applications

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Abstract

Climate influences marine ecosystems on a range of time scales, from weather-scale (days) through to climate-scale (hundreds of years). Understanding of interannual to decadal climate variability and impacts on marine industries has received less attention. Predictability up to 10 years ahead may come from large-scale climate modes in the ocean that can persist over these time scales. In Australia the key drivers of climate variability affecting the marine environment are the Southern Annular Mode, the Indian Ocean Dipole, the El Niño/Southern Oscillation, and the Interdecadal Pacific Oscillation, each has phases that are associated with different ocean circulation patterns and regional environmental variables. The roles of these drivers are illustrated with three case studies of extreme events—a marine heatwave in Western Australia, a coral bleaching of the Great Barrier Reef, and flooding in Queensland. Statistical and dynamical approaches are described to generate forecasts of climate drivers that can subsequently be translated to useful information for marine end users making decisions at these time scales. Considerable investment is still needed to support decadal forecasting including improvement of ocean-atmosphere models, enhancement of observing systems on all scales to support initiation of forecasting models, collection of important biological data, and integration of forecasts into decision support tools. Collaboration between forecast developers and marine resource sectors—fisheries, aquaculture, tourism, biodiversity management, infrastructure—is needed to support forecast-based tactical and strategic decisions that reduce environmental risk over annual to decadal time scales.

1. INTRODUCTION

1.1 Climate Drivers and Their Marine Impacts

In the last few centuries, there have been major disruptions of marine ecosystems by extreme environmental conditions. Prominent examples include fluctuations related to the El Niño/Southern Oscillation (ENSO) which caused South American Peruvian fisheries failures (Bakun and Broad, 2003) noted first in the 16th century (Garcia-Herrera et al., 2008), and more recently with the 1972/73 event (Valdivia, 1978). This event caused an intrusion of warm, nutrient-poor water from the vicinity of the equator southward along the coast of Peru, resulting in the collapse of anchovy catch from 13 to 2 million tonnes, and in addition to fisheries, impacted a range of dependent seabird and marine mammal populations. The water was more than 8°C above average in some regions (Glantz, 2001).

> The 1972–73 event clearly merits a place in the yet to be created El Niño 'Hall of Fame' as the event that energized the oceanographic, atmospheric and biological research communities and also prompted some of the first papers on the societal impacts of El Niño *(Glantz, 2001)*.

More recently, Mantua et al. (1997) noted widespread environmental changes related to interdecadal climate variations in the Pacific. Dramatic shifts in a variety of terrestrial and marine ecological factors in western North America coincided with the changes in the state of the ocean environment in the late 1970s which led to rapid changes in the production levels of major Alaskan commercial fish stocks of Alaskan pink and sockeye salmon (Beamish and Bouillon, 1993; Hollowed and Wooster, 1992; Litzow et al., 2014). Similar climate relationships have been observed for salmon populations in Washington, Oregon, and California as well as populations of demersal fish, crabs, and shrimp (Cloern et al., 2010; Litzow et al., 2014) associated with interdecadal climate variability, the Pacific Decadal Oscillation (PDO) in the northeast Pacific. It is now known that patterns of ocean variability on basin scales persist for some time—from a season to a decade or more. These patterns are known as climate phases and are associated with, for example, warmer or colder water, increased storminess, and changes in upwelling. The transition of the drivers to different phases is accompanied by changes in the average and extreme values in atmospheric and oceanic variables such as winds, sea surface temperature (SST), salinity and thermocline depth at regional scales, and shifts in stock productivity (Klaer et al., 2015). The periods of these phases occur over durations of six months to a decade—this time period is often seen as too difficult to forecast, as it represents transition from 'weather' prediction to decadal variability (Goddard et al., 2012).

Knowledge of the probability of future extreme events can be usefully applied to reduce risks to humans and support adaptation planning. Unfortunately predicting the future at yearly to decadal time scales is difficult. There are, however, some natural advantages that may assist ocean forecasting at these time scales. As the oceans absorb much of the solar energy that reaches earth they are a significant influence on Earth's weather and climate. Relative to the atmosphere the oceans lose heat much more slowly producing effects over seasonal to decadal time scales.

This 'decadal' time scale also corresponds with the practical time scales for which many policy, investment, and management decisions are being made. In order to manage risk on such practical time scales, we need to improve our skill at predicting climate and its impacts over the same period.

For example, the ability to vary the price of tuna day fishing licences depending on future El Niño state would contribute to the financial stability of Kiribati (Bell et al., 2013), knowledge on increased likelihood of cyclones would aid disaster management in Solomon Islands and Vanuatu (Cvitanovic et al., 2016), and information on environmental links to stock abundance would enhance fisheries in Australia (Fulton, 2011). Because of the importance of climate variability to economic and environmental well-being, these time scales are critical for decisions on marine infrastructure and resilience planning. For coastal aquaculture, similar strategic and long-term investment decisions are made over this time frame where climate variability affects local conditions. In the tourist sector the change in marine ecosystems has major implications for regional employment and infrastructure.

The climate phases, as in the historical ENSO events, can lead to extremes of SST challenging the biological tolerances of species in the prevailing marine environment. For example, the variability of ENSO provides dramatic impacts on tuna abundance between the western Pacific and the cooler nutrient-rich waters of the eastern equatorial Pacific, which is a prime feeding area for tuna (Lehodey et al., 2008). The change in tuna abundance means large changes in gross revenue between Pacific Island economies in the western Pacific compared with those in the central and eastern Pacific (Bell et al., 2013). The Interdecadal Pacific Oscillation (IPO) modulates ENSO phases (El Niño and La Niña) on decadal time scales. Thus, the IPO may move the 'climate' regime from one phase to another.

Changes in ocean climate continue to have large environmental and economic impacts, as we show in three case studies in Western Australia (WA), the Great Barrier Reef (GBR), and coastal Queensland. The case studies of the marine heatwave (MHW) in WA, coral bleaching of the GBR, and flooding in Queensland illustrate the impacts of the various climate drivers that effect Australia on the marine environment. The understanding of the climate drivers in Australia (eg, Risbey et al., 2009), and the forecasting of these can then be used to anticipate on seasonal climate time scales and the information generated can be used in decision support tools for marine applications. The principle of clear understanding of climate drivers in Australia can be used to understand climate drivers in any region. For example, the North Atlantic Oscillation (NAO) has definite impacts on the winter climate of Europe and beyond (Rodwell et al., 1999). Forecasts of the NAO (Scaife et al., 2014) can be used to then used to anticipate aspects of North American and European winter climate. Oceanic conditions around western

Europe can be then applied to estimate stock abundance (Brander and Mohn, 2004).

Decadal forecasting has the potential to reveal changes relevant to marine ecosystems and predict the impacts on sectors such as fisheries and coastal infrastructure, and to support strategic and investment scale decisions made by these sectors. For Australian fisheries, where ocean conditions affect stock abundance (Fulton, 2011; Hobday et al., 2011; Wayte, 2013), this impacts on the presence, or absence, of a fishery with associated investment in fishing vessels and infrastructure.

1.2 Extreme Events: Biological Tolerances and Impacts

There is an extensive literature that considers the risk of extreme events to human systems and ecosystems and how they may change due to climate change, including a recent special report of the Intergovernmental Panel on Climate Change (IPCC, 2012). One of the clear influences of climate drivers on marine systems is expressed via extreme events. The occurrence of a climate variable above (or below) a threshold value near the upper (or lower) end of the distribution of observed values of the variable is an extreme event. For simplicity, both extreme weather events and extreme climate events are referred to collectively as 'climate extremes' (IPCC, 2012). Climate extremes have normally been related to terrestrial and human systems, and therefore are related to temperature (heatwaves, frosts, extreme temperature both high and low), precipitation (high intensity rainfall, floods, hail snowstorms, droughts) and storms.

Under long-term climate change, changes in the mean value of climate variables over time are expected, as are changes in the variability or the distribution of values, all of which alter the frequency of extremes. For example, a simple shift of the entire distribution toward a warmer climate increases the frequency of extreme high temperatures, whereas increased temperature variability with no shift of the mean increases both high and low temperature extremes. Finally alteration of the shape of the distribution with, for example, an increased asymmetry towards the hotter part of the distribution increases the frequency of high extreme temperatures (Fig. 1). The different phases of large-scale climate drivers such as ENSO and PDO are also associated with different distributions of regional climate and oceanic variables, such as sea level (Holbrook et al., 2011) and temperature (Holbrook and Bindoff, 1997).

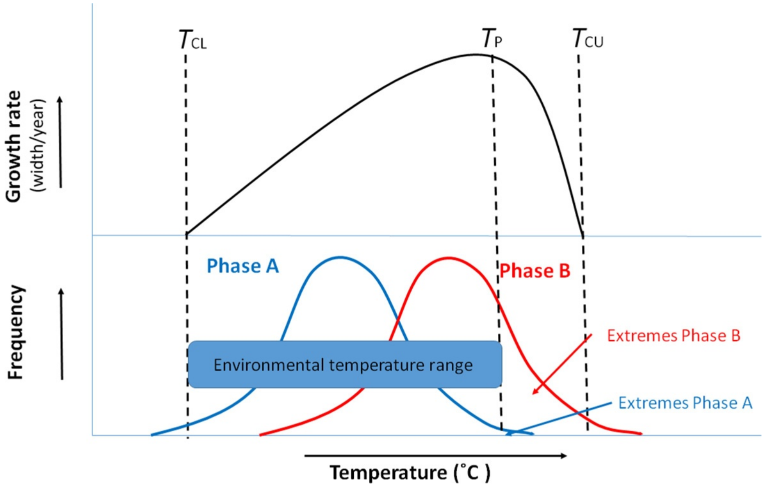

Fig. 1 (*Upper*) There is a near-linear increase in growth with temperature over a mid-range in temperatures for fish and microalgae, bounded by the lower critical temperature (T_{CL}) (°C) and pejus temperature (T_P). At temperatures above the growth tolerance limit ($>T_P$), growth rate declines with increasing temperature to the upper critical temperature (T_{CU}) after which growth ceases. (*Lower*) Distribution in temperature range for two states of a hypothetical climate driver. In phase A the mean and high extremes are lower than in phase B. An example species environmental temperature range is indicated by the *blue* (grey in the print version) *bar*. *(Upper) Adapted from Neuheimer, A.B., Thresher, R.E., Lyle, J.M., Semmens, J.M., 2011. Tolerance limit for fish growth exceeded by warming waters. Nat. Clim. Chang. 1, 110–113. Thompson, P.A., 2006. Effects of temperature and irradiance on marine microalgal growth and physiology, In: Subba Rao (Ed.), Algal Cultures, Analogues of Blooms and Applications. Science Publishers Inc., Enfield, New Hampshire, 571–638.*

Much of the available research on climate extremes is based on the use of so-called 'extremes indices' (Zhang et al., 2011). These indices are based either on the probability of occurrence of given quantities or on absolute or percentage threshold exceedance (relative to a fixed climatological period), but also include more complex definitions related to duration, intensity and persistence of extreme events. Therefore an event can be extreme as a result of the duration, intensity (magnitude above a reference value), spatial extent and timing (Perkins and Alexander, 2013). Unfortunately the definition and measurement of heat extremes can be ambiguous and inconsistent, generally being specific to only the group affected, or the respective study reporting the analysis. While MHWs are most commonly reported in the oceanic environment, extremes can also include excursions from usual values in oxygen, salinity, pH, bottom temperatures, rainfall, and winds (Brodeur et al., 2005; Zinke et al., 2015).

Despite awareness of these events, there is variation in how the physical processes are characterized. With regard to heatwaves, both atmospheric and marine researchers use a range of definitions to describe events, which has complicated comparative work. To address these issues for one type of marine extreme event, Hobday et al. (2016a) developed general definitions for MHWs. They propose that a prolonged discrete anomalously warm water event can be described by consistent measures of duration, intensity, and rate of development. In parallel with definitions of atmospheric heatwaves (Perkins and Alexander, 2013), Hobday et al. (2016a) suggest a definition of a MHW as an event that lasts a minimum of five days where temperatures are warmer than the 90th percentile value based on a 30-year historical baseline period. This definition recognizes that a MHW can occur at any time of year, and even extreme temperature events in a cool season can disrupt some biological communities (Hobday et al., 2016a). Although this minimum duration for defining these extreme events may seem short, in the marine environment once temperatures exceed such a threshold, MHWs invariably last for longer durations (Pearce and Feng, 2013). For example, unrelated extreme events in Australia lasted in the order of four weeks in 2011 and caused ecological impacts over wide areas of Western Australia (Feng et al., 2013) and the GBR (Marshall et al., 2013).

Extreme events lead to extreme impacts on species and ecosystems only when conditions are outside the bounds of typical or normal variability tolerated by species (Smith, 2011), for instance when individual physiological tolerance thresholds are exceeded (Neuheimer et al., 2011; Pörtner et al., 2014). By way of example, most marine organisms including fish are ectotherms or 'cold-blooded', thus environmental temperature determines their rate of growth and development. However, as in southern rock lobsters, *Jasus edwardsii* (Punt et al., 2006), net positive growth is bound by a lower temperature where there is no growth and an upper maximum, or pejus temperature (T_P), above which the growth rate decreases to zero (as cardiac output cannot keep pace with increased metabolism) (Fig. 1, upper). Further temperature increases lead to growth termination, anaerobic respiration, protein denaturation, permanent inactivation of enzymes, and eventual death. Temperature thresholds and tolerances are species-specific (Neuheimer et al., 2011). For fish species the environmental range for Banded Morwong is 11–18°C in the Tasman Sea with $T_P \sim 18$°C; Northern

Anchovy 8–24°C with $T_P \sim 24°C$ in the California Current (Brewer, 1976); Sole 3–22°C with $T_P \sim 22°C$ in the North Sea (Rijnsdorp et al., 2009).

Temperature exerts a similar fundamental control over microalgae (Eppley, 1972; Thompson, 2006) and other plankton (eg, Bijma et al., 1990; Lombard et al., 2009) where growth is also only possible within a relatively limited range. Over a given temperature range growth increases to a maximum, then above a critical temperature decreases quite rapidly to zero. For individual marine species the temperature range over which growth is possible is much less, with cosmopolitan and temperate species typically having a range of ~30°C (eg, very low growth at 5°C and zero growth at 35°C), while for some polar species the range may be <10°C (Fiala and Oriol, 1989). Phytoplankton community responses to changes in temperature thresholds depend on the relationship between temperature and growth for the species in the particular ecosystem (Boyd et al., 2013). The shape of the tolerance curves can vary from the idealized version shown in Fig. 1 (upper) but in general, as for fish species, there is an abrupt transition from maximum growth to death. This abrupt transition is the likely cause of the very large rise in endosymbiotic dinoflagellate death rates and coral beaching that occur with a relatively small increase in water temperature (Tchernov et al., 2004).

The frequency of extreme events that may exceed biological thresholds is related to the state of the ocean and atmospheric systems. For example, when climate drivers such as ENSO change their phase (Fig. 1, lower), the frequency distribution of environmental variables (eg, temperature, sea level, wind speed, salinity) can also change, which affects both the mean value and probability of extreme values. In the illustrated case with the mean temperature increase from Phase A to B, there is a large increase in frequency of high temperatures above the T_P which will be beyond the tolerance range of the particular species. Although biological conditioning (acclimation) can occur for low temperature extremes (Black, 1953; Brett, 1941, 1944), this does not occur at high temperature extremes when temperatures exceed the upper critical temperature. For high temperature extremes the duration above the threshold is the most important factor (Pörtner et al., 2014). The width of environmental range, or thermal window, varies across life stages of marine species, from egg and larval to adult stages (Pörtner et al., 2014). Thus, extremes above some threshold value can limit one life stage with overall population impacts.

There is early documentary evidence that climate drivers have led to Australian climate extremes since European settlement in the 18th and

19th centuries. Nicholls (1988) has shown that between 1788 and 1841, occurrence of Australian droughts match well with El Niño events in South America. The impacts on Australian society are substantial: the 1982/83 drought was estimated at $AUD 3 billion (Allan and Heathcote, 1987) as it caused crop failure, reduced farm cash surplus ($AUD 1.1 billion), reduced national employment (2%, 100,000 jobs) and contributed to conditions that were favourable for a severe dust storm and widespread bush fires, the latter of which covered 500,000 hectares and caused property damage worth $400 million. The focus of this chapter is the range of impacts in the ocean caused by marine extremes.

1.3 Outline of Review

In the following sections of this review, we review, analyse, and describe the climate drivers (key drivers of climate variability across the continent and marine situation at different times of the year) that affect the Australian marine environment, especially those that couple with oceanic drivers (ocean climate patterns of variability). We illustrate the effects of these climate drivers in three Australian case studies in Western Australia, the GBR and coastal Queensland that show regional impacts on physical, biological, and dependent human systems. Forecasts of these drivers (and their phase) and the resulting probability distribution of regional variables such as temperature and wind speed may reduce the impacts if proactive planning is possible. Forecasting methods based on persistence, statistical forecasting, and dynamical modelling with application to the Australian region are discussed. We then assess future directions to improve seasonal to decadal forecasting. This is important because the next decade will likely be 'the critical decade' in terms of climate change (Meinshausen et al., 2009) as key decisions are required to slow global warming as well as adapt to variability and extremes arising from the climate and oceanic drivers.

2. CLIMATE DRIVERS

There are multiple important climate and oceanic drivers that affect the marine environment in the Australian region on monthly to seasonal to decadal time scales. These include the SAM (Karoly et al., 1996), the Indian Ocean Dipole (IOD) (Saji et al., 1999), ENSO (Troup, 1965), and the IPO (Power et al., 1999). Other large-scale climate drivers such as the North Pacific Gyre Oscillation (NPGO) and NAO have more limited impact in Australia. The principles we discuss here are applicable to drivers in any region. Important drivers of Australian ocean climate can have a direct local impact or a remote 'teleconnection' to a region via the large-scale atmospheric and oceanic circulations (eg, Castillo-Jordán et al., 2016). We outline some of these behaviours and impacts in the following section, including the occurrence of extreme events.

2.1 Southern Annular Mode

The SAM is the leading mode of atmospheric variability south of 20°S (Karoly et al., 1996; Thompson and Wallace, 2000; Trenberth et al., 2005). It appears at all time scales from daily to interannual, and consists of a fluctuation in atmospheric pressure between the Antarctic region and the southern mid-latitudes. In the positive phase of the SAM anomalous low pressure occurs over Antarctica. The mid-latitude westerly wind maximum and the tracks of extra tropical storms (Kidston and Gerber, 2010; Yin, 2005) also shift towards the pole during the positive phase of the SAM, and towards the equator during the negative phase. In recent years, a high positive SAM has dominated during the austral autumn–winter and has been associated with a systematic regime transition in the Southern Hemisphere mid-tropospheric circulation post the late 1970s with a stronger and more zonal flow to the mid-latitudes winds (O'Kane et al., 2013b).

Thus, a negative SAM results in more (or stronger) storms and low pressure systems over southern Australia. Conversely a positive SAM results in storms tracking more to the south and weaker storms off the oceans to the south of Australia (Fig. 2A). Using station-based observations of temperature and rainfall to identify the influence of the SAM on land regions over the whole of the Southern Hemisphere, Gillett et al. (2006) note that the positive phase of the SAM is associated with a significant cooling over Antarctica and much of Australia and significant warming over Tasmania and the south of New Zealand, and these trends were also noted by Thompson et al. (2011). Freitas et al. (2015) have shown that these occurrences have led to positive SST anomalies in the oceans below about 40°S. The time series (Fig. 3A) shows a clear increase. Extreme negative seasons tend to be earlier in the record (1957, 1964, 1976, 1988, and 2002) and positive seasons more latterly (1959, 1993, 1998, 1999, and 2010). More of the negative extremes occur in the austral spring and summer, with positive extremes more prevalent in winter.

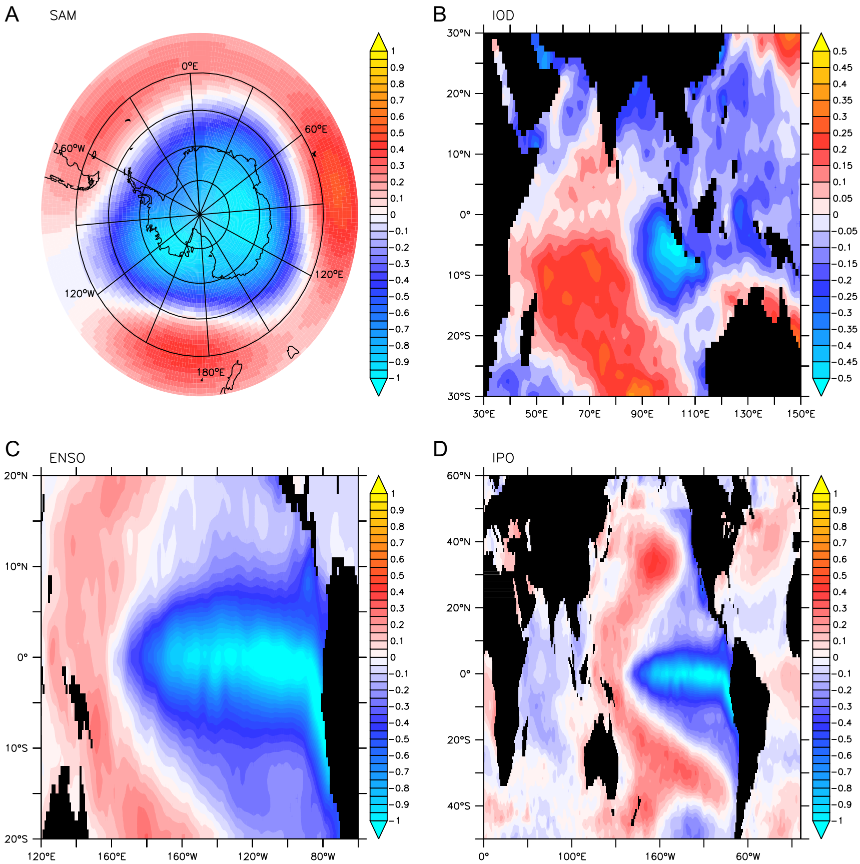

Fig. 2 Spatial 'maps' of the dominant modes of the four drivers. (A) Leading empirical orthogonal function (EOF) of monthly sea-level pressure depicting the Southern Annular Mode (SAM). (B) Composite monthly sea surface temperature (SST) anomalies from September to October depicting the Indian Ocean Dipole (IOD). (C) Leading EOF of SST in the domain 20°S–20°N, 120°E–60°W depicting cold-tongue ENSO. (D) Leading mode of singular value decomposition analysis of low-pass filtered seasonal average SST anomalies, after removal of the global mean SST, depicting the Interdecadal Pacific Oscillation (IPO).

2.2 Indian Ocean Dipole

The IOD is a coupled ocean and atmosphere phenomenon in the equatorial Indian Ocean that affects the climate of Australia and other countries that surround the Indian Ocean basin (Saji et al., 1999). It is a pattern of internal ocean variability with the positive phase characterized by anomalously low SST off Sumatra and high SST in the western Indian Ocean, and vice versa

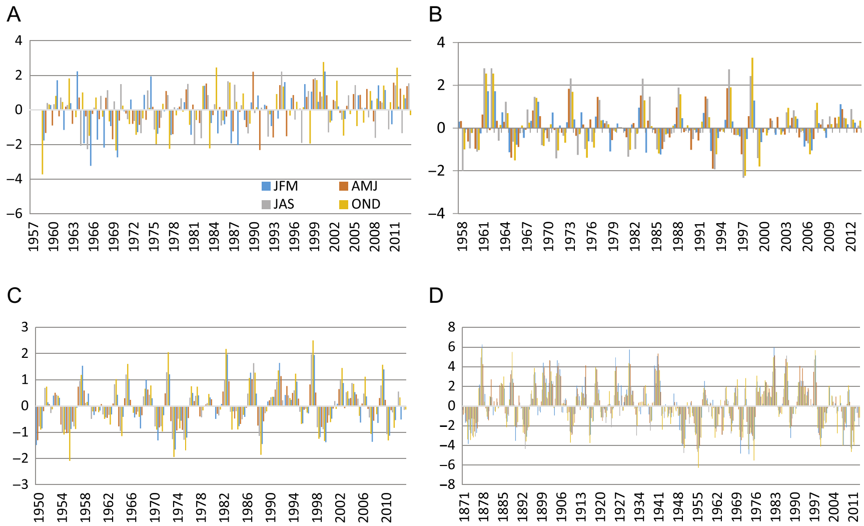

Fig. 3 Seasonal time series of (A) the Southern Annular Mode (SAM), (B) the Indian Ocean Dipole (IOD), (C) the Niño 3.4 index, and (D) the Interdecadal Pacific Oscillation (IPO). Note that the start dates of each panel differ. *Colours* (different shades of grey in the print) indicate the season, as indicated in the legend on the first panel.

for the negative phase, with accompanying wind and precipitation anomalies. The IOD is commonly measured by an index that is the difference between SST anomalies in the western (50°E to 70°E and 10°S to 10°N) and eastern (90°E to 110°E and 10°S to 0°S) equatorial Indian Ocean. A positive IOD period is characterized by cooler than normal water in the tropical eastern Indian Ocean and warmer than normal water in the tropical western Indian Ocean. A positive IOD SST pattern has been shown to be associated with a decrease in rainfall over parts of central and southern Australia. A negative IOD year is characterized by warmer than normal water in the tropical eastern Indian Ocean, near Indonesia, and cooler than normal water in the tropical western Indian Ocean, near Africa (Fig. 2B). A negative IOD SST pattern often results in an increase of rainfall over parts of Australia (Risbey et al., 2009).The time series fluctuates between positive and negative phases (Fig. 3B). Extreme positive seasons are at the beginning of the record and in the 1990s (1961, 1962, 1995, and 1998) with only a couple of negative seasons (1986, 1997). The dominant months for extreme IODs and positive seasons occur more latterly (1959, 1993, 1998, 1999, and 2010). The months July–September are the most important, with few extremes at other times of the year.

Seasonal phase locking is an important characteristic of the IOD time series. Thus significant anomalies appear around June, intensify in the following months and peak in October Saji et al. (1999) show that cool SST anomalies first appear in the vicinity of the Lombok strait by May–June, accompanied by moderate southeasterly wind anomalies in the southeastern tropical Indian Ocean. The cold anomalies intensify and appear to migrate towards the equator along the Indonesian coastline, while the western tropical Indian Ocean begins to warm up. Zonal wind anomalies along the equator and alongshore wind anomalies off Sumatra intensify together with the SST dipole. A dramatically rapid peaking of these features occurs in October, followed by a rapid demise.

2.3 El Niño/Southern Oscillation

The ENSO phenomenon is the principle source of interannual global climate variability. This highly coupled ocean-atmosphere phenomenon is centred in the tropical Pacific. El Niño/Southern Oscillation has significant climate and societal impacts both within the region and, through teleconnections, to many distant parts of the world (Glantz, 2001; McPhaden, 2004; McPhaden et al., 2006; Trenberth, 1991; Trenberth et al., 2007; Troup, 1965). El Niño/Southern Oscillation fluctuates between two phases, El Niño and La Niña, which disturb the normal Pacific atmospheric and oceanic circulations.

During El Niño events, the easterly trade winds weaken along the equator and a large part of the central-eastern equatorial Pacific experiences unusually warm SSTs (Fig. 2C). This is associated with a weakening of the zonal Walker Circulation and strengthening of the meridional Hadley Circulation. The centre of intense tropical convection shifts eastward towards the Date Line, and the Intertropical Convergence Zone (ITCZ) and the South Pacific Convergence Zone (SPCZ) move closer to the equator. The slope of the thermocline (separating warmer surface and cooler deeper waters) flattens across the Pacific and the Warm Pool shifts eastwards. La Niña events are typically opposite to those of El Niño events, with stronger trade winds and large parts of the central-eastern equatorial Pacific experiencing cooler than normal SSTs. The depth of the thermocline also increases with stronger east to west gradient to the depth of the thermocline during La Niña.

Both phases typically evolve over a period of 12–18 months and have some predictability once they have started to develop. Two commonly used indices of ENSO activity are (1) the Southern Oscillation Index (SOI) which measures the atmospheric component and is the anomalous sea-level pressure difference between Tahiti in the southwest Pacific and Darwin in northern Australia, and (2) the Niño 3.4 region (5°N–5°S, 170°W–120°W) average SST anomaly, which showed the oceanic component of ENSO. Niño 3.4 and the SOI are often coupled: the warm oceanic SST anomaly phase, El Niño, accompanies high air surface pressure in the western Pacific, while the cold SST anomaly phase, La Niña, accompanies low air surface pressure in the western Pacific. When they are coupled the ocean/atmosphere impacts are reinforced, as well as the persistence of an ENSO event is lengthened. For the period since 1950, 16 warm phase (El Niño) events and 18 cold phase (La Niña) events coupled, whilst 14 (eight warm phase and six cold phase) events did not couple between the ocean and atmosphere.

Here characteristics of ENSO from 1950 to 2014 are considered, where positive Niño 3.4 SST anomalies indicate an El Niño event. In the Niño 3.4 region large positive SST anomalies occur in 1982/83, 1991/92, and 1997/98 (Fig. 3C). Generally the first quarter of the year has a larger number of extreme values, followed by the third and fourth quarters. In comparison, large negative Niño 3.4 years are 1955/56, 1973/74, 1988/89, and 2010/11, where the extreme value occurs in the last quarter of the year.

2.4 Interdecadal Pacific Oscillation

The interannual variability of ENSO and the strength of its climate teleconnections are modulated on decadal time scales by a long-lived pattern of Pacific climate variability described as the PDO (Mantua et al., 1997; Zhang et al., 1997) or the IPO (Power et al., 1999). The PDO is the North Pacific part of a Pacific basin-wide pattern encompassed by the IPO and is described by an 'El Niño-like' pattern of Pacific SST anomalies (Fig. 2D) and appears to persist in either a warm or cool phase for several decades with as much variance in the Southern Hemisphere Pacific to at least 55°S, as in the Northern Hemisphere. The IPO modulates ENSO climate teleconnections to Australia (Power et al., 1999) and New Zealand (Salinger et al., 2001). Warm phases characterized the 1920s to 1940s and from the mid-1970s to, at least, the 1990s. In these periods ENSO was a weaker source of interannual climate variability. These warm phases were preceded and separated by IPO and PDO cool phases from the 1900s to 1920s and 1940s to 1970s, then since 1999 when ENSO was a major source of interannual climate variability (Deser et al., 2004). Decadal variability in the SST field of the Pacific is associated with decadal variability in atmospheric variables, such as sea-level pressure, winds, and precipitation (Burgman et al, 2008; Deser et al., 2004). For the unfiltered monthly values of the IPO averaged into four seasons or quarters (JFM, AMJ, JAS, OND), if the IPO is in a particular decadal phase, it can show variability in its strength (Fig. 3D). There were many more strong positive years, than weak negative years and generally positive years were strong in at least two quarters. No quarter was favoured for positive years. Some coincided with ENSO years: the strong positive years included 1877/78, 1888/89, 1904/05, 1930/31, 1940/41, 1982/83, 1986/87, and 1997/98. The strongly negative years were 1949/50, 1955/56, and 2010/11. There was predominance of occurrence in the last quarter of the year.

Several theories have been proposed to account for the decadal variability of ENSO, such as the phase of the IPO. These studies broadly propose either oceanic teleconnections, in which the Pacific equatorial zone is modified by either transport variations (Kleeman et al., 1999) or temperature anomalies via the North Pacific Subtropical Cell (Gu and Philander, 1997), or atmospheric teleconnections whereby decadal wind anomalies generated at mid-latitude extend far enough into the tropics to force the ocean circulation there. Routine monitoring of the SOI has shown that ENSO underwent a regime transition in the late 1970s with the period (1978–2007) one of unprecedented El Niño dominance. This step change in the SOI (Power and Smith, 2007) coincided with an abrupt change in SST and large-scale North Pacific winter circulation (eg, Trenberth and Hurrell, 1994). In that period there was a distinct character change in such aspects of the ENSO as progression and phase locking and an increase in both the frequency and intensity of El Niño and La Niña events during the 1980s and 1990s (Boucharel et al., 2009). One framework to understand these events is that the ENSO characteristics can be described in terms of a shift in the background state whereby interdecadal variation is viewed as a slowly changing mean state upon which ENSO evolves (Fedorov and Philander, 2000).

A recent study (Monselesan et al., 2015) has shown that ocean variability on decadal time scales resides in the subtropical oceans therefore identifying the extra-tropics as the region that can initiate transitions between different IPO phases is crucial to understanding decadal variability in the Pacific. Using models to understand where the intrinsic and or internal climate variability from ENSO regimes resides, and how it is modified by external forcings, O'Kane et al. (2014) have shown that the late 1970s transition coincided with the arrival of a large-scale, subsurface cold, and fresh water anomaly in the central tropical Pacific. Originating in the South East Pacific, density compensated temperature and salinity anomalies are known to be able to substantially perturb the central equatorial Pacific thermocline and salinity barrier layers in the western Pacific warm pool (Schneider, 2004). Positive (warm–salty) disturbances, known to occur due to late winter diapycnal (across the constant density water) mixing and isopycnal (constant density) outcropping, arise due to both subduction of subtropical mode waters and subsurface injection. On reaching the equatorial band these disturbances tend to deepen the thermocline reducing the model's ENSO. In contrast the emergence of negative (cold–fresh) disturbances at the equator are associated with a shoaling of the thermocline and El Niño events. Understanding the role of these remote drivers of the climate system is key to predicting the phasing of the IPO, and hence the change in the frequency distribution of regional environmental values, and the likely occurrence of extreme events.

3. CASE STUDIES: CLIMATE DRIVERS AND MARINE EXTREMES

Australia, as a continent of climate extremes (Nicholls et al., 1996), provides some insight into the connection between climate drivers and extremes. In the Australian marine environment, climate drivers as described in Section **2**, have been linked with MHWs and flooding in nearshore areas, which have in turn caused major impacts on marine ecosystems. We illustrate the impacts of climate drivers on marine and coastal environments with three examples from Australia where clear linkages between the climate driver, the extreme climatic event, and ecological impacts are described (Hodgkinson et al., 2014). These are the Western Australia MHW of 2011, the GBR coral bleaching events of 1997/98 and 2002, and flooding of Queensland estuarine areas in 2010/11. These Australian examples are illustrative of marine climate-driven extremes observed around the world.

3.1 Western Australian Marine Heatwave 2011

Record high SSTs were experienced along the Western Australian coast during the austral summer of 2010–11. In this area, the Leeuwin Current flows south along the Western Australian coast, characterized by warm low-salinity tropical waters, then turns eastward along the south coast (Ridgway and Condie, 2004). These water temperatures are modulated by the ENSO cycle with stronger southward flow and higher temperatures during a La Niña event and the converse during an El Niño episode. Typically the variability is up to ±1.5°C between the two periods (Feng et al., 2003, 2008).

The MHW evolved from October 2010, when temperatures were within the historical range. A small area of SST anomalies greater than 2°C then developed to the northwest and moved southeast to reach the Exmouth coast of WA during December. This warm pool then expanded both southwards and offshore in January and February 2011, with SST anomalies exceeding 3°C over a wide area in January and February before dissipating in March 2011 (Feng et al., 2013) (Fig. 4).

The SST warming anomalies of 2–4°C persisted for more than 10 weeks over 1000 km of coastline. The ecosystem response to this MHW is detailed by Wernberg et al. (2013), who found reef-associated communities exhibited variable responses to the extreme event. At warmer near shore locations (30°S) the community structure of benthic organisms was significantly different eight months later in November 2011 with an increase in tropical macroalgae and fish species, and a decrease in temperate species.

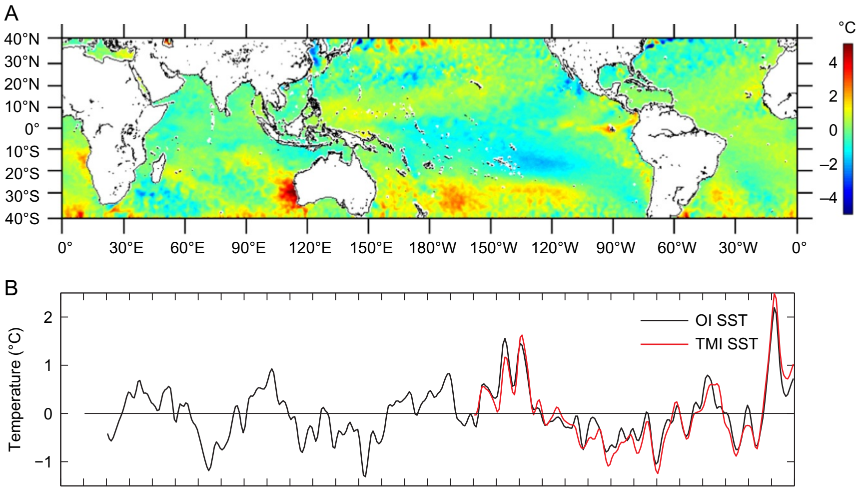

Fig. 4 (A) Sea surface temperature (SST) anomalies in TMI satellite SST during 21 February to 6 March 2011 at the peak of the Ningaloo Niño–marine heatwave event. The TMI is the satellite sensor from which SSTs are optimally interpolated (OI). (B) SST anomalies averaged over 32–26°S, 112–115°E off the west coast of Australia (where the interannual temperature variation is largely responding to the Leeuwin Current heat transport), derived from the Optimum Interpolation Sea Surface Temperature (OISST) and TMI SST products. *Figure adapted from Figs. 1 and 6 in Feng, M., McPhaden, M.J., Xie, S-P., Hafner, J., 2013. La Niña forces unprecedented Leeuwin Current warming in 2011. Sci. Rep. 3, 1277.*

Conversely, species at their cooler location (35°S) did not show any response to the heatwave. Wernberg et al. (2013) concluded biodiversity patterns of temperate seaweeds, sessile invertebrates, and demersal fish were significantly different after the warming event, which led to a reduction in the abundance of habitat-forming seaweeds and a subsequent shift from a poorly developed community structure towards more tropical fish communities. Those climate indices that were either the three highest or lowest values in each time series are considered to be of particular interest and are termed 'extreme' values here and in the two following case studies (Table 1).

During this heatwave, there were extreme values for some of the climate drivers: the IPO values are the third lowest seasonal averages on record, the SOI was the second highest in the past century, and when monthly values of SAM are considered, it was positive from March 2010 until February 2011, and record high positive monthly values were observed in 2010 for June, July, and November. Mechanistically, the concurrent occurrence of the 'in phase' development of positive SAM, with record values of SAM and the SOI, and near record values of the IPO reinforced the drivers to promote the MHW event.

The very strong La Niña and record strength in the Leeuwin current produced very high sea levels along the WA coast and a weakening of the normal easterly winds (Pearce and Feng, 2013). Feng et al. (2013) has dubbed the remote forcing as 'Ningaloo Niño' where much enhanced easterlies from the La Niña in the tropical Pacific and cyclonic wind anomalies in the southeast Indian Ocean forced an unseasonal southward extension of a strengthened Leeuwin Current in the austral (December–February) summer. This was on a background of a very negative IPO index indicating a multi-decadal trend in the Pacific of generally enhanced easterlies and more frequent La Niña events. The negative IPO enhanced the volume transport of the Indonesian Throughflow and upper ocean heat content in the southeast Indian Ocean (Feng et al., 2015), which may have induced strong regional air–sea coupling (Doi et al., 2015) and more frequent Ningaloo Niño events in recent decades (Feng et al., 2015).

Table 1 Climate Driver Index Values at the Time of the Western Australian Marine Heatwave for October–December 2010 and January–March 2011

Climate Driver	SAM	IOD	Niño 3.4	SOI	IPO
October–December 2010	**2.44**	−0.53	−1.31	**2.1**	**−4.66**
January–March 2011	0.19	0.11	−1.13	**2.1**	**−4.37**

Bolded values are extreme values (see text for definition). Southern Annular Mode, *SAM*; Indian Ocean Dipole, *IOD*; Southern Oscillation Index, *SOI*; Interdecadal Pacific Oscillation, *IPO*.

At the same time the very positive months of SAM values indicate a poleward contraction of the southern westerly winds with less westerly swells and southerly wind components (associated with the southern westerlies) transmitted northward along the WA coast. This may reinforce the development of a strong Leeuwin Current. Benthuysen et al. (2014) used a regional model to show that the peak temperatures in the broad mid-west coast of Australia during the event are predominantly due to poleward advection of warmer, tropical water. In a comprehensive analysis of Ningaloo Niño events between 1960 and 2011, Marshall et al. (2015) found that the onset stage from October to November is promoted by wind–evaporation–sea surface temperature (WES) feedback in association with cyclonic wind anomalies to the northwest of the Australian coast. The growth and southward expansion of positive SST anomalies along the Australian west coast is further supplemented by anomalous poleward advection of heat by the Leeuwin Current, which is coupled with the cyclonic anomalies off the coast. The strongest Ningaloo Niño events, such as the record 2011 event, occur in conjunction with La Niña conditions in the Pacific, which drives westerly wind anomalies to the northwest of Australia that can promote the WES feedback and accelerate the Leeuwin Current. However, many Ningaloo Niño events are independent of La Niña and some Ningaloo Niño events even occur during El Niño-like conditions. This is because the triggering of Ningaloo Niño events is most sensitive to antecedent SST anomalies in the far western Pacific, rather than in the central Pacific where ENSO typically has greatest magnitude. Although a positive SAM is a potential instigator of Ningaloo Niño, Marshall et al. (2015) found a much weaker relationship with the SAM, either as a predecessor in the September–November season or as a contemporaneous amplifier during the peak phase, compared with the far western Pacific SST anomalies.

If forecasts of these relevant climate drivers and the potentially associated conditions had been available, some impacts of the MHW might have been anticipated and coping strategies initiated as the event developed. For example, fisheries managers could have increased monitoring of both temperate and warmer water fish species so as to adjust catch of exploited species. Conservation managers for potentially impacted coral habitats can utilize adaptive management practices that enhance the resilience of marine systems by reducing local-scale anthropogenic impacts such as coastal runoff. Anticipatory planning may lead to even more rapid responses to recover damaged habitats after such events, such as the restocking of abalone (Pearce and Feng, 2013).

3.2 GBR Bleaching Events: 1998 and 2002

Several mass coral bleaching episodes have occurred on the GBR in the last three decades such as the bleaching events in January and February of 1998 and 2002 (Berkelmans et al., 2004). Bleaching, when the symbiotic algae are expelled from stressed corals, occurred on a large number of GBR coral reefs with approximately 42% (1998) and 54% (2002) of the reefs bleached to some extent (Berkelmans et al., 2004) in these years. Bleaching occurred following the development of record SSTs during the austral summer. The El Niño event in 1998 caused unusually high SST anomalies to develop and tropical waters were the warmest recorded in the instrumented record. More widely, mass coral bleaching was recorded in over 60 countries and island nations (Hoegh-Guldberg, 1999; ISRS, 1998). The cause of the 1998 event has been ascribed to elevated sea temperature and high solar radiation exacerbated by lowered seawater salinity. In Australia, major flooding occurred on 10 January 1998 lowering the salinity for up to seven weeks and widespread bleaching first became evident on 29 January 1998 after average daily temperatures had exceeded 31°C for 27 consecutive days (Berkelmans and Oliver, 1999). Satellite-derived SST anomalies of 1–2°C occurred on the southern and central GBR. For the 2002 event, bleaching also coincided with the maximum temperature period. Again temperatures in excess of 31°C appeared to be the trigger. Berkelmans et al. (2004) concluded that maximum temperature exceeding a threshold over any 3-day period best correlated with observed bleaching patterns, from the two bleaching years.

To resolve the influence of climate drivers, Redondo-Rodriguez et al. (2012) examined SST, sea-level pressure, surface winds, sea surface height, and ocean currents between ENSO events and GBR surface climate, and also examined the impact of the El Niño/La Niña Modoki phenomenon. The classical El Niño is associated with strong anomalous warming in the eastern equatorial Pacific, whereas El Niño Modoki (ENM) is associated with strong anomalous warming in the central Pacific, and cooling in the eastern and western tropical Pacific. Neither ENSO event was found as a primary driver of interannual climate variability on the GBR, but their influence is conspicuous. Classical ENSO events have a strong signature in the atmospheric circulation in the northern GBR, but no significant relationship with SSTs and the opposite applies for the southern GBR with above average SSTs. Conversely, El Niño/La Niña Modoki is significantly related to summer SSTs on the northern GBR, but not for the southern GBR. The indices in Table 2 demonstrate a relationship with Niño 3.4 index, which was very strong in 1997/98, and the SOI was negative

Table 2 Climate Driver Index Values for the 1998 and 2002 Coral Bleaching Events for the Preceding Months and Then January of Each Event

Climate Driver	SAM	IOD	Niño 3.4	SOI	IPO
October–December 1997	−1.95	**−2.23**	**2.50**	−1.4	**5.68**
January 1998	2.65	−1.04	**2.42**	−2.4	**5.51**
October–December 2001	1.69	−0.02	**1.45**	−1.3	−1.69
January 2002	2.22	−0.66	**1.12**	2.7	−1.03

Bolded values represent extreme values (see text for definition). Southern Annular Mode, *SAM*; Indian Ocean Dipole, *IOD*; Southern Oscillation Index, *SOI*; Interdecadal Pacific Oscillation, *IPO*.

indicating ocean/atmosphere coupling. This was less obvious in the 2001/02 event and the characteristics were more consistent with those of an ENM, showing that the type of El Niño event gives different patterns of warming along the extent of the GBR.

If forecasts of climate drivers are developed for this region conservation managers could adopt early warning systems to predict bleaching, assess the incident response, and then reduce recovery timeframes by mitigating local-scale stress from human-related activities at severely impacted sites, and support the natural resilience of habitats, as for the real-time response approaches to disease risk (Beeden et al., 2012).

3.3 Queensland Coastal Floods: 2010/11

The austral summer of 2010/11 saw catastrophic flooding over much of Queensland (Fig. 5). Southeast Queensland experienced above average to highest on record rainfall during December 2010. Cyclone 'Tasha' also crossed the coast near Babinda and caused flooding in the Fitzroy catchment in central Queensland (23°S) where the highest recorded rainfall was measured. Further rainfall in Queensland then followed in early January 2011, with major flooding in the Mary River catchment (26°S) and about the Sunshine Coast (27°S). Flooding then moved southward into the Pine and Brisbane River catchments. Heavy to very intense rainfall from 9-12 January 2011 caused major river flooding in the Brisbane and Bremer Rivers (28°S). More heavy rain occurred during and following severe Tropical Cyclone 'Yasi', which crossed the North Tropical Queensland coast on 3 February 2011 producing flooding over the North Tropical Coast and Central Coast regions of Queensland between 2-4 February. Summer rainfall totals of over 1000 mm were common along the coast (Fig. 5).

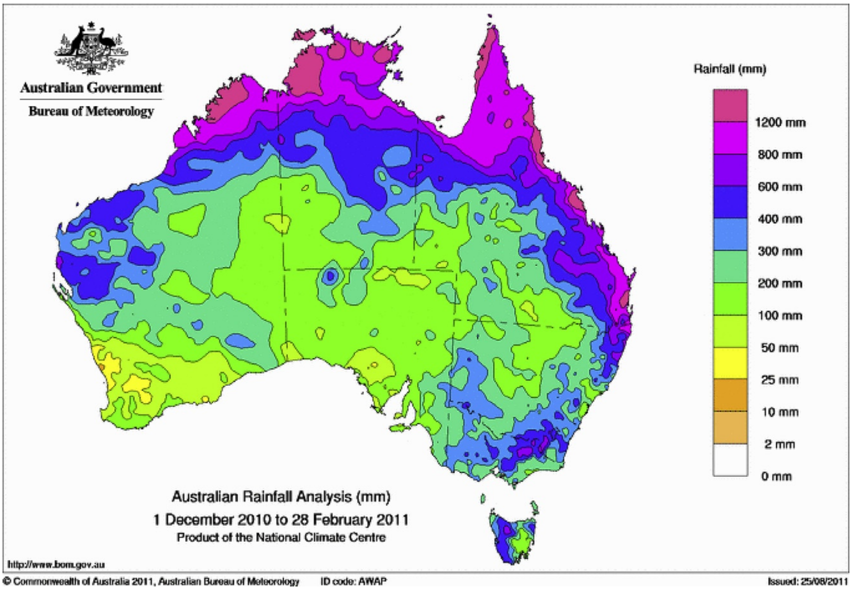

Fig. 5 Summer 2010/11 rainfall totals for Australia showing the very high totals in north-east Australia. *Source: Australian Bureau of Meteorology. Available at http://www.bom.gov.au/jsp/awap/rain/archive.jsp?colour=colour&map=totals&year=2011&month=2&period=3month&area=nat.*

Large influxes of freshwater exited these catchments and flowed into the GBR lagoon. Jones and Berkelmans (2014) examined the impacts of this flooding in Keppel Bay (23°S), located in the southern GBR. Between December 2010 and February 2011 the Fitzroy River in central Queensland reached a peak mean daily discharge of 1.16 million mega-litres/days over a period of 18 days resulting in a large flood plume entering the adjacent Keppel Bay. Flood waters dispersed into Keppel Bay from the Fitzroy River on a ~200 km^2 plume stretching 70 km north on both 14 December 2010 and 11 January 2011. Salinity levels prior to the event were 33–35 Practical Salinity Units (PSU) on the reef flat, then fell to 12 PSU on 12 January, with five days below 30 PSU. The reefs experienced the lowest salinity levels between 3 and 7 January. The fresh water was silt-laden, which reduced light penetration and may have contributed to seagrass and coral mortality (Collier et al., 2012, 2014).

The coral mortality in the section of Keppel Bay closest to the Fitzroy River resulted in almost 100% loss of coral cover on the reefs closest to the river mouth, and on the southern and western sides of the inner islands of Keppel Bay. Mortality decreased away from the river mouth, but around

40% of coral cover was killed. The severity of the coral mortality was caused by the level of exposure to low-salinity sea water, and there was no evidence of any affects from terrigenous pollutants. Marshall et al. (2013) surveyed the vulnerability of fishers and others to flooding and major tropical cyclones on the GBR and showed high exposure of these industries. Impacts included direct risk to life, property and infrastructure, and indirect risk from marine ecosystem damage. Fisheries were sensitive to these extremes with limited adaptive capacity, and a number of fishers left the industry in the months following the cyclone. Impacts on species in addition to those targeted by local fisheries in the GBR included direct and delayed mortality of seagrass (*Halodule pinifolia* and *Halophila ovalis*) (Longstaff and Dennison, 1999) dependent species such as the turtle, *Chelonia mydas* (Limpus and Nicholls, 1988) and dugong, *Dugong dugon* (Meager and Limpus, 2014).

The ENSO indices in this season indicate one of the strongest La Niña events since the late 1800s (Bureau of Meteorology, 2012; Hartmann et al., 2013): the SOI was the second highest in the last century, IPO the third lowest and Niño 3.4 was in the cold phase (Table 3). Collectively, these index values are consistent with observed stronger easterly circulation over Queensland and with a higher incidence of tropical cyclones in the Coral Sea compared with normal (Callaghan and Power, 2011; Diamond et al., 2013), which ultimately led to the flooding that brought disruption to the GBR marine ecosystems.

As was true in the other case studies, climate forecasting for these relevant drivers may have allowed proactive responses to the flood risk. These responses would be at longer time scales than the short-term weather forecast measures implemented to reduce the immediate direct risk to life, property, and infrastructure. For example, at longer time scales regional conservation managers for the GBR and the inshore regions could implement management responses in partnership with fishers and tourism operators to maximize the resilience of the GBR species and habitats such

Table 3 Climate Driver Index Values at the Time of the Queensland Floods for October–December 2010 and January–March 2011

Climate Driver	SAM	IOD	Niño 3.4	SOI	IPO
October–December 2010	**2.44**	0.53	−1.31	**2.1**	**−4.66**
January–March 2011	0.19	0.11	−1.13	**2.1**	**−4.37**

Bolded values are extreme values (see text for definition). Southern Annular Mode, *SAM*; Indian Ocean Dipole, *IOD*; Southern Oscillation Index, *SOI*; Interdecadal Pacific Oscillation, *IPO*.

as seagrass and turtle nesting beaches. Reef industries, researchers, communities, and Traditional Owners are all key partners in the protection and care of the GBR and many are proactively taking steps to support the resilience of the Reef. Focal areas include GBR biodiversity, working closely with those who use and rely on the GBR or its catchment for their recreation or business to help build a healthier and more resilient GBR, and the GBR water quality protection plan. For example, the crown-of-thorns starfish (COTS), *Acanthaster planci*, is one of the largest causes of coral cover loss on the GBR, along with cyclones and bleaching (De'ath et al., 2012; Morello et al., 2014; Pratchett, 2001). The ability to control and manage COTS relies on an understanding of both the biology and changes in the environment (Pratchett, 2001). Several authors have hypothesized that larval survival is enhanced by low salinities and high temperatures and intensified by phytoplankton production as a consequence of increased nutrients (natural and anthropogenic) derived from heavy rainfall and increased river inputs/terrestrial runoff (Fabricius et al., 2010). To reduce future COTS outbreaks, it is thus hypothesized that it is necessary to reduce anthropogenic nutrient inputs (eg, fertilizers and sewage) via a long-term, catchment-based, management strategy, and to increase the resilience of the system by maintaining ecosystem structure and functioning (eg, not overfishing predators) (Brodie, 1992; Morello et al., 2014).

4. FORECASTING CLIMATE DRIVERS

4.1 The Critical Decade

The threshold of dangerous anthropogenic climate change as defined (based largely on politics) by the United Nations Framework on Climate Change is an increase of 2°C in the mean global temperature. Meinshausen et al. (2009) have dubbed the 2010s the 'critical decade' because of global warming to date, and calculate that limiting cumulative carbon dioxide (CO_2) emissions over 2000–50 to 1000 Gt CO_2 yields a 25% probability of warming exceeding 2°C. Therefore major emissions reduction strategies and decisions need to be made and implemented during 2010–20 to avoid dangerous climate change. Even if global action is rapid, the next decade will experience climate variability and extremes that are different to historical patterns due to emissions already in the atmosphere. Thus, forecasting climatic conditions will help many aspects of society cope with this unprecedented change. The coming decade is in contrast to the Holocene period, the last 10,000 years, where the climate has been particularly stable.

Rockström et al. (2009) consider that during the Holocene period the climate and environment has operated within a narrow range of variables in which human and other systems have been able to adapt. Already temperatures during the 2010s have been increasing with temperatures reaching 1°C above preindustrial levels by 2015, with each year since 2011 warmer than the former (http://www.metoffice.gov.uk/news/releases/archive/2016/2015-global-temperature).

Rockström et al. (2009) identified and quantified planetary boundaries that must not be transgressed. However the assumption behind this transgression of the boundaries is that the rate of change is linear. The recent 2003 and 2010 heatwaves in Europe (Fig. 6) broke the 500-year record over half of Europe and shows a step change in decadal frequency. As with the Australian examples, the European heatwaves of 2003 and 2010 also impacted the ocean with a range of ecosystem impacts as coping thresholds were exceeded (Garrabou et al., 2009). After an extreme event, the various environmental parameters such as SST and salinity usually return to more typical values and species and ecosystems recover to previous states—for example, ENSO events off the South American coast when anchovy numbers decrease, then recover again (Klyashtorin, 2001). However, extreme events can also lead to persistent ecological change, as occurred following the WA marine heatwave where loss of algal habitats was not reversed (Wernberg et al., 2013), and thus offer a glimpse into future ecosystem states. Preconditions—the environmental conditions in the lead-up to a particular event—are important and can lead to amplified impacts. Nairn and Fawcett (2013, 2015) have considered the antecedent conditions that result in differing rates of heatwave incidence and intensity for three day land heatwaves in Australia. Antecedent conditions are also important in conditioning soils for flood events. Once soils are saturated high intensity precipitation will discharge greater volumes of fresh water from the rivers into coastal areas.

During the next decade, proactive preparation and adaptation to climate change and extremes will be assisted by forecasts that may be able to anticipate a change in the frequency of extreme events over the one to ten year time scales. Prior to the advent of climate models, climate forecasting approaches were based on anticipated averages or 'climate normals'—commonly derived from three-decade long average distributions for a range of climatological variables (eg, Fig. 1). This approach was obviously suitable for prediction of average conditions, but was of low reliability when anomalous events occurred (Katz and Brown, 1992). The global warming trend over the next few decades will alter the statistics of average and extremes, further

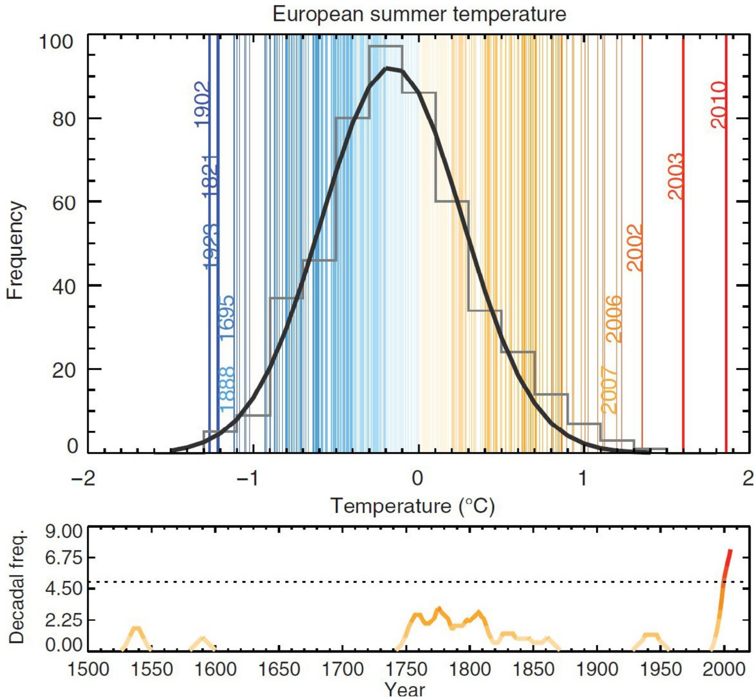

Fig. 6 The upper panel shows the statistical frequency distribution of European (35°N, 70°N; 25°W, 40°E) summer land-temperature anomalies (relative to the 1970–99 period) for the 1500–2010 period (vertical lines). Grey bars represent the distribution for the 1500–2002 period with a Gaussian fit shown in black. The lower panel shows the running decadal frequency of extreme summers, defined as those with a temperature above the 95th percentile of the 1500–2002 distribution. *Source: Barriopedro, D., Fisher, E.M., Luterbacher, J., Trigo, R.M., Garcia-Herrera, R., 2011. The hot summer of 2010: redrawing the temperature record map of Europe. Science 332, 220–224.*

reducing the usefulness of this approach. Climate warming to date (eg, ocean surface temperatures have warmed 0.85°C since observational records commenced; IPCC, 2013) has also modified the statistics of extremes. However, over the next one to ten years marine global warming trends are small compared with climate and oceanic variability. This variability is the most important in terms of altering statistical distributions of climate parameters, including extremes. In the marine environment the most important parameters to forecast are SST and salinity. Other variables of interest include stratification, freshwater input, oxygenation, and upwelling, however, time series of these variables for model validation are often limited. Seasonal to interannual prediction (see Section 4.2 has gone some way towards predicting the state of some climate drivers such as SAM, IOD, and ENSO. However, prediction of specific events is limited to relatively shorter time scales. For instance, a given atmospheric heatwave event, like the 2010 Russian event (Barriopedro et al., 2011) could be associated with the formation of a persistent mid-tropospheric anticyclone. Even employing state of the art ensemble Numerical Weather Prediction (NWP) systems, such events are predictable on time scales less than a week in agreement with theoretical estimates (O'Kane and Frederiksen, 2008). In the ocean, however, longer predictions are possible, as described in the next section.

4.2 Seasonal to Decadal Predictability of Climate Drivers

A focus on forecasting climate drivers is appropriate for a number of reasons, particularly for those that couple with oceanic regimes. Oceans act as the atmosphere's memory and store signals on seasonal to decadal time scales therefore including oceanic drivers and variables in the models has improved predictability. The various climate drivers are also clearly linked to regional variables. For example, Murphy and Ribbe (2004) have shown relationships between ENSO drivers and rainfall variability in southeast Queensland. The three case studies considered here (see Section **3**), all demonstrate clear signals from various climate drivers.

The ability to predict the seasonal variations of the Earth's climate dramatically improved from the early 1980s to the late 1990s. This period was bracketed by two of the largest El Niño events on record: the 1982–83 event, whose existence was unrecognized until many months after its onset; and the 1997–98 event which was well monitored and predicted from its early stages. After the late 1990s, our ability to predict climate fluctuations reached a plateau with little subsequent improvement in quality. Advances in climate research during the past decade have led to the understanding that modelling and predicting a given seasonal climate anomaly over any region is incomplete without a proper treatment of the effects of SST, sea ice, snow, soil wetness, snow cover, vegetation, stratospheric processes, and chemical composition of the atmosphere (eg, CO_2, ozone). The observed current climate changes are a combination of anthropogenic influences and natural variability. This problem of prediction and predictability of seasonal climate variability is necessarily multi-model and multi-institutional. The World Meteorological Organization has proposed that the multi-model approach is necessary and is being implemented in the World Climate Research Programme in the 2010s (Taylor et al., 2012). In the following sections we describe the two most widely used approaches to forecasting at time scales from seasonal to decadal: persistence forecasting and dynamical forecasting.

4.3 Persistence Forecasting

The persistence method is the simplest way of producing a forecast. The persistence method assumes that the conditions at the time of the forecast will continue into the future, superimposed on seasonal or other long-term climatological patterns. For seasonal forecasts, this means an ocean region that is currently 2°C warmer than average, will continue to be 2°C warmer than average later in the year (eg, Hobday et al., 2011). In the case of ENSO this means assuming that the tropical Pacific remains in an El Niño or La Niña state, or a climate driver stays in the current dynamical condition. Normally, persistence decreases with forecast lead time, even though the real ocean gives rise to runs of seasons to years with similar climate characteristics. To illustrate this, we present a simple analysis regarding the persistence of the four climate drivers introduced earlier. In each case, we selected the relevant time series for each driver and looked at the frequency of event lengths (defined by a switch between positive and negative phases as well as neutral phases for ENSO) at the native time scale of the time series (months to seasons). Time series were the standard products obtained from the British Antarctic Survey for SAM (Marshall, 2003; http://www.nerc-bas.ac.uk/icd/gjma/sam.html), from the HadISST dataset for IOD (http://www.jamstec.go.jp/frcgc/research/d1/iod/), and from the National Oceanic and Atmospheric Administration (NOAA) for the Niño 3.4 index (http://www.esrl.noaa.gov/psd/data/correlation/nina34.data). The IPO index is sourced from the UK Meteorological Office (C. K. Folland, personal communication) and derived from the low-frequency filtered 3rd Empirical Orthogonal Function of global data sets of seasonal SST (Folland et al., 1998).

4.3.1 Southern Annular Mode

Characterization of SAM phases from the time series 1957–2014 sourced from the British Antarctic Survey shows there is little persistence beyond the immediate month, with a decline in occurrence from the first month (~40%) down to 25% for the second month (Fig. 7A). This agrees with earlier conclusions drawn by Gerber et al. (2008) and Simpson et al. (2013) that the persistence of SAM is around 20–25 days at most, being driven by fluctuations in the polar jet stream around the Southern Oceans. There is also a trend towards increasingly positive SAM events. Grise et al. (2014) note that

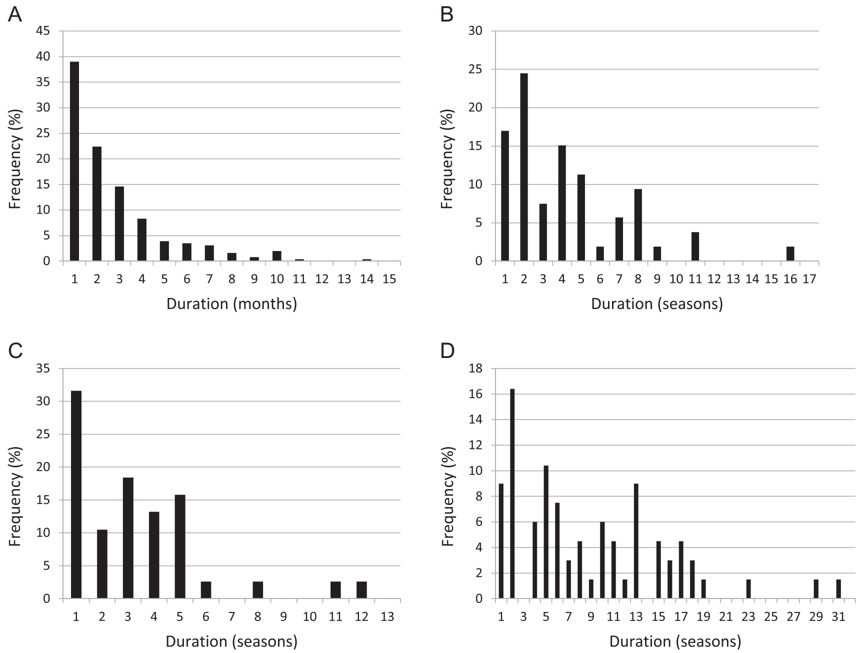

Fig. 7 Temporal persistence (% frequency) of the (A) Southern Annular Mode (SAM), seasonal persistence of the (B) Indian Ocean Dipole (IOD), (C) Niño 3.4, and (D) the Interdecadal Pacific Oscillation (IPO). A season is three months in length.

ozone depletion in the late 20th century induced a significant poleward shift in cyclone frequency over the Southern Ocean. A poleward shift in the tropospheric mid-latitude jet (ie, the SAM) has also occurred (Previdi and Polvani, 2014), weakening the westerly circulation further north (Thompson et al., 2011). As well from mid- to higher latitudes the variance displays spatially coherent features on time scales of 10–25 years, especially in the Southern Oceans (O'Kane et al., 2013a). This is consistent with the IPO time scales.

4.3.2 Indian Ocean Dipole

For IOD persistence the time series from 1958 to 2014 obtained from the Japan Agency for Marie-Earth Science and Technology was used (Fig. 7B); there was a peak at two seasons, particularly for positive events. This was markedly so out as far as four to six months, after which there was a drop off in duration, although longer persistence did occur out to four or five seasons—noted by Dommenget and Jansen (2009). Cai et al. (2014) note that the projected frequency of extreme positive IOD events will increase by almost a factor of three, from one event every 17.3 years during the 20th century to one event every 6.3 years over the 21st century. A mean state change—with weakening of both equatorial westerly winds and eastward oceanic currents in association with a faster warming in the western than the eastern equatorial Indian Ocean—facilitates more frequent occurrences of wind and oceanic current reversal. This leads to more frequent extreme positive IOD events, suggesting an increasing frequency of extreme climate and weather events in regions affected by the positive IOD.

4.3.3 El Niño/Southern Oscillation

The seasonal persistence for ENSO events from the 1950–2014 time series (sourced from NOAA) as measured by Niño 3.4 anomalies is shown in Fig. 7C, which has not been separated by time of year. Although monthly persistence can be examined, as Niño 3.4 SST anomalies occur in a larger area of the equatorial Pacific, these anomalies persist for several months. For Niño 3.4 neutral situation about 60% of the cases persisted for one or two seasons, with the other third lasting between four to seven seasons. The analysis did not account for the time of year when the neutral state commenced.

The persistence changed for both warm and cool SST anomaly episodes combined (Fig. 7C) with a third lasting one season, then the other 60% persisting between two and five seasons. When stratified between warm and cool SST anomaly events a distinct difference occurred in persistence. Almost 80% of warm events lasted from two to five seasons. In contrast the majority (about 40%) of cold events last a season in duration, while most of the others lasted two to six seasons in duration, although one lasted 12 seasons. Persistence is highest from July to January for seasonal Niño 3.4 SST forecasts (slightly east of Niño 3.4) because of the growth of SST events, and then decreases on seasonal lead time forecasts until May (Torrence and Webster, 1998). Given this persistence, numerous schemes have been developed to predict Niño 3.4 SST anomalies. For example, predictions of monthly Niño 3.4 SST anomalies with lead times of up to 11 months have been produced using predictive discriminant analysis, canonical variate analysis, four forms of generalized linear models, and multiple linear regressions with probabilities derived by integration of the prediction intervals (Mason and Mimmack, 2002). This generally shows that the prediction skill is lowest in the second quarter, and then increases to a peak in austral summer (December–February) once an event is well established. However, Zhao et al. (2015) have shown that predictive skill for ENSO in the early

21st century declined sharply relative to the last two decades of the 20th century. This decline coincides with a shift in Pacific climate to increased trade winds and colder temperatures in the eastern Pacific, associated with the phase change of the IPO. This shift in background climate has also acted to reduce ENSO predictability because the atmosphere–ocean coupling that drives ENSO has weakened.

4.3.4 Interdecadal Pacific Oscillation

The seasonal unfiltered IPO persistence, characterized by the time series from 1871 to 2014 sourced from the U.K. Meteorological Office (Folland et al., 1998), is shown in Fig. 7D. Positive IPO phases, once commenced, lasted typically from two to four years, with extremes up to seven years. Negative phases, upon commencement were typically one to five years with a six year extreme.

When the low-pass filtered index is considered (Fig. 8) the decadal-scale nature of the positive and negative phases are obvious. For the period 1900–2014, positive phases occurred from 1900–1908, 1914–44, and 1977–97. Negative phases occurred from 1909–13, 1945–76, and from 1998. It appears that the current negative phase could be terminating. This gives the IPO persistence from years to decades—the challenge being able to foreshadow the phase change. Typical events show remarkable persistence relative to that attributed to ENSO events during the 20th century with major IPO eras persisting for 20 to 30 years (Mantua et al., 1997; Minobe, 1997). Probably the most notable feature of the filtered IPO index is the long-lived multiseasonal to multiyear persistence that characterizes

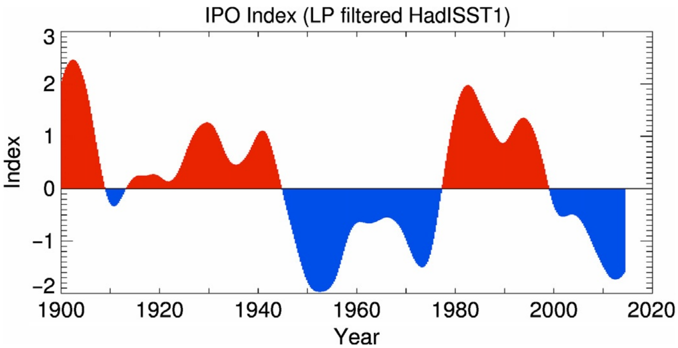

Fig. 8 Low-pass filtered Interdecadal Pacific Oscillation (IPO) index from 1900 to 2014. *Source: United Kingdom Meteorological Office Hadley Centre.*

Table 4 Summary of Climate Driver Persistence, with Regard to Multiyear Forecasts, Based on Fig. 7

Climate Driver	Useful Persistence
Southern Annular Mode	<30 days
Indian Ocean Dipole	4–6 months
ENSO–Niño 3.4	9–12 months
Interdecadal Pacific Oscillation	1–2 decades

much of its variability in the 20th century. The challenge is to predict the change in IPO phase.

Summary. A qualitative summary of persistence forecasting of the four climate drivers assessed here for the Australian region shows there is an increase in persistence in the progression SAM, IOD, ENSO (Niño3.4 index), and IPO (Table 4). This reflects the degree of coupling with the atmosphere (none in the case of SAM and high for ENSO) and the oceanic memory. Oceanic memory increases in the progression IOD (intraseasonal), ENSO (seasonal) then IPO (decadal). These time scales will influence the confidence that can be ascribed to forecasts.

4.4 Dynamical Forecasts

An alternative to persistence forecasts is dynamical approaches where climate models are initiated with observed conditions to produce time-evolving forecasts. These forecasts can be evaluated in the same way as described for the statistical approaches, and assessment of the skill of predicted real-time probalistic climate forecasts are not repeated here (Barnston and Mason, 2011). Indices representing the climate drivers (IOD, SAM, IPO, ENSO) can be extracted from modelled fields, just as occurs with historical observations. The challenge is to assess how well the models can reproduce climate modes and provide reliable climate indices. With respect to dynamical modelling and decadal climate prediction, there have been several international coordinated climate-modelling projects such as the Ensembles-Based Predictions of Climate Changes and their Impacts Project and more recently CMIP5 (Hewitt and Griggs, 2004; Meehl et al., 2014). The decadal climate prediction element of the CMIP5 provides a multi-model dataset of decadal hindcasts and predictions. These simulations provide model output for assessing predictability and predictions on time scales from 1 to 30 years. Hindcasts are used for comparison with historical data and lend confidence to future projections when the agreement between model output and observations is high. They also provide insights into the dynamics of the climate system, such as identifying the mechanisms in the Pacific Ocean associated with the IPO. At the largest scale, Meehl et al. (2014) showed prediction skill in the Pacific was less than the Atlantic and Indian Oceans. This reflects the Pacific being inherently more sensitive to uncertainty in the initial state and to uncertainty in the mechanisms of internally generated climate variability. Meehl et al. (2014) concluded that decadal climate predictions could provide useful information to a wide group of stakeholders, with temperature having the greatest signal-to-noise ratio, hence showing the most promise. While Meehl et al. (2014) focussed on physical variables, in the tropical Pacific attempts have also been made to forecast biological fluctuations such as Net Primary Productivity (NPP). Seferian et al. (2013) showed some predictive skill for NPP out to three years, which was longer than for SST (1 year).

Numerical Weather Prediction provides important guidance into how to build a prediction system. Initially, deterministic NWP forecasts were used and early attempts to establish the theoretical limits of predictability of such forecasts focussed on error growth determined from the divergence of pairs of initially close states (Charney and Stern, 1961; Kasahara, 1972; Smagorinsky, 1963). For a deterministic forecast the time period of predictability is set by errors in the initial conditions that arise from limitations in observing system and the inherent nonlinearity in the system that cause different initial states to diverge with time (error growth). While the concept of one forecast based on one initial state underlies the basic prediction system, it is now accepted that weather forecasting should be regarded as a statistical problem of forecasting the probability density function of the future atmospheric state. Now ensemble weather forecasts are used, whereby a suite of initial perturbations are provided and run forward in time to produce a suite of forecasts from which the probability of the predicted weather state is determined. Crucial to producing useful forecast information is the need to adequately span the probability distribution of the future states. To characterize the potentially predictable future climate, a large number of forecasts with different random initial states is required. This approach places enormous computational cost on the prediction system whereby performance is severely limited by computational restrictions on the ensemble size. Recently, new methods of ensemble prediction have been developed that can identify the dynamically significant regions of instability associated with rapid forecast error growth that is responsible for limiting predictability. Using this information in determining the initial forecast perturbations in the ensemble prediction system enables one to determine the possibility of regime transitions between climate states (eg, the phases of the IPO). The identification of regions of rapid growing 'errors' can provide guidance as to where the important dynamics reside and where to target observations critical to enable skilful forecasts. Outside of weather prediction, this dynamical ensemble prediction approach has been used in a diverse range of forecast applications from predicting eddy formation in the East Australian Current (EAC) (O'Kane et al., 2011), tropical cyclone evolution (Sandery and O'Kane, 2013), Atlantic meridional overturning variability (Zanna et al., 2011) and tropical instability waves (Hoffman et al., 2009).

To help understand how the climate system generates variability it is useful to review what we know about climate variability. It is well recognized that interannual variability is strongly influenced by the coupling of the winds to the tropical ocean thermocline. In the subtropical and mid-latitude oceans, variability manifests on longer time scales and is closely associated with Rossby wave propagation. Broadly speaking, the ocean variability in the tropics to subtropics is in part dependent on the depth of the thermocline. In general, the mechanisms by which oceanic internal variability is communicated between the subtropics and tropics are not well understood (Liu, 2012). O'Kane et al. (2014) note that large mean potential density gradients extending from the mid-latitudes to the subtropical and tropical oceans might act as waveguides allowing baroclinic Rossby waves to communicate information from the extratropics to the tropics on time scales up to decades. De Viron et al. (2013) found significant correlations between large-scale variations in observed SST and the leading modes of the major climate indices on interannual time scales. At middle and high latitudes, internal atmospheric variability associated with the annular modes has been found to be the dominant source of uncertainty in the simulated climate response (Deser et al., 2012). However, the natural vacillation cycles of the annular modes are poorly characterized. Moreover it is recognized that the annular modes can undergo systematic changes in response to anthropogenic forcing as illustrated, for example, by the trend to a positive phase of the SAM over recent decades (O'Kane et al., 2013b).

Kravtsov et al. (2007) showed that intrinsic climate variability in the coupled system renders the atmosphere nonlinearly sensitive to SST anomalies and consequently to long-term changes in heat fluxes, which feedback via the ocean to induce low-frequency atmospheric variations. Such regime transitions are the dominant source of the internal decadal variability in the climate system. These studies motivate an examination of the spatiotemporal distribution of SST variance as an indicator of the time scales of the ocean–atmosphere coupling. Fig. 9 shows the tropics dominates the variability at less than five years, but as one moves to longer time scales the variability moves into the extratropics.

4.5 Statistical Translation

The forecasts generated by numerical weather and climate models provide outputs on the spatial and temporal resolutions of the models. This can vary spatially from tens of kilometres for a weather forecast to hundreds of kilometres for a climate projection. These scales do not necessarily match those of applications models, which often cover a region and employ much finer spatial and temporal scales. The potential mismatch in scales between climate forecast information and application models can be particularly problematic for variables that are spatially heterogeneous and have sharp temporal peaks, such as precipitation. Large area averaging tends to remove the peaks from these variables and may not capture extreme events. In these cases it may be necessary to provide a form of translation between climate model scale outputs and local or point values of the same variables. These translations can be carried out in a variety of ways. Sometimes a high-resolution mesoscale model may be nested inside a climate model over the area of interest to provide finer scale information, but the nesting does not necessarily produce the same output as a global model with the same resolution. Further, the large-scale fields contain biases and errors that are not generally corrected by the nested model (Risbey and O'Kane, 2011). Moreover, other methods include the use of statistical rules relating outputs on the larger scale to finer spatial scale variations. In many cases it may be appropriate to employ a range of different translation methods to test the relative sensitivity of each (Mearns et al., 1999).

Typical applications of model outputs on land have included hydrology and agriculture. For hydrology, climate model outputs are translated to basin scale and used to assess changes in flow regimes under climate change scenarios (Gleick, 1989), and weather forecast outputs are used to assess flood risk in hydrological models (Cloke and Pappenberger, 2009). For agriculture, model output is typically translated to farm scale and applied to crop models to assess projected changes in crop output under climate scenarios (Parry et al., 2004) or for seasonal range forecasts.

Relative to land, there has been less work in the marine domain to assess changes in the marine environment in response to seasonal and climate

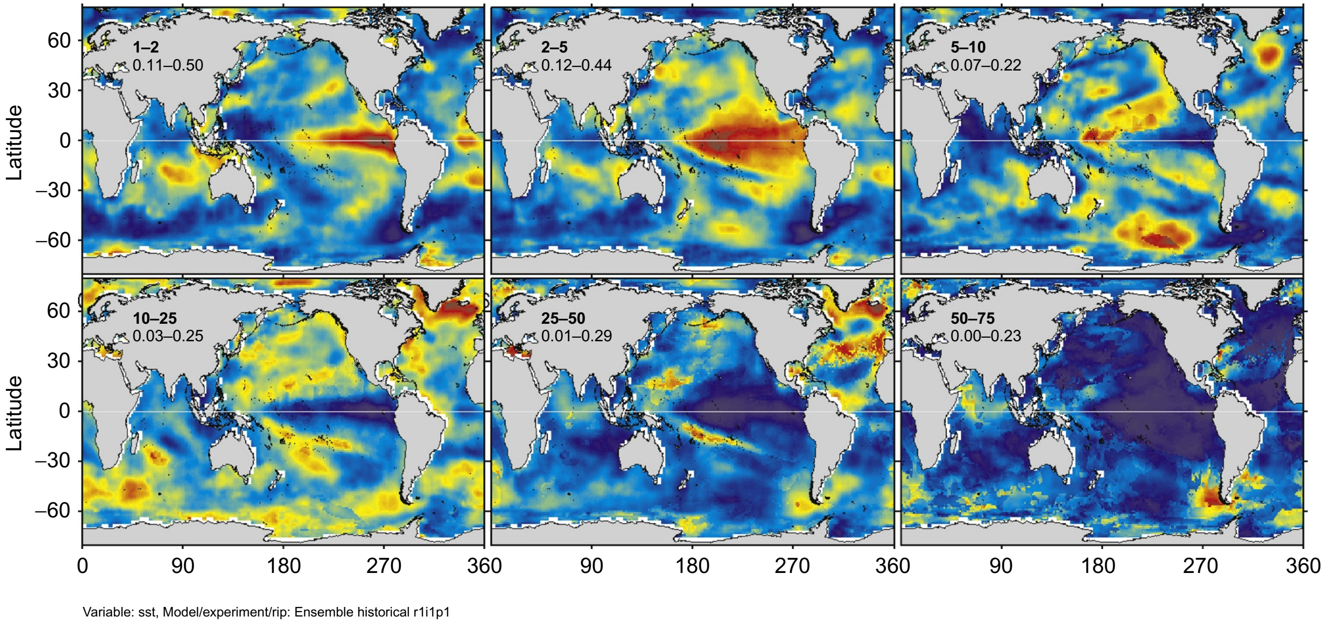

Fig. 9 The ensemble mean of sea surface temperature (SST) fractional in-band variances calculated via singular spectral analysis from detrended HAD4KRIG-CW (January 1850 to March 2014), NOAA-ERSL-V3 (January 1854 to June 2014), and COBE2 (January 1850 to December 2013) data. The combined variance at any given location (grid point) across all time bands sums to 1. Time scale bands (*bold font*) are in years and relative explained variance range (*normal font*) as a fraction of the total variance are given on the Eurasian continent. Shading is scaled to the variance range in each subplot such that red (grey in the print version) indicates the maximum relative explained variance and blue the minimum. Regions of high variance indicate where the internal climate 'memory' resides and where the coupling to the atmosphere is sustained. *Figure modified from Monselesan, D.P., O'Kane, T.J., Risbey, J.S., Church, J., 2015. Internal climate memory in observations and models. Geophys. Res. Lett. doi:10.1002/2014GL062765.*

forecasts. Seasonal forecast model output has been applied to regional marine domains for fisheries management of southern bluefin tuna (*Thunnus maccoyii*) (Eveson et al., 2015; Hobday et al., 2011) and for marine farming and reef management (Hobday et al., 2016b), such as for coral bleaching of the GBR (Spillman, 2011). Fisheries, marine aquaculture, and reefs are often highly susceptible to variations on multiyear time scales, but multiyear forecasts have not yet been applied in this context.

5. FUTURE DIRECTIONS FOR CLIMATE FORECASTING

In the following section, we identify critical research required to deliver multiyear to decadal information for managing marine resources. The discussion focusses on four research areas: (1) the climate forecasting system, (2) data needs for the forecast system, (3) integration of forecast into decision support tools, and (4) understanding end-user needs.

5.1 Primary Research Needs to Support Climate Forecasts

To deliver a credible decadal climate forecasting system requires four key ingredients: (1) a credible climate model, (2) a model initialization system, (3) an ensemble and forecasting system, and (4) an evaluation system to assess both hindcasts and forecasts.

5.1.1 Climate Models

Climate models have undergone significant improvements in recent years through better parameterizations and higher resolutions (eg, Rougier et al., 2009). While the climate models show encouraging reproduction of historical variability (Stocker et al., 2013), they still need further improvements as decadal climate predictions still identify model error (representation of ocean processes) as a principle source of uncertainty (Kirtman et al., 2013). This error is often associated with climate simulation having regional biases in the ocean state. One example is the warm tongue bias in climate simulations of the equatorial Pacific Ocean, where the warm upper ocean water of the western equatorial Pacific extends too far east (Grose et al., 2014). This bias leads to errors in the location of the South Pacific Convergence Zone and in the regions of high equatorial rainfall (Brown et al., 2015). Correcting such biases in the climate model is needed to produce better models and better decadal forecasts. Ongoing support for improving climate models is needed with further effort to improve biogeochemical processes to ultimately enable the forecasting of biological processes like primary productivity.

Existing climate models should also be used to elucidate the processes driving variability on multiyear and longer time scales. This is necessary because advanced ensemble approaches, like bred vectors (O'Kane et al., 2011), rely on an understanding of the relevant dynamical mechanisms underpinning decadal predictability. Although interannual variability is strongly influenced by the coupling of sea surface with atmosphere in the tropics, for decadal variability the tropical ocean thermocline (O'Kane et al., 2013a) and variability in the oceanic extratropics of the Southern Hemisphere (O'Kane et al., 2013b) are important. Identifying mechanisms of decadal variability in the model and their impact on the climate system is needed and will provide important insight into what can be predicted by decadal forecasts. It is also necessary to evaluate models simulations to ensure that they obtain the correct climate variability for the right reasons. Once the models are shown to capture observed processes of variability, we then have more faith in the models for testing predictability and making forecasts on multiyear time scales.

5.1.2 Model Initialization

The prediction of the fully coupled climate system requires an initial state to be specified based upon observations. By using observations to initialize the climate models one has the potential to assess the initial state influence on the climate evolution in addition to the inherent variability existing within the climate system (Kirtman et al., 2013). The key observations required for model initialization are linked to the forecast time scale. For predictions of a season to a year, SST, sea ice extent and upper ocean heat content, soil moisture, snow cover, and state of surface vegetation over land are all important variables to the initial state. For the decadal prediction, increased information on the ocean three-dimensional temperature and salinity is critical. To do primary productivity forecasting, the required initial information would extend to upper ocean nutrient fields.

For decadal forecasts, biases in the climate model are manifested as a rapid adjustment of the climate model after initialization towards the climate model preferred state. To tackle this drift issue two approaches could be deployed. One is an 'anomaly initialization' where models are initialized with observed anomalies added to the modelled climate, and the mean model climate state is subtracted to obtain anomaly forecast. A second approach is to use data assimilation as the model evolves to improve its realism. Both of these approaches need to be explored independently and together to assess their suitability for improving decadal forecasts.

An initial state for the coupled model forecast can be assembled through a data assimilation model that uses the model to help dynamically extrapolate the limited observations in time and space. However, often with coupled model forecasts the oceanic and atmospheric components are run independently with specified boundary conditions at the air–sea interface. The separate initial conditions cannot be fully consistent because they ignore interactions between the ocean and atmosphere. Because the background states of these models are usually different, combining the two leads to 'initialization shocks' at the atmosphere–ocean interface followed by a slow drift to the new background state of the combined system. Developing a coupled atmosphere and oceanic assimilation is required for more effective initialization of the coupled model to reduce initialization shock and increase the accuracy of model forecast.

5.1.3 Ensemble Forecasting

Ensemble forecasting is a numerical prediction method that is used to generate a representative sample of the possible future states of the climate (O'Kane, 2010). Ensemble forecasting outperforms individual forecasts (Lorenz, 1965), a well-documented result for numerical weather forecasting (O'Kane et al., 2008). A similar approach to decadal forecasting should be pursued to maximize the predictive capabilities of forecast systems (Baehr and Piontek, 2014). Due to the computational cost of including many members to the ensemble, new methods that identify the regions and processes of rapid error growth must be explored to build an efficient ensemble prediction system (O'Kane et al., 2011). Research into how to combine new ensemble methods with the more traditional approach will be needed to build a robust and efficient ensemble forecasting system.

5.1.4 Evaluation of the Forecasting System

A critical step for any forecasting system is the rigorous evaluation of the forecasts. By making hindcasts one can evaluate the performance of the forecasting system and assess how altering the model, the initialization, and the ensemble system changes forecast skill. This is an essential task and one that can be used to provide some quantitative estimate of uncertainty to future forecasts. An additional outcome of the evaluation effort is resolving which components of the climate system are predictable and which are not.

Assessing the predictability of the climate system for decadal forecasting is an essential step to justifying the effort to build a forecasting system.

5.2 Data Needs to Support Climate Model Development

Data needs go well beyond those discussed earlier in the context of climate and forecast models. Later, we summarize some of those data needs, particularly those to support further model development and refinement, biological data that are needed for applications, and additional studies that support the need for forecasting.

5.2.1 Physical Data

Model-based prediction relies on having good initial oceanic and atmospheric conditions, but it also requires good understanding of processes or causal relationships at relevant scales—both for model development, assessment and on-going bias correction (eg, through data assimilation) and ground truthing. In terms of physical processes and data, this will require observing systems on both regional and local scales. Examples include long-term commitments to supply observations for the major ocean basins. Key programmes include the Tropical Pacific Observing System (TPOS), the Tropical Ocean Global Atmosphere (TOGA) programme (McPhaden et al., 1998), the Tropical Atmosphere Ocean (TAO) mooring array, the Indian Ocean Observing System (IndOOS) (Masumoto et al., 2009), volunteer observing ship (VOS) measurements and networks of island, and coastal sea-level measurements stations in the Pacific and Indian Oceans. Such networks could complement information obtained at large scales from remotely sensed SST and sea surface height, and from the Argo float observing programme (Roemmich et al., 2009), which provide contemporaneous measurements of both temperature and salinity over the upper 2 km of the global ocean. For reliable forecasts such data streams must be maintained in the long term, because the changing nature of the oceans and their variability means that ocean forecasts would soon degrade without renewal of data streams.

Similar long-term commitments are required at national and regional scales. For example, the Integrated Marine Observing System (IMOS) is investing about $AUD145 million to monitor decadal variations in the ocean, climate variability and extremes around Australia and in the Southern Ocean (IMOS, 2014; Lynch et al., 2014). A long-term plan is required for the IMOS observing system, not only to see it sustainable and to optimize the spatial coverage of the observations on the continental shelves, but also to extend into biological observations (Lynch et al., 2014).

5.2.2 Biological Time Series

For many marine applications, forecasts of the biological patterns may be required for decision making, for example, in fisheries and aquaculture. Extending forecasting from the physical environment to biological patterns may not require complex ecosystem models but will require having good biological time series, as well as good process understanding. For example, in the case of individual species, a simple forecasting approach may be built based on information about how environmental variables affect the distribution of fish (Eveson et al., 2015), growth conditions (Spillman and Hobday, 2014), or the bleaching risk to corals (Spillman, 2011).

All of the challenges and needs acknowledged for physical data and forecasting, that were discussed in Section *5.2.1*, hold for biological variables, with the difficulties and needs amplified by the uncertainty and variability added by ecological interactions and plasticity. It is not simply a matter of identifying a small number of essential variables for biological processes (though much effort is being put into doing just that, eg, Hayes et al., 2015), but of making sure there is good coverage of those indicators that provide insight into the status and function of stocks or entire ecosystems. Biological data are already monitored for some groups (eg, planktonic producers) or in specific locations (eg, the survey-based coverage of fished ecosystems off North America and Europe). However, such data are not universally collected—for example, fishery-independent surveys of even a subset of species are rare in countries even as affluent as Australia—and so sustainable means of supporting the long-term collection of key biological data that describes system state, or reduces uncertainty, are required.

One monitoring approach that shows great promise in this area is to include end users (eg, fishers) in the collection of data; where operators are already interacting with variables of interest or are in appropriate locations at appropriate times and data collection does not add undue overheads, then there is a great potential for collaboration between science and industry to deliver reliable data streams (Hobday et al., 2016b; Nicol et al., 2013). The greatest value can be gained from such initiatives if they are well structured around indicators that have maximum information content or are key to reducing uncertainty around system state, function, or variability (Hobday et al., 2016b). Much as modelling has helped identify key locations for the placement of Argo floats and coastal moorings to better constrain oceanographic forecasts (Oke and Sakov, 2012), so too the collection of specific data (eg, on plankton composition or fish community composition) can enable management of risk from climate variability as there is a better understanding of system state and function (Lynch et al., 2014; Nicol et al., 2013).

Past experience with monitoring, as well as model-based evaluation of indicators, has shown that a range of indicators will need to be monitored (Fulton et al., 2005; Link, 2005) to forecast biological patterns. These suites of indicators need to cover a wide range of processes and biological groups on various time and space scales, as no single indicator can summarize the entire state of the system or simultaneously provide early warning of system change while characterizing function at broad scales—this involves indicators capturing information from fine to quite large spatial and temporal scales. Obviously collecting information across such a wide set of scales and variables could be quite a costly and challenging exercise. While intensive collections have periodically been undertaken (eg, the North Sea; ICES, 1997) they are infeasible on a year to year basis and more cost-effective programmes based around routine and easily measured indicators are required. The evolution of the long-term monitoring programs in places such as the northeast United States show how such schemes have been structured and brought together by combining information from many sources, such as remote sensing, ships of opportunity, and fisheries oriented surveys (Collie et al., 2009; Smith, 2004). The value of such long-term ecosystem-scale time series is evident in the new understanding provided around the relative roles of climate, variability, and other pressures such as fishing (Link et al., 2010; Nicol et al., 2013). These programmes have also shown that indicators do not need to be exceedingly complex or abstract, much can be garnered from the relative dynamics of functional groups (eg, pelagic vs demersal predatory fish) or their biomass ratios (eg, planktivores vs piscivores; Caddy and Garibaldi, 2000; Nicol et al., 2013).

In the context of decadal forecasting, there is the likely need for the collection of new data sets that reflect the processes working at scales not typically covered by existing monitoring schemes. In addition, there is a need for monitoring of processes and not just status. Without knowledge of how the system is functioning it will be difficult to be sure that causal mechanisms used to link physical forecasts and biological expectations (eg, aquaculture production or coral health) are correctly included in forecasting models.

5.2.3 Impact Studies: Attribution and Evaluation

One of the key aspects of forecasting and attribution is understanding the relative influence of all relevant drivers. Long-term time series are one of the few ways of getting such understanding, particularly in real world conditions—laboratory experiments can provide some insights, but typically fail to account for the interacting effects of multiple drivers (Gattuso et al., 2015).

In addition to understanding system function and clarifying the attribution of past change, impact studies have an additional function—to inform on the benefits gained from the use of forecasts. Given the potential expense involved in collecting broad scale information in support of forecasts, and given the financial resources potentially being committed on the back of such forecasts, evaluation of their performance will be a necessity. While some of this can be done using the same methods (model-based evaluations and counterfactuals) already implemented to explore the utility of a broad range of indicators (eg, Blanchard et al., 2014; Fulton et al., 2005), there is also a place for new impact studies that indicate what has been delivered via the use of forecasts and to inform refinement of model development and forecasting methods.

5.3 Integration of Forecast Results into Decision Support Tools

Simply having the capacity to perform forecasts is sufficient to see that information taken up by operators or regulators. An important extra step for uptake is to see forecast results integrated into decision support tools. Such integration can come in two forms. The most straightforward is to deliver the information from the forecast in the same user interfaces used by managers to access other information sources, similar to the way in which ocean forecasts and the 'eReefs Dashboard' have been integrated into the weather forecast reporting by the Australian Bureau of Meteorology (http://www.bom.gov.au).

Another way of using forecast information in decision support tools is to fold the decadal forecasts into the physical forcing of resource assessment models (eg, via linking recruitment to environmental drivers in fisheries assessment models) or long-term strategic models (eg, ecosystem models). In concert with a move towards an ecosystem approach to fisheries over the past two decades, and increasing recognition of the impacts of climate change, marine single-species and ecosystem models are increasingly being coupled to physical and climate models, either dynamically or by being driven by the outputs of these models. This has in turn resulted in a need for a closer coupling between the temporal and spatial scales of the climate and biological models. End-to-end models such as Atlantis (Fulton, 2010) typically require regional climate variables to appropriately link with the scale of the biological dynamics, whereas at the other extreme, fisheries stock assessment models require local-scale predictions (eg, Norman-Lopez et al., 2013). Ecosystem models such as SEAPODYM (Lehodey et al., 2008), OSMOSE (Shin et al., 2010), APECOSM (Maury et al., 2007) and MICE (Plagányi et al., 2011, 2013), and inclusive 'end-to-end' models (eg, Atlantis) are increasingly incorporating a broader suite of abiotic drivers such as dissolved CO_2, sea-level rise and the effects of storms in addition to the more commonly used variables such as SST (Fulton, 2010; Rose et al., 2010). Ongoing refinements in this regard are focussed on representation of features such as relationships between water column properties and rates of growth, consumption, reproduction, mortality, and behaviour (eg, Fasham, 1993; Wild-Allen et al., 2010). Hand-in-hand with the inclusion of these additional drivers has come the realization that a broader set of ecological processes are relevant. This has seen a push to adjust response models, such as the inclusion of the evolution of impacted species and biodiversity turnover operating at decadal scales. While many models still assume no evolution or adaptation (ie, parameters for growth and other biological processes remain static), models are increasingly allowing for phenotypic plasticity (eg, through agent-based approaches, as in OSMOSE), adaptation (in line with photoacclimation in biogeochemical models) or dynamic parameter setting—either via optimization of specific properties and traits (Zhang et al., 2003) or simplistic representation of evolutionary selective pressure (Fulton and Gorton, 2014).

The handling of decadal-scale phenomena, variability and adaptive or evolutionary responses in ecosystem models is still in relative infancy. Consequently, given the uncertainties regarding the structure and function of ecosystems and the role of environmental factors in mediating the dynamics, it is generally recognized that multiple models of the same system are ideal for testing the robustness of model outputs (Fulton et al., 2003; Hill et al., 2007). This is particularly true when the processes and appropriate representations remain as poorly understood as for those associated with decadal-scale forecasts. Thus, models are increasingly being developed to integrate across the range of uncertainty, ranging from uncertainty in climate projections, to uncertainties in quantifying the impacts of changes in abiotic variables on biotic variables, as well as uncertainties regarding the population dynamics of marine species. For example, Plagányi et al. (2013) provided a biological complement to climate ensemble modelling approaches and account for important sources of uncertainty that are an integral part of effective risk management decision making. Similarly, Ianelli et al. (2015) used climate and trophic information for three species of groundfish in the Bering Sea in a multi-model inference framework that combines information from alternative models to better characterize uncertainty.

An important area in need of further research concerns improving both understanding (through both empirical and modelling studies) and prediction of the impacts of extreme events on the structure and functioning of ecosystems. The handling of such events is currently crude (eg, footprints of mortality or impact) and more research is needed in order to facilitate better representation of these events, a better understanding of their true impacts and to facilitate adaptive management and industry responses, either through early intervention or strategic planning in anticipation of changes ahead (Plagányi et al., 2014b). This is particularly important in the context of the functioning of marine ecosystems, because marine species may exhibit abrupt nonlinear responses that are challenging to model. It is important to understand when the system is approaching a tipping point so that interventions can be made in a timely manner. One area showing some early promise is in using increasing variance of properties of the system as a leading statistical early warning signal of regime shifts (see also Carpenter et al., 2008; Plagányi et al., 2014a; Scheffer et al., 2009; van de Leemput et al., 2015).

Even with such early warning systems in place, the breadth of spatial and temporal scales operating in marine systems means understanding and mitigating the full suite of biological, economic, and social impacts of extreme events remains a challenge. One way of trying to tackle this task is by integrating forecasts of environmental conditions into ecological and resource models (as suggested in Section **5.3** for fisheries assessment models). The performance of such approaches and the range of potential outcomes can be explored with a simulation-based decision support tool known as Management Strategy Evaluation (MSE). This is essentially a risk assessment method that focusses on the identification and modelling of uncertainties (FAO, 2008; Sainsbury et al., 2000; Smith et al., 2007) to evaluate the performance of alternative management strategies, most often in fisheries. Management Strategy Evaluation simulations can also include the effects of climate change impacts on fisheries and ecosystems (Fulton, 2010; Hollowed et al., 2011; Plagányi et al., 2011). For example, Plagányi et al. (2013) use an MSE approach to compare the performance of alternative sea cucumber management strategies when accounting for uncertainty in biological understanding and climate impacts. Thus, not only the resilience of a biological system, but also the broader socioecological system, to forecasted extreme events can be explored with MSE in 'flight simulation mode' (Fulton, 2010) to identify management strategies that can mitigate negative impacts while also trying to balance the triple bottom line objectives (social, economic, and environmental) defined under policy instruments like Australia's Federal Fisheries Management Act.

5.4 End-User Needs for Marine Forecasts

Physical processes in the ocean play a crucial role in the dynamics of the species and ecosystems that are dependent on the marine environment, and therefore impact the societies that are dependent upon these resources. Changes in the physical system lead to large-scale changes in the abundance, distribution, and/or productivity of the fish (Brander, 2010). These have impacts on aquaculture and fisheries. Global capture fisheries production has stabilized in the last 20 years around 90 million tonnes (FAO, 2014). In contrast, world aquaculture production has been growing rapidly, reaching 67 million tonnes by 2012, and is now a major industry for many coastal and rural communities. Additionally, as aquaculture is located in specific locations, forecasts are very important for operations and planning, with likely growth in end users in coming years (Hobday et al., 2016b). Offshore activities associated with wind and energy installations, cable laying, maritime transport, coastal infrastructure, insurance industry, military activities, and tourism are also sensitive to sea conditions, and can benefit from marine forecasts.

5.4.1 Application of Marine Forecasts

The operational proof of the value of marine forecasts will come in the user applications. There are many marine, coastal, and terrestrial industries that will directly benefit from improved extreme events forecasting. Insurance and accounting companies along with research initiatives are increasingly being asked to assess the business costs associated with extreme events and mitigation methods taken to reduce risk. Industrial sectors requiring significant infrastructure investment are those with the keenest interests in forecasts of future extreme events. In the ocean, MHWs, storms and storm surges, and drought all pose investment threats. They damage infrastructure, cause delays to construction, disrupt operations and supply chains, increase operating costs, and increase the risk of accidents and associated environmental and social impacts and potential litigation (Smith, 2013). For example, the winds and flooding that came with cyclone Yasi in 2011 shut down 85% of coal mines in Queensland, costing $AUD 2.5 billion. Similarly the storm surge from Hurricane Katrina caused well in excess of $US 1 billion in damage, and the closure of nine refineries along the Gulf of Mexico, resulting in the total shutdown of oil production in the region for six months (cutting U.S. annual oil production by over 20%).

Share prices and billions in investment dollars hinge on the distribution, frequency, and intensity of extreme events. The insurance industry in particular is keenly interested in such forecasting methods as they can allow for targeted defensive mitigation measures that reduce vulnerability to weather-related damage and mean that increases in recorded weather-related loss events do not lead to overwhelming increases in normalized economic and insured losses (Ward and Ranger, 2010). There are also co-benefits to be found from short- to medium-term forecasts for 'ridge to reef' catchment management, with agricultural producers, forestry operations, and other catchment users able to target their production methods, cycles and infrastructure developments to cope with climate-related drivers and extreme events, which in turn also provides benefits for downstream receiving waters that would be impacted by runoff and turbidity if unsuitable practices continued in the absence of forecasts.

It is not only catchment practices and industrial infrastructure at risk from extreme events. Planners are interested in forecasts as coastal communities and the transportation industry both have significant investments in the coastal zone, mostly in buildings, roads, rail lines, jetties, seawalls, groynes, and ports. These highly modified environments are susceptible to damage from inundation, sea-level rise, waves, storm surge, currents, deposition loads, runoff, and wind. The risks to the built infrastructure are from physical changes or disturbances in the climate and are likely to grow if extreme events become more frequent or more intense (Neumann et al., 2015). Climate variability and extremes with a growing coastal population are likely to require increased management to minimize losses of property and life. It will also increase costs for end users in the coastal zone with changes to the food and water supply plus increased insurance costs for many individuals, families, and businesses. Relative to the risks posed to other sectors, the largely physical risks for coastal infrastructure are reasonably well-documented and mitigation strategies are quite advanced, with interested readers referred to reviews of risks covered by McGranahan et al. (2007) and for Australia by the Department of Climate Change (2009, 2011) and McEvoy and Mullett (2013).

Another set of key uses of coastal ecosystems that is growing through time is tourism and recreation. Climate itself is a primary factor influencing tourist choices: factors include the frequency of storms and the seasonal distribution of temperature and precipitation. Beyond direct comfort considerations, climate variability will also influence tourism indirectly through impacts on biodiversity and ecosystem health. The GBR is an internationally renowned tourist destination that is increasingly exposed to significant risks associated with climate. Cyclones are amongst the key drivers of recent observed declines in coral cover (De'ath et al., 2012). Future changes in tropical cyclones extremes is likely to see more physical damage to coral reefs and to a range of nearshore benthic and littoral zone communities (Great Barrier Reef Marine Park Authority, 2014). Combined with rising CO_2 and falling pH (ocean acidification) these stressors are likely to cause increased coral decline. These threats are well recognized however and the GBR may represent one of the few situations within Australia where there are research plans in place (Great Barrier Reef Marine Park Authority, 2014) and significant progress on possible mitigation strategies for extremes and variability. For most of Australia, however, there are major gaps in the knowledge of how climate change will affect the natural and cultural resources critical for tourism. Forecasting of extreme events that impact coral reefs can help reef managers implement contingency plans (Spillman, 2011).

Patchy preparedness is symptomatic of many of Australia's other natural resource-based industries. Fishers are experienced in dealing with the physical risks of weather, but the changes in frequency or severity of storms associated with variability and extremes may make the sea state less suitable for fishing, or necessitate the use of more seaworthy vessels. Climate-related shifts in species distributions are already leading to changing operator attitudes to appropriate vessel sizes, though not without much social comment. Knowledge of the likely conditions will be important in decision making on strategic time scales such as what sort of boat will be needed in five years. Beyond the immediate technological demands of operating in climate affected seas there are also issues around the status of the fish stocks. Australia's wild fisheries are known to experience considerable annual variability in recruitment, production, and catch. For example, recruitment into Australia's most valuable single-species fishery, the western rock lobster, has been strongly associated with climate signals such as ENSO (Caputi et al., 2001). The discovery of simple correlations between environmental state (eg, SST) and recruitment should encourage more research into the underlying mechanisms. Correlative models are likely to have little predictive capacity as climate trends or extremes approach thresholds. More sophisticated statistical models of populations are making very rapid improvements (eg, Hollowed et al., 2009, 2011; Ianelli et al., 2011; Szuwalski and Punt, 2012). Stock recruitment models provide reasonable predictions allowing targets to be set for future commercial catches, but are only beginning to make allowance for the variability in environmental drivers and regime changes (Wayte, 2013). Nevertheless, work to date demonstrates that there are clear advantages to environmentally based, near real-time modifications to fishing zones in terms of improved catch rates and reduced bycatch of nontarget species (Hobday et al., 2010). It is also leading to new forms of fisheries management based around dynamically defined fishing zones rather than static zoning (Hobday et al., 2014). Success on these immediate management relevant scales has helped transform the thinking of operators and managers so that they begin to embrace longer term perspectives. For example, in the Great Australian Bight (GAB), decadal-scale ocean temperature forecasts have highlighted the changing nature of the region and have alerted the industry to the likely future shift in the timing of the fishing season—rises in SST will mean that the preferred habitat range for southern bluefin tuna will become available earlier in the year (Eveson et al., 2015). The forecasts also show that in the extreme, the GAB may become so warm that the current preferred habitat range for southern bluefin tuna would no longer be available, such that fish may stop using this region unless they alter their preferred habitat range. This highlights the importance of scientists continuing to monitor and update biological models with new data (Hobday et al., 2016b).

As previously discussed, strategic models looking at the longer term climate influences on marine ecosystems are being used for some Australian fisheries (eg, Fulton and Gorton, 2014), but this is not yet the case for all fisheries. In addition, mechanistic models of complex marine food webs are not universally effective in terms of predicting the abundance or distribution of all marine taxa. While some species or functional groups (eg, sharks) can be captured with some fidelity, others (eg, gelatinous species) are much less reliable and improvements in this science should provide better guidance to wild fishers and managers in the future, and also to conservation. Habitat and biodiversity management faces many climate-related challenges, including the influence of extreme events. In deciding on the research priorities for the prediction of climate variability and extremes we should ask: Is there important variability at the annual to decadal scales? If so then how much does this variability cost in terms of social, economic, and ecological damage? If the variability is high and the costs are high then forecasting this variability should be a priority. We already know that coastal species experience a range in conditions of a similar magnitude to that predicted for oceanic species over the next half century (Shaw et al., 2013), due to the reduced scope for vertical mixing in the shallow waters. Thermal stress and acidification are not the only challenging conditions facing coastal species. Excess nutrients in the coastal zone cause a decline in water quality and are linked with the decline and disappearance of seagrasses (Burkholder et al., 2007; Grech et al., 2012), large macroalgae (Connell et al., 2008), and loss of corals (De'ath et al., 2012; Hughes et al., 2003). Changing precipitation also means more variable salinity, another very strong determinant of suitable habitat for many obligate freshwater and marine species. For a continent like Australia that mostly has low and erratic rainfall (McMahon, 1982; Nicholls et al., 1996), rare but extreme events can dramatically reshape coastal ecology (Paerl et al., 2006). Greater extremes in precipitation will lead to expanded estuary zones inhabited by euryhaline species or those that quickly colonize between events. The magnitude and rate of change and variability will be a key determinant of coastal outcomes. Ghedini et al. (2015) have demonstrated in laboratory conditions that species (and ecosystems) can adapt when faced with gradual change, but the addition of extreme events in combination with the slow directional change pushes the species and communities past compensation thresholds, leading to major change. The point of these thresholds and the resulting magnitude of biological effects of extremes are extremely difficult to predict. Changes are likely to be the most profound when they result from a loss in the capacity of the environment to support a wide range of other biota. Mangroves, seagrass beds, kelp forests, and phytoplankton all profoundly determine the higher trophic level community in the coastal zone. Consequently, the ecology of the coastal zone is vulnerable to these climate extremes, especially where they may exacerbate any negative, and often more direct, impacts from billions of inhabitants (Lotze et al., 2006; Vitousek et al., 1997; Vörösmarty et al., 2000). Given the range of challenges it is clear that we still have a long way to go to even develop an appropriate mitigation plan (McCauley et al., 2015).

There are many other examples of industries and societal sectors that could benefit from extreme events and decadal forecasting. A final one to mention here is aquaculture. Aquaculture production now rivals wild capture fisheries worldwide (FAO, 2014). With roughly an $AUD 1 billion in production in 2012/13 (Savage and Hobsbawn, 2015) aquaculture has become a major industry for many coastal and rural communities in Australia. Although aquaculture can be a significant source of eutrophication, it requires high water quality and the industry is supportive of good environmental practices. The top Australian aquaculture species (by value) are salmon (*Salmo salar*), tuna (*T. maccoyii*), oysters (*Crassostrea gigas* and

Pinctada maxima) (edible and pearl) and prawns (*Penaeus japonicas*, *P. monodon*, and *P. merguiensis*). Of these, salmon are already close to their pejus temperature and therefore highly sensitive to changes in water temperatures on interannual to decadal time scales. Forecasts are therefore useful for the industry in terms of managing feeding, general farming practices, and future developments, respectively (Spillman and Hobday, 2014). Variability in precipitation, as much as temperature, poses significant risks to the aquaculture of oysters and prawns because they are often cultivated in estuaries. The stress of low salinity is often compounded by low dissolved oxygen. Increased runoff decreases salinity, delivers a nutrient load to the estuary and often stratifies it, limiting gas exchange with the atmosphere. The combination of stresses is catastrophic to many animals. All aquaculture species are at risk if oxygen concentrations decline, although tuna and salmon are more susceptible than oysters. Oysters are also at risk due to falling pH (increasing acidity), although significant economic losses have so far only been reported from North American aquaculture operations (Feely et al., 2012). The estimation of the current status, trends and predicted future status of climate-mediated chemical changes in water quality should be undertaken in the main shellfish production areas. If deemed a high risk then the development of a predictive capability at a range of time scales would facilitate mitigation measures (Feely et al., 2012). Beyond the purely physical, a range of biologically related risks from parasites (eg, amoebic gill disease) to pests (eg, jellyfish, harmful phytoplankton blooms) already impact on aquaculture production.

Quantitative research on their climatic trends is limited and most are dealt with in a reactive manner. Some of these risks are predictable and there would be value in developing mitigation options including prediction on various time scales. This would require dedicated research for at least some of these species for which current mechanistic models are poor (eg, jellyfish); however, short-term predictive models do exist for some species (Gershwin et al., 2014).

5.4.2 Helping End Users Manage Risk

There are risks in both using and not using a climate forecast. Because climate forecasts are necessarily probabilistic, they are not always correct. In any individual year or month there is a chance that a particular forecast may be incorrect or misinterpreted, resulting in short-term decision-making risks. Nevertheless, these short-term risks should be outweighed by the long-term environmental gains that can be achieved through the use of forecasts over multiple forecast periods. The risk of not using a forecast is not factoring in information about relevant climate changes and making decisions that are less optimal than those that do use forecast information.

If the forecast has skill, then over time with repeated use, one will be in a better position by using the forecast than if not (Asseng et al., 2012). The higher the skill, the shorter the period of time over which forecasts need to be followed for the user to be confident of attaining better outcomes compared to assuming average conditions. This means that the user needs to be aware how long it ought to take to assure benefit from use of the forecast, and how this relates to other risks in their enterprise. Backing a forecast is always a gamble that carries risks. Ideally, the climate forecast should be used in the context of other risks in an integrated decision framework to reduce exposure to incorrect forecasts.

5.4.3 Developing a Successful Forecasting System

Much of our discussion has focussed on developing and evaluating forecasting models, as this is the crux of any forecasting system. However, additional steps are required to develop a system that will be successful in helping end users manage the impacts and risks of climate change. Hobday et al. (2016b) advocate a three stage approach that involves: assessing end-user needs, developing and evaluating forecast tools to address these needs (as discussed), and delivering forecasts to the end user. Although this approach was proposed with regard to seasonal forecasts, it is equally applicable to longer term climate forecasts. As part of the first stage, engagement with end users is critical in order to define the problems that forecasting can address, determine the critical time scales, and discuss realistic expectations about forecast skill. While remote communication via phone calls and email is possible, direct visits are much more effective for building understanding (and trust) of both scientists and end users. The last phase involves not only delivering the forecasts but also educating end users about forecast interpretation (eg, about uncertainty and probabilistic forecasts) and seeking feedback so the forecast system can be improved. Forecasts can be delivered via reports emailed directly to users, or through a public or password-protected website. The most appropriate method will be case specific. With small user groups, email allows feedback and a greater personal engagement with the users; however, web-based delivery is more sustainable in the long-term as it can be almost fully automated (with the ultimate goal of being managed by the end users). Several examples of websites being used to present seasonal forecasts in support of fishery applications already exist, including

1. http://www.gmri.org/our-work/research/projects/gulf-maine-lobster-forecasting, which provides forecasts of the timing of the upcoming lobster season in Gulf of Maine (up to 3 months lead time);
2. http://www.cmar.csiro.au/gab-forecasts/index.html, which provides forecasts of the distribution of southern bluefin tuna in the GAB (up to 2 months lead time);
3. http://www.nanoos.org/products/j-scope/forecasts.php, which provides forecasts of sardine distribution off the west coast of North America (up to 9 months lead time).

As discussed by Marshall et al. (2011), even when strategies to reduce the impacts of climate change on a resource industry have been identified, end users are often still reluctant to adopt climate forecasts. To overcome this, ongoing support and education regarding the strengths and limitations of forecasts is critical—it is important that end users understand that forecasts can be inaccurate, but that sustained use should lead to more positive outcomes in the long term than assuming average conditions (Asseng et al., 2012; Marshall et al., 2011). In this regard, having industry coinvestigators and/or knowledge brokers to facilitate communication between scientists and end users, and to aid in dissemination and interpretation of forecasts, can lead to greater end-user uptake. This approach was highly successful in the seasonal forecasting of southern bluefin tuna distribution project mentioned above, in which case a research scientist employed by the Australian tuna fishing industry, and based in the main fishing port, was an integral member of the project team (Eveson et al., 2015).

6. CONCLUSION

This review substantiates that some predictability in ocean conditions up to 10 years ahead may come from the persistence and predictability of large-scale climate modes, illustrated via four key drivers of climate variability that affect the Australian marine environment: the SAM, the IOD, the ENSO, and the IPO. In addition to differences in mean ocean conditions, the frequency of extreme events, such as MHWs and flooding, may differ between climate phases. These rare events may lead to conditions that are outside the normal ranges over which biota and humans can easily adjust or modify their behaviour, and thus prediction of extremes as part of a forecast system are particularly useful for marine applications. To allow reliable forecasts of average and extreme conditions at these time scales, considerable investment is still needed to support decadal forecasting. Focus should include improvement of ocean-atmosphere models and enhancement of ocean and atmosphere observing and monitoring systems on both regional and local scales to support initiation of forecasting models and further development of ensemble forecasting. To be useful for many marine applications, regional and local downscaling is required to produce information at a scale useful for decision making. Biological data that can be included into forecast models, such as primary production and species composition, may need dedicated collection efforts. Further research is also needed to support integration of forecasts into decision support tools, especially in end-to-end ecosystems models, to allow prediction of the impacts of changes in climate phases and associated mean conditions and extreme events on marine species and ecosystems. Seasonal forecasts provide a bridge between weather and decadal forecasting and have been developed for a limited number of marine users, providing guidance for applications over longer time scales. Overall, close engagement between forecast developers and marine resource sectors—fisheries, aquaculture, tourism, habitat and biodiversity management, infrastructure—is needed to support tactical and strategic decision making and subsequent management of environmental risk on decadal time scales.

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REFERENCES

Allan, R.J., Heathcote, R.L., 1987. The 1982–83 drought in Australia. In: Glantz, M., Katz, R., Kranz, M. (Eds.), The Societal Impacts Associated with the 1982–83 Worldwide Climatic Anomalies. UNEP, National Center for Atmospheric Research, Boulder, Colorado, pp. 19–23.

Asseng, S., McIntosh, P.C., Wang, G., Khimashia, N., 2012. Optimal N fertiliser management based on a seasonal forecast. Eur. J. Agron. 38, 66–73.

Baehr, J., Piontek, R., 2014. Ensemble initialization of the oceanic component of a coupled model through bred vectors at seasonal-to-interannual timescales. Geosci. Model Dev. 7, 453–461.

Bakun, A., Broad, K., 2003. Environmental 'loopholes' and fish population dynamics: comparative pattern recognition with focus on El Nino effects in the Pacific. Fish. Oceanogr. 12 (4–5), 458–473.

Barnston, A.G., Mason, S.J., 2011. Evaluation of IRI's seasonal climate forecasts for the extreme 15% tails. Weather Forecast 26, 545–554. http://dx.doi.org/10.1175/WAF-D-10-05009.1.

Barriopedro, D., Fisher, E.M., Luterbacher, J., Trigo, R.M., Garcia-Herrera, R., 2011. The hot summer of 2010: redrawing the temperature record map of Europe. Science 332, 220–224.

Beamish, R.J., Bouillon, D.R., 1993. Pacific salmon production trends in relation to climate. Can. J. Fish. Aquat. Sci. 50, 1002–1016.

Beeden, R., Maynard, J.A., Marshall, P.A., Heron, S.F., Willis, B.L., 2012. A framework for responding to coral disease outbreaks that facilitates adaptive management. Environ. Manag. 49, 1–13.

Bell, J.D., Ganachaud, A., Gehrke, P.C., Griffiths, S.P., Hobday, A.J., Hoegh-Guldberg, O., Johnson, J.E., Le Borgne, R., Lehodey, P., Lough, J.M., Matear, R.J., Pickering, T.D., Pratchett, M.S., Sen Gupta, A., Senina, I., Waycott, M., 2013. Mixed responses of tropical Pacific fisheries and aquaculture to climate change. Nat. Clim. Chang. 3 (6), 591–599. http://dx.doi.org/10.1038/NCLIMATE1838.

Benthuysen, J., Feng, M., Zhong, L., 2014. Spatial patterns of warming off Western Australia during the 2011 Ningaloo Niño: quantifying impacts of remote and local forcing. Cont. Shelf Res. 91, 232–246.

Berkelmans, R., De'arth, G., Kininmonth, S., Skirving, W., 2004. A comparison of the 1998 and 2002 coral bleaching events on the Great Barrier Reef: spatial correlations, patterns and predictions. Coral Reefs 23, 74–83.

Berkelmans, R., Oliver, J.K., 1999. Large scale bleaching of corals on the Great Barrier Reef. Coral Reefs 18, 55–60.

Bijma, J., Faber, W.W.J., Hemleben, C., 1990. Temperature and salinity limits for growth and survival of some planktonic foraminifers in laboratory cultures. J. Foraminifer. Res. 20, 95–116.

Black, E.C., 1953. Upper lethal temperatures of some British Columbia freshwater fishes. J. Fish. Res. Board Can. 10, 196–210.

Blanchard, J.L., Anderson, K.H., Scott, F., Hintzen, N.T., Piet, G.J., Jennings, S., 2014. Evaluating targets and trade-offs among fisheries and conservation objectives using a multispecies size spectrum model. J. Appl. Ecol 51 (3), 612–622. http://dx.doi.org/10.1111/1365-2664.12238.

Boucharel, J., Dewitte, B., Garel, B., du Penhoat, Y., 2009. ENSOs non-stationary and non-Gaussian character: the role of climate shifts. Nonlinear Process. Geophys. 16, 453–473.

Boyd, P.W., Rynearson, T.A., Armstrong, E.A., Fu, F., et al., 2013. Marine phytoplankton temperature versus growth responses from polar to tropical waters—outcome of a scientific community-wide study. PLoS One 8, e63091.

Brander, K., Mohn, R., 2004. Effect of the North Atlantic Oscillation on recruitment of Atlantic cod (Gadus morhua). Can. J. Fish. Aquat. Sci. 61 (9), 1558–1564. http://dx.doi.org/10.1139/f04-087.

Brander, K., 2010. Impacts of climate change on fisheries. J. Mar. Syst. 79, 389–402.

Brett, J.R., 1941. Tempering versus acclimation in the planting of speckled trout. Trans. Am. Fish. Soc. 70, 397–403.

Brett, J.R., 1944. Some lethal temperature relations of Algonquin Park fishes. Publ. Ontario Fish. Res. Lab. No. 63. Univ. of Toronto Studies Biol. Ser. No. 52. University of Toronto Press, Toronto.

Brewer, G.D., 1976. Thermal tolerance and resistance of the northern anchovy *Engraulis mordax*. Fish. Bull. 74, 433–445.

Brodeur, R.D., Fisher, J.P., Emmett, R.L., Morgan, C.A., Casillas, E., 2005. Species composition and community structure of pelagic nekton off Oregon and Washington under variable oceanographic conditions. Mar. Ecol. Prog. Ser. 298, 41–57.

Brodie, J., 1992. Enhancement of larval and juvenile survival and recruitment in *Acanthatser planci* from the effects of terrestrial runoff: a review. Mar. Freshw. Res. 43, 539–553.
Brown, J.N., Langlais, C., Sen Gupta, A., 2015. Projected sea surface temperature changes in the equatorial Pacific relative to the Warm Pool edge. Deep Sea Res. II 113, 47–58.
Bureau of Meteorology, 2012. Recording-Breaking La Niña Events: An Analysis of the La Niña life Cycle and the Impacts and Significance of the 2010–11 and 2011–12 La Niña Events in Australia. Bureau of Meteorology, Melbourne, Victoria, Australia. July 2012.
Burgman, R.J., Clement, A.C., Mitas, C.M., Chen, J., Esslinger, K., 2008. Evidence for atmospheric variability over the Pacific on decadal timescales. Geophys. Res. Lett. 35, L01704.
Burkholder, J.M., Tomasko, D.A., Touchette, B.W., 2007. Seagrasses and eutrophication. J. Exp. Mar. Biol. Ecol. 350, 46–72.
Caddy, J.F., Garibaldi, L., 2000. Apparent changes in the trophic composition of world marine harvests: the perspective from the FAO capture database. Ocean Coast. Manag. 43, 615–655.
Cai, W., Santoso, A., Wang, G., Weller, E., Wu, L., Ashok, K., Masumoto, K., Yamagata, T., 2014. Increased frequency of extreme Indian Ocean Dipole events due to greenhouse warming. Nature 510, 254–258.
Callaghan, J., Power, S., 2011. Variability and decline in the number of severe land-falling tropical cyclones over eastern Australia since the late nineteenth century. Clim. Dyn. 37, 647–662.
Caputi, N., Chubb, C.F., Pearce, A., 2001. Environmental effects on recruitment of the western rock lobster, *Panulirus cygnus*. Mar. Freshw. Res. 52 (8), 1167–1174.
Carpenter, S., Brock, W., Cole, J., Kitchell, J., Pace, M., 2008. Leading indicators of trophic cascades. Ecol. Lett. 11, 128–138.
Castillo-Jordán, C., Klaer, N.L., Tuck, G.N., Frusher, S.D., Cubillos, L.A., Tracey, S.R., Salinger, M.M., 2016. Coincident recruitment patterns of Southern Hemisphere fishes. Can. J. Fish. Aquat. Sci. 73 (2), 270–278.
Charney, J.G., Stern, M.E., 1961. On the stability on internal baroclinic jets in a rotating atmosphere. J. Atmos. Sci. 19, 159–172.
Cloern, J.E., Hieb, K.A., Jacobson, T., Sanso, B., Di Lorenzo, E., Stacey, M.T., Largier, J.L., Meiring, W., Peterson, W.T., Powell, T.M., Winder, M., Jassby, A.D., 2010. Biological communities in San Francisco Bay track large-scale climate forcing over the North Pacific. Geophys. Res. Lett. 37, L21602.
Cloke, H., Pappenberger, F., 2009. Ensemble flood forecasting: a review. J. Hydrol. 375 (3–4), 613–626.
Collie, J.S., Gifford, D.J., Steele, J.H., 2009. End-to-end foodweb control of fish production on Georges Bank. ICES J. Mar. Sci. 66, 2223–2232.
Collier, C.J., Villacorta Rath, A.C., Van Dijk, J., Takahashi, M., Waycott, M., 2014. Seagrass proliferation precedes mortality during hypo-salinity events: a stress-induced morphometric response. PLoS One 9 (4), 1–11.
Collier, C.J., Waycott, M., McKenzie, L.J., 2012. Light thresholds derived from seagrass loss in the coastal zone of the northern Great Barrier Reef, Australia. Ecol. Indic. 23, 211–219.
Connell, S.D., Russell, B.D., Turner, D.J., Shepherd, S.A., Kildea, T., Miller, D., Airoldi, L., Cheshire, A., 2008. Recovering a lost baseline: missing kelp forests from a metropolitan coast. Mar. Ecol. Prog. Ser. 360, 63–72.
Cvitanovic, C., Crimp, S., Fleming, A., Bell, J., Howden, M., Hobday, A., Taylor, M., Cunningham, R., 2016. Linking adaptation science to action to build food secure and climate adapted Pacific Island communities. Clim. Risk Manag. 11, 53–62. http://dx.doi.org/10.1016/j.crm.2016.01.003.

De Viron, O., Dickey, J.O., Ghil, M., 2013. Global modes of climate variability. Geophys. Res. Lett. 40, 1832–1837.
De'ath, G., Fabricius, K.E., Sweatman, H., Puotinen, M., 2012. The 27-year decline of coral cover on the Great Barrier Reef and its causes. Proc. Natl. Acad. Sci. U.S.A. 109, 17995–17999.
Department of Climate Change, 2009. Climate Change. Risks to Australia's Coast: A First Pass National Assessment. Department of Climate Change, Canberra, Australia. ISBN: 978-1-921298-71-4. www.climatechange.gov.au. Commonwealth of Australia, 168 pp.
Department of Climate Change, 2011. Climate Change Risks to Coastal Buildings and Infrastructure. A Supplement to the First Pass National Assessment. Department of Climate Change and Energy Efficiency, Canberra, Australia. ISBN: 978-1-921299-62-9. Commonwealth of Australia, 20 pp.
Deser, C., Phillips, A., Bourdette, V., Teng, H., 2012. Uncertainty in climate change projections: the role of internal variability. Clim. Dyn. 38, 527–546.
Deser, C., Phillips, A.S., Hurrell, J.W., 2004. Pacific interdecadal climate variability: linkages between the tropics and the north Pacific during boreal winter since 1900. J. Climate 17, 3109–3124.
Diamond, H.J., Lorrey, A.M., Renwick, J.A., 2013. A Southwest Pacific tropical cyclone climatology and linkages to the El Niño–Southern Oscillation. J. Climate 26, 3–25.
Doi, T., Behera, S.K., Yamagata, T., 2015. An interdecadal regime shift in rainfall predictability related to the Ningaloo Niño in the late 1990. J. Geophys. Res. Oceans 120, 1388–1396. http://dx.doi.org/10.1002/2014JC010562.
Dommenget, D., Jansen, M., 2009. Predictions of Indian Ocean SST indices with a simple statistical model: a null hypothesis. J. Climate 22, 4930–4938.
Eppley, R.W., 1972. Temperature and phytoplankton growth in the sea. Fish. Bull. 70 (4), 1063–1085.
Eveson, J.P., Hobday, A.J., Hartog, J.R., Spillman, C.M., Rough, K.M., 2015. Seasonal forecasting of tuna habitat in the Great Australian Bight. Fish. Res. 170, 39–49.
Fabricius, K., Okaji, K., De'ath, G., 2010. Three lines of evidence to link outbreaks of the crown-of-thorns seastar *Acanthaster planci* to the release of larval food limitation. Coral Reefs 29, 593–605. http://dx.doi.org/10.1007/s00338-010-0628-z.
FAO, 2008. Best practices in ecosystem modelling for informing an ecosystem approach to fisheries. FAO Fisheries Technical Guidelines for Responsible Fisheries. No. 4, Suppl. 2, 1–78.
FAO, 2014. The State of World Fisheries and Aquaculture 2014: Opportunities and Challenges. FAO, Rome. 223 pp.
Fasham, M.J., 1993. Modelling the marine biota. The global carbon cycle, NATO ASI Series. Series 1. Glob. Environ. Change 15, 1–599.
Fedorov, A., Philander, S., 2000. Is El Nino changing? Science 288, 1997–2002.
Feely, R.A., Klinger, T., Newton, J.A., Chadsey, M., 2012. Scientific Summary of Ocean Acidification in Washington State Marine Waters: NOAA OAR Special Report.
Feng, M., Biastoch, A., Boning, C., Caputi, N., Meyers, G., 2008. Seasonal and interannual variations of upper ocean heat balance off the west coast of Australia. J. Geophys. Res. 113, C12025.
Feng, M., Hendon, H.H., Xie, S.-P., Marshall, A.G., Schiller, A., Kosaka, Y., Caputi, N., Pearce, A., 2015. Decadal increase in Ningaloo Niño since the late 1990s. Geophys. Res. Lett. 42, 104–112.
Feng, M., McPhaden, M.J., Xie, S.-P., Hafner, J., 2013. La Niña forces unprecedented Leeuwin Current warming in 2011. Sci. Rep. 3, 1277.
Feng, M., Meyers, G., Pearce, A., Wijffels, S., 2003. Annual and interannual variations of the Leeuwin Current at 32°S. J. Geophys. Res. 108 (C11), 3355.

Fiala, M., Oriol, L., 1989. Light-temperature interactions on the growth of Antarctic diatoms. Polar Biol. 10, 629–636.

Folland, C.K., Parker, D.E., Colman, A.W., Washington, R., 1998. Large Scale Modes of Ocean Surface Temperature Since the Late Nineteenth Century. Hadley Centre, UK Meteorological Office. Clim. Res. Tech. Note CRTN 81, 45 pp.

Freitas, A.C.V., Frederiksen, J.S., Whelan, J., O'Kane, T.J., Ambrizzi, T., 2015. Observed and simulated inter-decadal changes in the structure of Southern hemisphere large-scale circulation. Clim. Dyn 45, 2993–3017. http://dx.doi.org/10.1007/s00382-015-2519-z.

Fulton, E.A., 2010. Approaches to end-to-end ecosystem models. J. Mar. Syst. 81, 171–183.

Fulton, E.A., 2011. Interesting times: winners, losers, and system shifts under climate change around Australia. ICES J. Mar. Sci. 68 (6), 1329–1342.

Fulton, E.A., Gorton, R., 2014. Adaptive Futures for SE Australian Fisheries and Aquaculture: Climate Adaptation Simulations. CSIRO, Australia. 309 pp.

Fulton, E.A., Smith, A.D.M., Johnson, C.R., 2003. Effect of complexity on marine ecosystem models. Mar. Ecol. Prog. Ser. 253, 1–16.

Fulton, E.A., Smith, A.D.M., Punt, A.E., 2005. Which ecological indicators can robustly detect effects of fishing? ICES J. Mar. Sci. 62, 540–551.

Garcia-Herrera, R., Diaz, H.F., Garcia, R.R., Prieto, M.R., Barriopedro, R., Moyano, R., Hernandez, E., 2008. A chronology of El Nino events from primary documentary sources in Northern Peru. J. Climate 21, 1948–1962.

Garrabou, J., Coma, R., Bensoussan, N., Bally, M., Chevaldonne, P., Cigliano, M., Diaz, D., Harmelin, J.G., Gambi, M.C., Kersting, D.K., Ledoux, J.B., Lejeusne, C., Linares, C., Marschal, C., Perez, T., Ribes, M., Romano, J.C., Serrano, E., Teixido, N., Torrents, O., Zabala, M., Zuberer, F., Cerrano, C., 2009. Mass mortality in Northwestern Mediterranean rocky benthic communities: effects of the 2003 heat wave. Glob. Chang. Biol. 15, 1090–1103.

Gattuso, J.-P., Magnan, A., Billé, R., Cheung, W.W.L., Howes, E.L., Joos, F., Allemand, D., Bopp, L., Cooley, S.R., Eakin, C.M., Hoegh-Guldberg, O., Kelly, R.P., Pörtner, H.-O., Rogers, A.D., Baxter, J.M., Laffoley, D., Osborn, D., Rankovic, A., Rochette, J., Sumaila, U.R., Treyer, S., Turley, C., 2015. Contrasting futures for ocean and society from different anthropogenic CO_2 emissions scenarios. Science 349 (6243). http://dx.doi.org/10.1126/science.aac4722.

Gerber, E.P., Voronin, S., Polvani, L.M., 2008. Testing the annular mode autocorrelation time scale in simple atmospheric general circulation models. Mon. Weather Rev. 136 (4), 1523–1536.

Gershwin, L., Condie, S.A., Mansbridge, J.V., Richardson, A.J., 2014. Dangerous jellyfish blooms are predictable. J. R. Soc. Interface 11. http://dx.doi.org/10.1098/rsif.2013.1168.

Ghedini, G., Russell, B.D., Connell, S.D., 2015. Trophic compensation reinforces resistance: herbivory absorbs the increasing effects of multiple disturbances. Ecol. Lett. 18, 182–187.

Gillett, N.P., Kell, T.D., Jones, P.D., 2006. Regional climate impacts of the Southern Annular Mode. Geophys. Res. Lett. 33, L23704.

Glantz, M.H., 2001. Currents of Change: Impact of El Niño and La Niña on Climate and Society. Cambridge University Press, Cambridge, UK.

Gleick, P.H., 1989. Climate change, hydrology, and water resources. Rev. Geophys. 27, 329–344.

Goddard, L., Hurrell, J.W., Kirtman, B.P., Murphy, J., Stockdale, T., Vera, C., 2012. Two time scales for the price of one (almost). Bull. Am. Meteorol. Soc. 2012, 621–629.

Great Barrier Reef Marine Park Authority, 2014. Great Barrier Reef Outlook Report 2014. GBRMPA, Townsville, Australia. 311 pp.

Grech, A., Chartrand-Miller, K., Erftemeijer, P., Fonseca, M., McKenzie, L., Rasheed, M., Taylor, H., Coles, R., 2012. A comparison of threats, vulnerabilities and management approaches in global seagrass bioregions. Environ. Res. Lett. 7, 024006.

Grise, K.M., Son, S.-W., Correa, G.J.P., Polvani, L.M., 2014. The response of extratropical cyclones in the southern hemisphere to stratospheric ozone depletion in the 20th century. Atmos. Sci. Lett. 15, 29–36.

Grose, M.R., Brown, J.N., Narsey, S., Brown, J.R., Murphy, B.F., Langlais, C., Gupta, A.S., Moise, A.F., Irving, D.B., 2014. Assessment of the CMIP5 global climate model simulations of the western tropical Pacific climate system and comparison to CMIP3. Int. J. Climatol. 34 (12), 3382–3399.

Gu, D., Philander, S., 1997. Interdecadal climate fluctuations that depend on exchanges between the tropics and the extra-tropics. Science 275, 805–807.

Hartmann, D.L., Klein Tank, A.G.M., Rusticucci, M., Alexander, L.V., Brönnimann, S., Charabi, Y., Dentener, F.J., Dlugokencky, E.J., Easterling, D.J., Kaplan, A., Soden, B.J., Thorne, P.W., Wild, M., Zhai, P.M., 2013. Observations: atmosphere and surface. In: Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (Eds.), Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 159–254.

Hayes, K.R., Dambacher, J.M., Thompson, P., Hosack, G.R., Dunstan, P., Bax, N.J., Fulton, E.A., Hartog, J., Hobday, A., Bradford, R., Foster, S., Hedge, P., Smith, D.C., 2015. Identifying biological indicators for managing oceanic ecosystems. Ecol. Indic. 57, 409–419.

Hewitt, C.D., Griggs, D.J., 2004. Ensembles-based predictions of climate changes and their impacts (ENSEMBLES). Eos 85 (52), 566.

Hill, S.L., Watters, G.M., Punt, A.E., McAllister, M.K., Quéré, C.L., Turner, J., 2007. Model uncertainty in the ecosystem approach to fisheries. Fish Fish. 8, 315–336.

Hobday, A.J., Spillman, C.M., Eveson, J.P., Hartog, J.R., 2016a. Seasonal forecasting for decision support in marine fisheries and aquaculture. Fish. Oceanogr 25 (S1), 45–56. http://dx.doi.org/10.1111/fog.12083.

Hobday, A.J., Alexander, L.V., Perkins, S.E., Smale, D.A., Straub, S.C., Benthuysen, J., Burrows, M.T., Donat, M., Feng, M., Holbrook, N.J., Moore, P.J., Oliver, E.C.J., Scannell, H., Sen Gupta, A., Wernberg, T., 2016b. A hierarchical approach to defining marine heatwaves. Prog. Oceanogr. 141, 227–238. http://dx.doi.org/10.1016/j.pocean.2015.12.014.

Hobday, A.J., Hartog, J.R., Spillman, C.M., Alves, O., 2011. Seasonal forecasting of tuna habitat for dynamic spatial management. Can. J. Fish. Aquat. Sci. 68 (5), 898–911.

Hobday, A.J., Hartog, J.R., Timmiss, T., Fielding, J., 2010. Dynamic spatial zoning to manage southern bluefin tuna (Thunnus maccoyii) capture in a multi-species longline fishery. Fish. Oceanogr. 19, 243–253.

Hobday, A.J., Maxwell, S.M., Forgie, J., McDonald, J., Darby, M., Seto, K., Bailey, H., Bograd, S.J., Briscoe, D.K., Costa, D.P., Crowder, L.B., Dunn, D.C., Fossette, S., Halpin, P.N., Hartog, J.R., Hazen, E.L., Lascelles, B.G., Lewison, R.L., Poulos, G., Powers, A., 2014. Dynamic ocean management: integrating scientific and technological capacity with law, policy and management. Stanford Environ. Law J. 33, 125–165.

Hodgkinson, J.A., Hobday, A.J., Pinkard, E.A., 2014. Climate adaptation in Australia's resource-extraction industries: ready or not? Reg. Environ. Chang. 14 (4), 1663–1678. http://dx.doi.org/10.1007/s10113-014-0618-8.

Hoegh-Guldberg, O., 1999. Climate change, coral bleaching and the future of the world's coral reefs. Mar. Freshw. Res. 50, 839–866.

Hoffman, M.J.E., Kalnay, E., Carton, J.A., Yang, S.-C., 2009. Use of breeding to detect and explain instabilities in the global ocean. Geophys. Res. Lett. 36, L12608.

Holbrook, N.L., Bindoff, N.L., 1997. Interannual and decadal temperature variability in the Southwest Pacific Ocean between 1955 and 1988. J. Climate 10, 1035–1049.

Holbrook, N.J., Goodwin, I.D., McGregor, S., Molina, E., Power, S.B., 2011. ENSO to multi-decadal timescale changes in East Australian Current transports and Fort Denison sea level: Oceanic Rossby waves as the connecting mechanism. Deep Sea Res. II: Top. Stud. Oceanogr. 58, 547–558.

Hollowed, A., A'mar, T., Barbeaux, S., Bond, N., Ianelli, J., Spencer, P., Wilderbuer, T., 2011. Integrating ecosystem aspects and climate change forecasting into stock assessments. ASFC Quarterly Report Research Feature, July–August–September. NOAA Alaska Fisheries Science Center, Seattle, Washington, USA.

Hollowed, A.B., Bond, N.A., Wilderbuer, T.K., Stockhausen, W.T., A'Mar, Z.T., Beamish, R.J., Overland, J.E., Schirripa, M.J., 2009. A framework for modelling fish and shellfish responses to future climate change. ICES J. Mar. Sci. 66, 1584–1594.

Hollowed, A.B., Wooster, W.S., 1992. Variability of winter ocean conditions and strong year classes of Northeast Pacific groundfish. ICES Mar. Sci. Symp. 195, 433–444.

Hughes, T.P., Baird, A.H., Bellwood, D.R., Connolly, S.R., Folke, C., Grosberg, R., Hoegh-Guldberg, O., Jackson, J.B.C., Kleypas, J., Lough, J.M., Marshall, P., Nyström, M., Palumbi, S.R., Pandolfi, J.M., Rosen, B., Roughgarden, J., 2003. Climate change, human impacts, and the resilience of coral reefs. Science 301, 929–933.

Ianelli, J., Holsman, K.K., Punt, A.E., Aydin, K., 2015. Multi-model inference for incorporating trophic and climate uncertainty into stock assessments. Deep Sea Res. II: Top. Stud. Oceanogr. http://dx.doi.org/10.1016/j.dsr2.2015.04.002.

Ianelli, J.N., Hollowed, A.B., Haynie, A.C., Mueter, F.J., Bond, N.A., 2011. Evaluating management strategies for eastern Bering Sea walleye pollock (Theragra chalcogramma) in a changing environment. ICES J. Mar. Sci. 68, 1297–1304.

ICES, 1997. Database Report of the Stomach Sampling Project 1991. ICES, Copenhagen. 422 pp.

IMOS, 2014. IMOS National Science and Implementation Plan 2015–25. University of Tasmania, Hobart, Australia.

IPCC (Intergovernmental Panel on Climate Change), 2012. Managing the risks of extreme events and disasters to advance climate change adaptation. In: Field, C.B., Barros, V., Stocker, T.F., Qin, D., Dokken, D.J., Ebi, K.L., Mastrandrea, M.D., Mach, K.L., Plattner, G.-K., Allen, S.K., Tignor, M., Midgley, P.M. (Eds.), A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, and New York, USA.

IPCC (Intergovernmental Panel on Climate Change), 2013. Summary for policymakers. In: Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (Eds.), Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 3–34.

ISRS (International Society for Reef Studies), 1998. Statement on Global Coral Bleaching in 1997–1998. International Society for Reef Studies. December 1998. http://coralreefs.org/publications/briefing-papers/.

Jones, A.M., Berkelmans, R., 2014. Flood impacts in Keppel Bay, Southern Great Barrier Reef in the aftermath of cyclonic rainfall. PLoS One 9 (1), e84739.

Karoly, D., Hope, P., Jones, D., 1996. Decadal variations of the southern hemisphere circulation. Int. J. Climatol. 16 (7), 723–738.

Kasahara, A., 1972. Simulation experiments for meteorological observing systems for GARP. Bull. Am. Meteorol. Soc. 53, 252–264.

Katz, R.W., Brown, B.G., 1992. Extreme events in a changing climate: variability is more important than averages. Clim. Change 21 (3), 289–302.

Kidston, J., Gerber, E.P., 2010. Intermodel variability of the poleward shift of the austral jet stream in the CMIP3 integrations linked to biases in 20th century climatology. Geophys. Res. Lett. 37, L09708.

Kirtman, B., Power, S.B., Adedoyin, J.A., Boer, G.J., Bojariu, R., Camilloni, I., Doblas-Reyes, F.J., Fiore, A.M., Kimoto, M., Meehl, G.A., Prather, M., Sarr, A., Schär, C., Sutton, R., van Oldenborgh, G.J., Vecchi, G., Wang, H.J., 2013. Near-term climate change: projections and predictability. In: Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (Eds.), Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Klaer, N.L., O'Boyle, R.N., Deroba, J.J., Wayte, S.E., Little, L.R., Alade, L.A., Rago, P.J., et al., 2015. How much evidence is required for acceptance of productivity regime shifts in fish stock assessments: are we letting managers off the hook? Fish. Res. 168, 49–55.

Kleeman, R., McCreary, J., Klinger, B., 1999. A mechanism for the decadal variation of ENSO. Geophys. Res. Lett. 26, 1743–1746.

Klyashtorin, L.B., 2001. Climate change and long-term fluctuations of commercial catches: the possibility of forecasting. FAO Fisheries Technical Paper No. 410, FAO, Rome. 86 pp.

Kravtsov, S., Dewar, W.K., Berloff, P., McWilliams, J.C., Ghil, M., 2007. A highly nonlinear coupled mode of decadal variability in a mid-latitude ocean-atmosphere model. Dyn. Atmos. Oceans 43, 123–150.

Lehodey, P., Senina, I., Murtugudde, R., 2008. A spatial ecosystem and populations dynamics model (SEAPODYM)—modeling of tuna and tuna-like populations. Prog. Oceanogr. 78, 304–318.

Limpus, C.J., Nicholls, N., 1988. The Southern Oscillation regulates the annual numbers of green turtles (*Chelonia mydas*) breeding around northern Australia. Aust. Wildl. Res. 15, 157–161. http://dx.doi.org/10.1071/wr9880157.

Link, J.S., 2005. Translating ecosystem indicators into decision criteria. ICES J. Mar. Sci. 62, 569–576.

Link, J.S., Yemane, D., Shannon, L.J., Coll, M., Shin, Y.-J., Hill, L., Borges, M.F., 2010. Relating marine ecosystem indicators to fishing and environmental drivers: an elucidation of contrasting responses. ICES J. Mar. Sci. 67, 787–795.

Litzow, M.A., Mueter, F.J., Hobday, A.J., 2014. Reassessing regime shifts in the North Pacific: incremental climate change and commercial fishing are necessary for explaining decadal-scale biological variability. Glob. Chang. Biol. 20, 38–50.

Liu, Z., 2012. Dynamics of interdecadal climate variability: a historical perspective. J. Climate 25, 1963–1995.

Lombard, F., Labeyrie, L., Michel, E., Spero, H.J., Lea, D.W., 2009. Modelling the temperature dependent growth rates of planktonic foraminifera. Mar. Micropaleontol. 70, 1–7.

Longstaff, B.J., Dennison, W.C., 1999. Seagrass survival during pulsed turbidity events: the effects of light deprivation on the seagrasses *Halodule pinifolia* and *Halophila ovalis*. Aquat. Bot. 65, 105–121. http://dx.doi.org/10.1016/s0304-3770(99)00035-2.

Lorenz, E.N., 1965. A study of the predictability of a 28-variable atmospheric model. Tellus 17, 321. http://dx.doi.org/10.1111/j.2153-3490.1965.tb01424.x.

Lotze, H.K., Lenihan, H.S., Bourque, B.J., Bradbury, R.H., Cooke, R.G., Kay, M.C., Kidwell, S.M., Kirby, M.X., Peterson, C.H., Jackson, J.B., 2006. Depletion, degradation, and recovery potential of estuaries and coastal seas. Science 312, 1806–1809.

Lynch, T.P., Morello, E.B., Evans, K., Richardson, A.J., Rochester, W., Steinberg, C.R., Roughan, M., Thompson, P., Middleton, J.F., Feng, M., Sherrington, R., Brando, V., Tilbrook, B., Ridgway, K., Allen, S., Doherty, P., Hill, K., Moltmann, T.C., 2014. IMOS National Reference Stations: a continental-wide physical, chemical and biological coastal observing system. PLoS One 9 (12), e113652. http://dx.doi.org/10.1371/journal.pone.0113652.

Mantua, N.J., Hare, S.R., Zhang, Y., Wallace, J.M., Francis, R.C., 1997. A Pacific interdecadal climate oscillation with impacts on salmon production. Bull. Am. Meteorol. Soc. 78, 1069–1079.

Marshall, A.G., Hendon, H.H., Feng, M., Schiller, A., 2015. Initiation and amplification of the Ningaloo Niño. Clim. Dyn 45, 2367–2385. http://dx.doi.org/10.1007/s00382-015-2477-5.

Marshall, G.J., 2003. Trends in the southern annular mode from observations and reanalyses. J. Climate 16 (24), 4134.

Marshall, N.A., Gordon, I.J., Ash, A.J., 2011. The reluctance of resource-users to adopt seasonal climate forecasts to enhance resilience to climate variability on the rangelands. Clim. Chang. Econ. 3–4, 511–529. http://dx.doi.org/10.1007/s10584-010-9962-y.

Marshall, N.A., Tobin, R.C., Marshall, P.A., Gooch, M., Hobday, A.J., 2013. Social vulnerability of marine resource users to extreme weather events. Ecosystems 16 (5), 797–809.

Mason, S.J., Mimmack, G.M., 2002. Comparison of some statistical methods of probabilistic forecasting of ENSO. J. Climate 15, 8–25.

Masumoto, Y., Yu, W., Meyers, G., et al., 2009. Observing systems in the Indian Ocean. Community White Paper, OceanObs'09.

Maury, O., Faugeras, B., Shin, Y.-J., Poggiale, J.-C., Ari, T.B., Marsac, F., 2007. Modeling environmental effects on the size-structured energy flow through marine ecosystems. Part 1: the model. Prog. Oceanogr. 74, 479–499.

McCauley, D.J., Pinsky, M.L., Palumbi, S.R., Estes, J.A., Joyce, F.H., Warner, R.R., 2015. Marine defaunation: animal loss in the global ocean. Science 347, 6219. http://dx.doi.org/10.1126/science.1255641.

McEvoy, D., Mullett, J., 2013. Enhancing the resilience of seaports to a changing climate: research synthesis and implications for policy and practice. Work Package 4 of Enhancing the Resilience of Seaports to a Changing Climate Report Series, National Climate Change Adaptation Research Facility, Gold Coast. 49 pp.

McGranahan, G., Balk, D., Anderson, B., 2007. The rising tide: assessing the risks of climate change and human settlements in low elevation coastal zones. Environ. Urbanization 19 (1), 17–37. http://dx.doi.org/10.1177/0956247807076960.

McMahon, T.A., 1982. World hydrology: does Australia fit? In: Proceedings of the Hydrology and Water Resources Symposium, Melbourne. Institution of Engineers, Australia, Canberra, pp. 1–7.

McPhaden, M.J., 2004. Evolution of the 2002/03 El Niño. Bull. Am. Meteorol. Soc. 85, 677–695.

McPhaden, M.J., Busalacchi, A.J., Cheney, R., Donguy, J.-R., Gage, K.S., Halpern, D., Ji, M., Julian, P., Meyers, G., Mitchum, G.T., Niiler, P.P., Picaut, J., Reynolds, R.W., Smith, N., Takeuchi, K., 1998. The tropical ocean-global atmosphere observing system: a decade of progress. J. Geophys. Res. 103, 169–240.

McPhaden, M.J., Zebiak, S.E., Glantz, M.H., 2006. ENSO as an integrating concept in earth science. Science 314, 1740–1745.

Meager, J.J., Limpus, C., 2014. Mortality of inshore marine mammals in eastern Australia is predicted by freshwater discharge and air temperature. PLoS One 9 (4), e94849. http://dx.doi.org/10.1371/journal.pone.0094849.

Mearns, L.O., Bogardi, I., Giorgi, F., Matyasovszky, I., Palecki, M., 1999. Comparison of climate change scenarios generated from regional climate model experiments and statistical downscaling. J. Geophys. Res. Atmos. 104 (D6), 6603–6621.

Meehl, G.A., Goddard, L., Boer, G., Burgman, R., Branstator, G., Cassou, C., Corti, S., Danabasoglu, G., Doblas-Reyes, F., Hawkins, E., Karspeck, A., Kimoto, M., Kumar, A., Matei, D., Mignot, J., Msadek, R., Navarra, A., Pohlmann, H., Rienecker, M., Rosati, T., Schneider, E., Smith, D., Sutton, R., Teng, H., van Oldenborgh, G.J., Vecchi, G., Yeager, S., 2014. Decadal climate prediction: an update from the trenches. Bull. Am. Meteorol. Soc. 95, 243–267.

Meinshausen, M., Meinhausen, N., Hare, W., Raper, S.C.B., Frieler, K., Knutti, R., Frame, D.J., Allen, M.R., 2009. Greenhouse-gas emission targets for limiting global warming to 2°C. Nature 458, 1158–1162.

Minobe, S., 1997. A 50–70 year climatic oscillation over the North Pacific and North America. Geophys. Res. Lett. 24, 683–686.

Monselesan, D.P., O'Kane, T.J., Risbey, J.S., Church, J., 2015. Internal climate memory in observations and models. Geophys. Res. Lett. 42, 1232–1242 http://dx.doi.org/10.1002/2014GL062765.

Morello, E., Plagányi, É., Babcock, R., Sweatman, H., Hillary, R., Punt, A.E., 2014. Model to manage and reduce crown-of-thorns starfish outbreaks. Mar. Ecol. Prog. Ser. 512, 167–183. http://dx.doi.org/10.3354/meps10858.

Murphy, B.F., Ribbe, J., 2004. Variability of southeast Queensland rainfall and its predictors. Int. J. Climatol. 24 (6), 703–721.

Nairn, J., Fawcett, R., 2013. Defining Heatwaves: Heatwave Defined as a Heat-Impact Event Servicing All Community and Business Sectors in Australia. Centre for Australian Weather and Climate Research, Melbourne, Australia.

Nairn, J., Fawcett, R., 2015. The excess heat factor: a metric for heatwave intensity and its use in classifying heatwave severity. Int. J. Environ. Res. Public Health 12, 227–253.

Neuheimer, A.B., Thresher, R.E., Lyle, J.M., Semmens, J.M., 2011. Tolerance limit for fish growth exceeded by warming waters. Nat. Clim. Chang. 1, 110–113.

Neumann, B., Vafeidis, A.T., Zimmermann, J., Nicholls, R.J., 2015. Future coastal population growth and exposure to sea-level rise and coastal flooding - a global assessment. PLoS One 10 (3), e0118571. http://dx.doi.org/10.1371/journal.pone.0118571.

Nicholls, N., 1988. More on early ENSOs: evidence from Australian documentary sources. Bull. Am. Meteorol. Soc. 69, 4–6.

Nicholls, N., Drosdowsky, W., Lavery, B., 1996. Australian rainfall variability and change. Weather 52, 66–72.

Nicol, S.J., Allain, V., Pilling, G.M., Polovina, J., Coll, M., Bell, J., Dalzell, P., Sharples, P., Olson, R., Griffiths, S., Dambacher, J.M., Young, J., Lewis, A., Hampton, J., Molina, J.J., Hoyle, S., Briand, K., Bax, N., Lehodey, P., Williams, P., 2013. An ocean observation system for monitoring the affects of climate change on the ecology and sustainability of pelagic fisheries in the Pacific Ocean. Clim. Change 119, 131–145. http://dx.doi.org/10.1007/s10584-012-0598-y.

Norman-Lopez, A., Plagányi, E., Skewes, T., Poloczanska, E., Dennis, D., Gibbs, M., Bayliss, P., 2013. Linking physiological, population and socio-economic assessments of climate-change impacts on fisheries. Fish. Res. 148, 18–26.

O'Kane, T.J., Matear, R., Chamberlain, M., Oke, P., 2014. ENSO regimes and the late 1970s climate regime shift: the role of synoptic weather and South Pacific ocean spiciness. J. Comput. Phys. 271, 19–38.

O'Kane, T.J., Risbey, J.S., Franzke, C., Horenko, I., Monselesan, D.P., 2013. Changes in the metastability of the midlatitude southern hemisphere circulation and the utility of nonstationary cluster analysis and split-flow blocking indices as diagnostic tools. J. Atmos. Sci. 70, 824–842.

O'Kane, T., 2010. Special issue (ensemble prediction and data assimilation): introduction. Aust. Meteorol. Oceanogr. J. 59, 1.

O'Kane, T.J., Frederiksen, J.S., 2008. A comparison of statistical dynamical and ensemble prediction methods during blocking. J. Atmos. Sci. 65, 426–447.

O'Kane, T.J., Matear, R., Chamberlain, M., Risbey, J., Sloyan, B., Horenko, I., 2013. Decadal variability in an OGCM Southern Ocean: intrinsic modes, forced modes and metastable states. Ocean Model. 69, 1–21.

O'Kane, T.J., Oke, P.R., Sandery, P.A., 2011. Predicting the East Australian Current. Ocean Model. 39, 251–266.

O'Kane, T.J., Naughton, M., Xiao, Y., 2008. AGREPS: the Australian global and regional ensemble prediction system. Anziam J. 50, C308–C321.

Oke, P.R., Sakov, P., 2012. Assessing the footprint of a regional ocean observing system. J. Mar. Syst. 105–108, 30–51.

Paerl, H.W., Valdes, L.M., Joyner, A.R., Peierls, B.L., Piehler, M.F., Riggs, S.R., Christian, R.R., Eby, L.A., Crowder, L.B., Ramus, J.S., Clesceri, E.J., Buzzelli, C.P., Luettich, R.A., 2006. Ecological response to hurricane events in the Pamlico Sound system, North Carolina, and implications for assessment and management in a regime of increased frequency. Estuar. Coast. Shelf Sci. 29 (6A), 1033–1045.

Parry, M., Rosenzweig, C., Iglesias, A., Livermore, M., Fischer, G., 2004. Effects of climate change on global food production under SRES emissions and socio-economic scenarios. Glob. Environ. Chang. 14 (1), 53–67.

Pearce, A., Feng, M., 2013. The rise and fall of the "marine heat wave" off Western Australia during the summer of 2010/2011. J. Mar. Syst. 111–112, 139–156.

Perkins, S.E., Alexander, L.V., 2013. On the measurement of heat waves. J. Climate 26, 4500–4517.

Plagányi, É.E., Ellis, N., Blamey, L.K., Morello, E.B., Norman-Lopez, A., Robinson, W., Sporcic, M., Sweatman, H., 2014. Ecosystem modelling provides clues to understanding ecological tipping points. Mar. Ecol. Prog. Ser. 512, 99–113.

Plagányi, É.E., Punt, A.E., Hillary, R., Morello, E.B., Thebaud, O., Hutton, T., Pillans, R.D., Thorson, J.T., Fulton, E.A., Smith, A.D.M., Smith, F., Bayliss, P., Haywood, M., Lyne, V., Rothlisberg, P.C., 2014. Multispecies fisheries management and conservation: tactical applications using models of intermediate complexity. Fish Fish. 15, 1–22.

Plagányi, É.E., Skewes, T.D., Dowling, N.A., Haddon, M., 2013. Risk management tools for sustainable fisheries management under changing climate: a sea cucumber example. Clim. Change 119, 181–197.

Plagányi, É.E., Weeks, S.J., Skewes, T.D., Gibbs, M.T., Poloczanska, E.S., Norman-Lopez, A., Blamey, L.K., Soares, M., Robinson, W.M.L., 2011. Assessing the adequacy of current fisheries management under changing climate: a southern synopsis. ICES J. Mar. Sci. 68, 1305–1317.

Pörtner, H.-O., Karl, D.M., Boyd, P.W., Cheung, W.W.L., Lluch-Cota, S.E., Nojiri, Y., Schmidt, D.N., Zavialov, P.O., 2014. Ocean systems. In: Field, C.B., Barros, V.R., Dokken, D.J., Mach, K.J., Mastrandrea, M.D., Bilir, T.E., Chatterjee, M., Ebi, K.L., Estrada, Y.O., Genova, R.C., Girma, B., Kissel, E.S., Levy, A.N., MacCracken, S., Mastrandrea, P.R., White, L.L. (Eds.), Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 411–484.

Power, S., Casey, T., Folland, C., Colman, A., Mehta, V., 1999. Interdecadal modulation of the impact of ENSO on Australia. Clim. Dyn. 15, 319–324.

Power, S.B., Smith, I.N., 2007. Weakening of the Walker Circulation and apparent dominance of El Niño both reach record levels, but has ENSO really changed? Geophys. Res. Lett. 34, L18702.

Pratchett, M., 2001. Dynamics of Outbreak Populations of Crown-of-Thorns Starfish (*Acanthaster planci* L.), and Their Effects on Coral Reef Ecosystems. School of Marine Biology and Aquaculture, James Cook University, Townsville. 262 pp.

Previdi, M., Polvani, L.M., 2014. Climate system response to stratospheric ozone depletion and recovery. Q. J. Roy. Meteorol. Soc. 140 (685), 2401–2419.

Punt, A.E., Hobday, D., Gerhard, J., Troynikov, V.S., 2006. Modelling growth of rock lobsters, Jasus edwardsii, off Victoria, Australia using models that allow for individual variation in growth parameters. Fish. Res. 82, 119–130.

Redondo-Rodriguez, A., Weeks, S.J., Berkelmans, R., Hoegh-Guldberg, O., Lough, J.M., 2012. Climate variability of the Great Barrier Reef in relation to the tropical Pacific and El Niño-Southern Oscillation. Mar. Freshw. Res. 63, 34–47.

Ridgway, K.R., Condie, S.A., 2004. The 5500-km-long boundary flow off western and southern Australia. J. Geophys. Res. 109, C04017.

Rijnsdorp, A., Peck, M.A., Engelhard, G.H., Möllmann, C., Pinnegar, J.K., 2009. Resolving the effect of climate change on fish populations. ICES J. Mar. Sci. 66, 1570–1583.

Risbey, J., O'Kane, T.J., 2011. Sources of knowledge and ignorance in climate research. Clim. Change 108 (4), 755–773.

Risbey, J.S., Pook, M.J., McIntosh, P.C., Wheeler, M.C., Hendon, H.H., 2009. On the remote drivers of rainfall variability in Australia. Mon. Weather Rev. 137, 3233–3253.

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F.S., Lambin, E., Lenton, T.M., Scheffer, M., Folke, C., Schellnhuber, H.J., Nykvist, B., de Wit, C.A., Hughes, T., van der Leeuw, S., Rodhe, H., Sörlin, S., Snyder, P.K., Costanza, R., Svedin, U., Falkenmark, M., Karlberg, L., Corell, R.W., Fabry, V.J., Hansen, J., Walker, B., Liverman, D., Richardson, K., Crutzen, P., Foley, J., 2009. A safe operating space for humanity. Nature 461, 472–475.

Rodwell, M.J., Rowell, D.P., Folland, C.K., 1999. Oceanic forcing of the wintertime North Atlantic Oscillation and European climate. Nature 398, 320–323. http://dx.doi.org/10.1038/18648.

Roemmich, D., Johnson, G.C., Riser, S., Davis, R., Gilson, J., Owens, W.B., Garzoli, S.L., Schmid, C., Ignaszewski, M., 2009. The Argo Program: observing the global ocean with profiling floats. Oceanography 22 (2), 34–43.

Rose, K.A., Allen, J.I., Artioli, Y., Barange, M., Blackford, J., Carlotti, F., Cropp, R., Daewel, U., Edwards, K., Flynn, K., Hill, S.L., HilleRisLambers, R., Huse, G., Mackinson, S., Megrey, B., Moll, A., Rivkin, R., Salihoglu, B., Schrum, C., Shannon, L., Shin, Y.-J., Smith, S.L., Smith, C., Solidoro, C., St. John, M., Zhou, M., 2010. End-to-end models for the analysis of marine ecosystems: challenges, issues, and next steps. Mar. Coast. Fish. 2, 115–130.

Rougier, J., Sexton, D.M.H., Murphy, J.M., Stainforth, D., 2009. Analyzing the climate sensitivity of the HadSM3 climate model using ensembles from different but related experiments. J. Clim. 22, 3540–3557.

Sainsbury, K.J., Punt, A.E., Smith, A.D.M., 2000. Design of operational management strategies for achieving fishery ecosystem objectives. ICES J. Mar. Sci. 57, 731–741.

Saji, N.H., Goswami, B.N., Vinayachandran, P.N., Yamagata, T., 1999. A dipole mode in the tropical Indian Ocean. Nature 401, 360–363.

Salinger, M.J., Renwick, J.A., Mullan, A.B., 2001. Interdecadal Pacific Oscillation and South Pacific climate. Int. J. Climatol. 21 (14), 1705–1721.

Sandery, P., O'Kane, T.J., 2013. Coupled initialization in an ocean-atmosphere tropical cyclone prediction system. Q. J. Roy. Meteorol. Soc. 140, 82–95.

Savage, J., Hobsbawn, P., 2015. Australian Fisheries and Aquaculture Statistics 2014, Fisheries Research and Development Corporation Project 2014/245. ABARES, Canberra. December, CC BY 3.0.

Scaife, A.A., Arribas, A., Blockley, E., Brookshaw, A., Clark, R.T., Dunstone, N., Eade, R., Fereday, D., Folland, C.K., Gordon, M., Hermanson, L., Knight, J.R., Lea, D.J., MacLachlan, C., Maidens, A., Martin, M., Peterson, A.K., Smith, D., Vellinga, M., Wallace, E., Waters, J., Williams, A., 2014. Skillful long range prediction of European and North American Winters. Geophys. Res. Lett. 41 (7), 2514–2519.

Scheffer, M., Bascompte, J., Brock, W.A., Brovkin, V., Carpenter, S.R., Dakos, V., Held, H., Van Nes, E.H., Rietkerk, M., Sugihara, G., 2009. Early-warning signals for critical transitions. Nature 461, 53–59.

Schneider, N., 2004. The response of tropical climate to the equatorial emergence of spiciness anomalies. J. Climate 17 (3), 1083–1095.

Seferian, R., et al., 2013. The multi-year predictability of tropical marine productivity. Proc. Natl. Acad. Sci. U.S.A. 1–5.

Shaw, E.C., McNeil, B.I., Tilbrook, B., Matear, R.J., Bates, M.L., 2013. Anthropogenic changes to seawater buffer capacity combined with natural reef metabolism induce extreme future coral reef CO_2 conditions. Glob. Chang. Biol. 19, 1632–1641.

Shin, Y.J., Shannon, L.J., Bundy, A., Coll, M., Aydin, K., Bez, N., Blanchard, J.L., Borges, M.D., Diallo, I., Diaz, E., Heymans, J.J., Hill, L., Johannesen, E., Jouffre, D., Kifani, S., Labrosse, P., Link, J.S., Mackinson, S., Masski, H., Mollmann, C., Neira, S., Ojaveer, H., Abdallahi, K.O.M., Perry, I., Thiao, D., Yemane, D., Cury, P.M., 2010. Using indicators for evaluating, comparing, and communicating the ecological status of exploited marine ecosystems. 2. Setting the scene. ICES J. Mar. Sci. 67, 692–716.

Simpson, I.R., Shepherd, T.G., Hitchcock, P., Scinocca, J.F., 2013. Southern annular mode dynamics in observations and models. Part II: Eddy feedbacks. J. Climate 26, 5220–5241.

Smagorinsky, J., 1963. General circulation experiments with the primitive equations I. The basic experiments. Mon. Weather Rev. 91, 99–164.

Smith, A.D.M., Fulton, E.J., Hobday, A.J., Smith, D.C., Shoulder, P., 2007. Scientific tools to support the practical implementation of ecosystem-based fisheries management. ICES J. Mar. Sci. 64, 633–639.

Smith, M.D., 2011. An ecological perspective on extreme climatic events: a synthetic definition and framework to guide future research. J. Ecol. 99, 656–663.

Smith, M.H., 2013. Assessing Climate Change Risks and Opportunities for Investors—Oil and Gas Sector. ANU, Canberra. 20 pp.

Smith, T.D., 2004. The Woods Hole bottom trawl resource survey: development of fisheries-independent multi-species monitoring. ICES Mar. Sci. Symp. 215, 474–482.

Spillman, C., 2011. Operational real-time seasonal forecasts for coral reef management. J. Oper. Oceanogr. 4 (1), 13–22.

Spillman, C.M., Hobday, A.J., 2014. Dynamical seasonal ocean forecasts to aid salmon farm management in a climate hotspot. Clim. Risk Manag. 1, 25–38.

Stocker, T.F., Qin, D., Plattner, G.-K., Alexander, L.V., Allen, S.K., Bindoff, N.L., Bréon, F.-M., Church, J.A., Cubasch, U., Emori, S., Forster, P., Friedlingstein, P., Gillett, N., Gregory, J.M., Hartmann, D.L., Jansen, E., Kirtman, B., Knutti, R., Krishna Kumar, K., Lemke, P., Marotzke, J., Masson-Delmotte, V., Meehl, G.A., Mokhov, I.I., Piao, S., Ramaswamy, V., Randall, D., Rhein, M., Rojas, M., Sabine, C., Shindell, D., Talley, L.D., Vaughan, D.G., Xie, S.-P., 2013. Technical summary. In: Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (Eds.), Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Szuwalski, C.S., Punt, A.E., 2013. Fisheries management for regime-based ecosystems: a management strategy evaluation for the snow crab fishery in the eastern Bering Sea. ICES J. Mar. Sci 70 (5), 955–967. http://dx.doi.org/10.1093/icesjms/fss182.

Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. Bull. Am. Meteorol. Soc. 93, 485–498. http://dx.doi.org/10.1175/BAMS-D-11-00094.1.

Tchernov, D., Gorbunov, M.Y., de Vargas, C., Narayan Yadav, S., Milligan, A.J., et al., 2004. Membrane lipids of symbiotic algae are diagnostic of sensitivity to thermal bleaching in corals. Proc. Natl. Acad. Sci. U.S.A. 101, 13531–13535.

Thompson, D.W.J., Solomon, S., Kushner, P.J., England, M.H., Grise, K.M., Karoly, D.J., 2011. Signatures of the Antarctic ozone hole in southern hemisphere surface climate change. Nat. Geosci. 4, 741–749.

Thompson, D.W.J., Wallace, J.M., 2000. Annular modes in the extratropical circulation. Part I: month-to-month variability. J. Climate 13, 1000–1016.

Thompson, P.A., 2006. Effects of temperature and irradiance on marine microalgal growth and physiology. In: Rao, S. (Ed.), Algal Cultures, Analogues of Blooms and Applications. Science Publishers Inc., Enfield, New Hampshire, pp. 571–638.

Torrence, C., Webster, P.J., 1998. The annual cycle of persistence in the El Niño/Southern Oscillation. Q. J. Roy. Meteorol. Soc. 124, 1985–2004.

Trenberth, K., Hurrell, J., 1994. Decadal atmosphere–ocean variations in the Pacific. Clim. Dyn. 9, 303–319.

Trenberth, K.E., 1991. General characteristics of El Niño-Southern Oscillation. In: Glantz, M.H., Katz, R.W., Nicholls, N. (Eds.), Teleconnections Linking Worldwide Climate Anomalies. Scientific Basis and Societal Impact. Cambridge University Press, Cambridge, pp. 13–42.

Trenberth, K.E., Jones, P.D., Ambenje, P., Bojariu, R., Easterling, D., Klein Tank, A., Parker, D., Rahimzadeh, F., Renwick, J.A., Rusticucci, M., Soden, B., Zhai, P., 2007. Observations: surface and atmospheric climate change. In: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M. (Eds.), Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 235–336.

Trenberth, K.E., Stepaniak, D.P., Smith, L., 2005. Interannual variability of the patterns of atmospheric mass distribution. J. Climate 18, 2812–2825.

Troup, A.J., 1965. The southern oscillation. Q. J. Roy. Meteorol. Soc. 91, 490–506.

Valdivia, J., 1978. The anchoveta and El Niño. Rapp. P.-V. Réun. Cons. Int. Explor. Mer. 173, 196–202.

van de Leemput, I.A., van Nes, E.H., Scheffer, M., 2015. Resilience of alternative states in spatially extended ecosystems. PLoS One 10 (2), e0116859.

Vitousek, P.M., Mooney, H.A., Lubchenko, J., Mellilo, J.M., 1997. Human domination of Earth's ecosystem. Science 277, 494–499.

Vörösmarty, C.J., Green, P., Salisbury, J., Lammers, R.B., 2000. Global water resources: vulnerability from climate change and population growth. Science 289, 284–288.

Ward, R., Ranger, N., 2010. Trends in economic and insured losses from weather-related events: a new analysis. Insurance Industry Brief—The Munich RE Programme of the Centre for Climate Change Economics and Policy. University of Leeds, UK24 pp, Available at cccep.ac.uk/wp-content/uploads/.../economic-trends-insured-losses.pdf.

Wayte, S.E., 2013. Management implications of including a climate-induced recruitment shift in the stock assessment for jackass morwong (Nemadactylus macropterus) in south-eastern Australia. Fish. Res. 142, 47–55.

Wernberg, T., Smale, D.A., Tuya, F., Thomsen, M.S., Langlois, T.J., Bennett, S., Rousseaux, C., 2013. An extreme climatic event alters marine ecosystem structure in a global biodiversity hotspot. Nat. Clim. Chang. 3, 78–82.

Wild-Allen, K., Herzfeld, M., Thompson, P.A., Rosebrock, U., Parslow, J., Volkman, J.K., 2010. Applied coastal biogeochemical modelling to quantify the environmental impact of fish farm nutrients and inform managers. J. Mar. Syst. 81, 134–147.

Yin, J.H., 2005. A consistent poleward shift of the storm tracks in simulations of 21st century climate. Geophys. Res. Lett. 32, L18701.

Zanna, L., Heimbach, P., Moore, A.M., Tziperman, E., 2011. Optimal excitation of interannual Atlantic meridional overturning circulation variability. J. Climate 24 (2), 413–427.

Zhang, J., Jørgensen, S.E., Tan, C.O., Beklioglu, M., 2003. A structurally dynamic modelling—Lake Mogan, Turkey as a case study. Ecol. Model. 164, 103–120.

Zhang, X., Alexander, L., Hegerl, G.C., Jones, P., Klein Tank, A., Peterson, T.C., Trewin, B., Zwiers, F.W., 2011. Indices for monitoring changes in extremes based on daily temperature and precipitation data. WIREs Clim. Chang. 2, 851–870. http://dx.doi.org/10.1002/wcc.147.

Zhang, Y., Wallace, J.M., Battisti, D.S., 1997. ENSO-like variability: 1900-93. J. Climate 10, 1004–1020.

Zhao, M., Hendon, H.H., Alves, O., Liu, G., Wang, G., 2015. Weakened ENSO predictability in the early 21st century. In: ENSO Workshop Australia 2015 ENSO Extremes and Diversity: Dynamics, Teleconnection, and Impacts University of New South Wales, Sydney, 4th–6th February. http://www.cawcr.gov.au/projects/vicci/documents/16%20-%20Harry%20Hendon.pdf.

Zinke, J., Hoell, A., Lough, J., Feng, M., Kuret, A.J., Clarke, H., Ricca, V., Rankenburg, K., McCulloch, M.T., 2015. Coral record of southeast Indian Ocean marine heatwaves with intensified Western Pacific temperature gradient. Nat. Commun. 6. http://dx.doi.org/10.1038/ncomms9562.