Environmental Science
Processes & Impacts

Accepted Manuscript

Journal Name
Environmental Science: Processes & Impacts
Dynamic Article Links ►

Cite this: DOI: 10.1039/c0xx00000x

www.rsc.org/xxxxxx

ARTICLE TYPE

The use of climatologies and Bayesian models to link observations to outcomes; an example from the Torres Strait

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Received (in XXX, XXX) Xth XXXXXXXXX 20XX, Accepted Xth XXXXXXXXX 20XX
DOI: 10.1039/b000000x

After wide spread coral bleaching in the Torres Strait in 2009-10 a monitoring program was established under the National Environmental Research Program and run by the Torres Strait Regional Authority to identify ocean conditions that may lead to future bleaching. One component of this program was a real time ocean monitoring station located between Thursday and Horn Islands in the south-western part of the Torres Strait. A key outcome of the project was to make the scientific data and knowledge available to the local communities in a form that they could engage with and with which they could act to instigate outcomes relevant to their needs. The project developed climatologies to give context to the temperature data allowing for historical limits to define the significance of the real time data as related to the longer term mean. This allowed the identification of 'normal', 'significant' and 'extreme' temperature events which could be linked into appropriate responses. Bayesian models were used to encapsulate the current scientific knowledge about the drivers and responses involved in coral bleaching. These models were used to convert the environmental parameters to an output index reflecting the current and future likelihood of coral bleaching occurring. Two web sites were used to integrate the real time data, climatology data and the bleaching indices generated from the Bayesian models. The first was a more technical site developed for the local environmental managers within the Torres Strait Regional Authority, the second was targeted at the general public with a display located within the local radio station and broadcast on a daily basis. Engagement with the project has been high to the point where additional monitoring stations and data display kiosks are to be installed in the near future. The combination of climatologies to give context and conceptual models to embody system knowledge has allowed the project to go from delivering simple measurements to being able to deliver knowledge about the system in a format that engages the local community and that can be used to facilitate environmental management outcomes.

Introduction

Coral bleaching is a recognised threat to coral reefs worldwide with wide-scale bleaching and subsequent mortality observed in 1998[1] and on the Great Barrier Reef of Australia in 1998 and 2002[2]. Increased coral bleaching is also identified as a potential outcome of future climate scenarios[3]. Widespread coral bleaching was observed in the Torres Strait, located between mainland Australia and Papua New Guinea, for the first time in the southern 2009-10 summer. Anecdotal and traditional ecological knowledge suggests that coral bleaching has not occurred in this region in over 30 years or more. Until this event, it was assumed that areas near the tropics were more temperature tolerant due to the ocean thermostat phenomenon[4]. The instrumental record of the past 130+ years for tropical Australia which shows highest rate of warming in southern latitudes and lowest rates in the northern latitudes[5], also suggests that these northern areas are likely to have a relatively low risk of coral bleaching. However, the 2009-10 summer in the Torres Strait and reports of bleaching events elsewhere in low latitude coral reef systems[6-9] challenges the notion of low bleaching risk in equatorial regions.

An ocean monitoring project for the Torres Strait was established in 2012 under the Australian Government's National Environmental Research Program (NERP) in collaboration with the Torres Strait Regional Authority (TSRA), which has governmental authority for the region. The monitoring program includes temperature loggers on reefs around the Torres Strait and a real-time ocean monitoring station off Thursday Island in the southern part of the Strait.

The final component is monthly satellite temperature and chlorophyll-a anomaly products for the Torres Strait using MODIS Sea Surface Temperature[10] and chlorophyll-*a*/photic depth[11] data linked into climate forecast models[12, 13] (POAMA-2).

The temperature logger component compliments a legacy program that included loggers at Thursday Island in Torres Strait from 1998[5].

A key output from the project was the development of bleaching risk indices, both as current risk and the future or forecast risk.

This was done in two ways. The first was a regional view based on the monthly satellite anomaly products[14], the second was based on the real time in-situ data. This paper focuses on the development of a bleaching risk warning system and associated products using the real time in-situ data.

The people of the Torres Strait have a strong cultural link to the sea and so engagement with the local communities was a critical part of the project. Engagement was facilitated by involving local rangers in the work (such as deploying and exchanging loggers, and participation in benthic surveys) and by delivering the scientific outcomes in a way that could be understood by the local community. This paper describes the use of climatologies and Bayesian models, along with web sites and social media, to deliver relevant information to local communities in a way that engages them and facilitates direct community level outcomes.

Materials and Methods

Real Time Data

A real time observing system was installed on a channel marker at Madge Reef, between Thursday and Horn Islands, at Latitude 10° 35.695' South, Longitude 142° 13.222' East. The station consisted of an above water meteorological station (Vaisala™ WXT520 – air temperature, pressure, humidity, rainfall and wind speed / direction) complimented by a LI-COR™ LI-192 light meter measuring Photosynthetically Active Radiation (PAR).

The in-water instruments consisted of a Seabird Electronics™ SBE37 CTD sensor (Conductivity, Temperature and Depth via pressure) which gives salinity, water depth and water temperature along with a Seabird Electronics™ SBE39 temperature sensor. The CTD was located on the bottom in around five metres of water at the base of the reef with the SBE39 temperature sensor located on the reef crest at three metres depth.

The above water systems included a solar powered data logger and modem allowing the real time data to be recorded and transmitted every ten minutes. Quality control was performed using simple range and rate-of-change checks with the data then being inserted into a database. From there data were made available as near real time data via a web based data system[15].

Metrological data from a nearby land-based station on Horn Island (eight kilometres away), run by the Australian Bureau of Meteorology (BoM), was captured from their web site[16] along with forecast wind speeds for the following morning and afternoon[17].

Climatologies

Using data from existing temperature logger programs[18] it was possible to get thirteen years of water temperature data from Thursday Island, ~1km from the Madge Reef real-time station. The raw data consisted of a combination of thirty and ten-minute temperature records; these were filtered to remove bad data via range and rate-of-change checks. The data were then averaged by ordinal day of the year (1-366); that is all data for the 1st of January were averaged to produce an average temperature and associated standard deviation for that day.

The resulting climatology (Fig. 1) is the mean ordinal day temperature, the recorded minimum and maximum temperatures from the logger data and the standard deviation of the temperature representing the variability for each day (Fig. 2).

The ordinal day values were then modelled using a simple polynomial to produce a smoother climate curve.

The climatology shows a tropical monsoonal pattern with stable summer monsoonal dominated temperatures until April when the monsoon system weakens and temperatures fall to a low in mid-winter (early August) before rising back to summer temperatures in early December. Winter temperatures tend to be more stable with low variability while the periods before and after the monsoon have the highest variability (Fig 2).

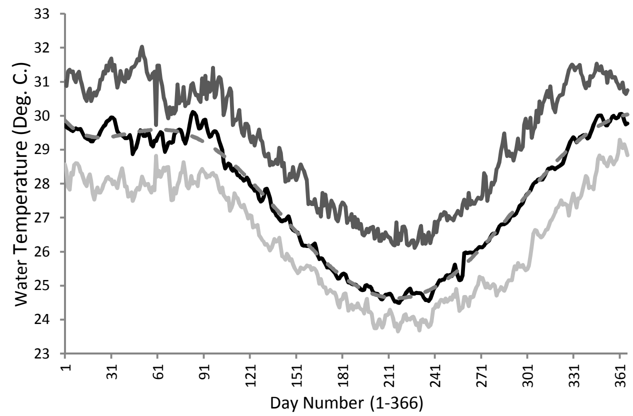

Fig. 1 Climatology for Thursday Island showing the mean temperatures (black line), the observed daily maximum (dark grey) and minimum (light grey) temperatures along with fitted climatology model (grey dashed line) (R^2 = 0.9877, n=366).

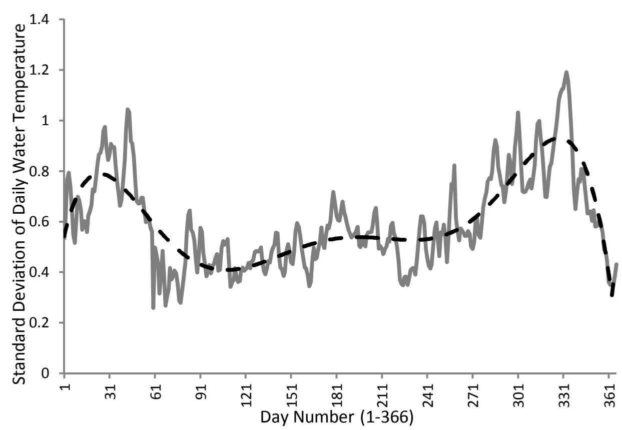

Fig. 2 Climatology for Thursday Island showing the standard deviation of the daily averaged water temperatures along with fitted model (dashed line) (R^2 = 0.680, n=366).

The modelled ordinal day average temperatures along with the modelled variability form the final climatology. Temperatures within plus or minus two standard deviations of the climatology were be considered to be 'normal' as they accounted for 95% of the data variability. Daily average temperatures between the two and three standard deviation limits were considered to be 'significant'. Temperatures outside the three standard deviation limits were considered to be 'extreme' temperature events and would instigate appropriate management actions. These management actions were not defined a-priori for the Torres Strait, but are likely to be modelled on the Great Barrier Reef experience where communication, mapping, monitoring, coordination and resource allocation are key action items[19-21].

Bleaching Thresholds

As part of this project a bleaching threshold was developed for the Thursday Island region using observed and experimental data (Fig. 3). The threshold works as 'dose curve' with temperature and duration of exposure in warm summers as key variables responsible for bleaching and mortality on coral reefs[2, 22, 23]. For example a daily average water temperature of 31.3 °C for a single day may not result in bleaching but may if this temperature is maintained for three or more days. The bleaching threshold is therefore a cumulative exposure curve where bleaching likelihood is determined by a line equidistant between the warmest year where no bleaching took place and the coolest year when bleaching is known to have occurred (Fig 3, Table 1).

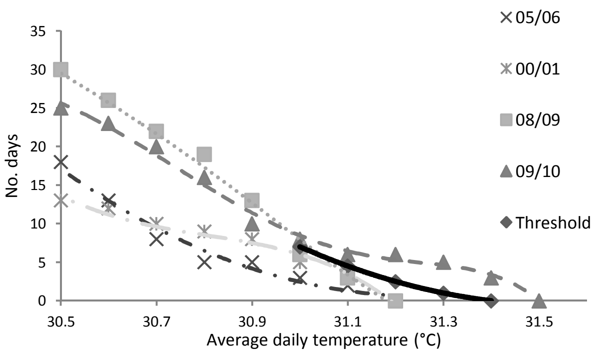

Fig. 3 Bleaching threshold for reefs in the Thursday Island region compiled from observed and experimental data (black line) as temperature exposure (temperature and time), note the 2009-10 line (triangles) when bleaching was observed.

Table 1 Bleaching thresholds for Thursday Island.

Daily Avg. Temp (˚C.)	Duration before bleaching (days)
31.0	7.0
31.1	4.5
31.2	2.5
31.4	1.0
>=31.5	0

Bayesian Models

Other factors are known to contribute to bleaching as well, including light and salinity, however these relationships are empirically less well defined. As such, and in the context of the complexity of marine systems, Bayesian models have become the preferred tool for integrating data and knowledge to better understand ecological relationships and drivers of change[10, 24, 25]. Bayesian Models work by defining a series of relationships (inputs → responses) in terms of probabilities, these relationships can be formed into a network so that inputs or events can flow through a series of probabilistic relationships to produce an output value reflecting the summed network probabilities.

As Bayesian models do not need absolute values they deal well with 'fuzzy' relationships, such as if event X occurs then response Y will occur within a set of probabilities. Bayesian models also deal with both numeric and category inputs and so can deal with observations and relative values (high/low, good/bad). As such it becomes possible to embody the knowledge about a system as a series of probabilistic relationships using both formal (measured) and informal (approximate or guessed) inputs.

For this project two Bayesian Models were produced. The first was a Bleaching Risk model which modelled the risk of coral bleaching given the current conditions, as measured by the real time data. As such it focused on those parameters linked to coral bleaching such as water temperature, light and salinity[26-29]. In particular, high light, high temperature and low salinity are demonstrably linked to bleaching events mechanistically and physiologically[29-32].

In the model (Fig 4) temperature is expressed as the number of days at or higher than the discrete temperature increments on the bleaching threshold curve (Fig 3 / Table 1). Light is measured in two ways. The first is the total light received in a day as the sum of the ten minute surface PAR readings (*SumDailyPAR* in Fig. 4) clipped from 8am to 4pm. This gives the total light budget for the day. The second measures the peak light stress as the time above a threshold set empirically to represent sunny versus cloudy conditions[33]. For this work, this value was set to 1,800 µmol sec^{-1} m^{-2} and is represented by the *CountMaxPAR* box in Fig 4. Salinity is also included to allow for the interaction of low-salinity events preceding or following heat-wave conditions which are a normal part of the marine climate in Torres Strait.

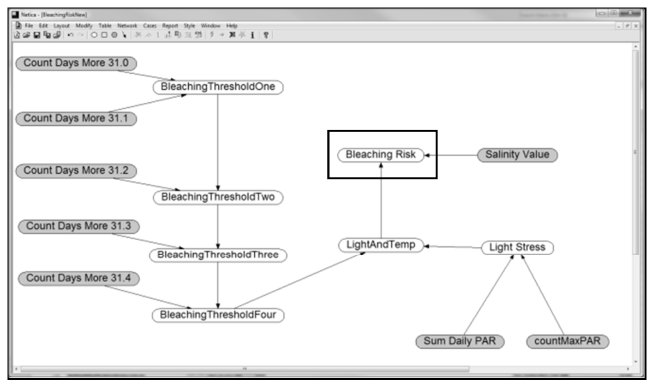

Fig. 4 Bleaching Risk model, input parameters are shown as grey ovals, calculated parameters as white ovals, final bleaching index is shown in the black rectangle.

To make the temperature model simpler the various discrete temperature increments are implemented in a stepwise manner so that the first two increments give a summed value which is then added to the next increment and so on. The two light measures are also combined into a single resulting light model which, with the salinity and final temperature model, gives the final resulting risk index. The final bleaching index is scaled between 0 (no risk of bleaching, probability = 0) and 5 (extreme risk of bleaching, probability =1) for output and use in the web site.

The second model was a Bleaching Forecast model. This model looks to identify times of heat and light accumulation (increased risk) and dissipation (reduced risk). As temperature and light are the primary proximal causal agents of coral bleaching[34, 35], measuring times when these stresses increase or decrease gives some indication of the actual stress on corals and so the future likelihood of bleaching.

The Forecast index combined with the Risk index produce the current bleaching likelihood and the chance that this will increase or decrease in the near future.

The Forecast model was de-coupled from the Risk model in that the current bleaching risk was not a factor in calculating the future bleaching risk, although the water temperature as related to the climatology was. The reason for decoupling was to identify periods of heat and light accumulation / dissipation independently of the current risk.

As with the risk model, the forecast model groups like measures into sub-measures which are then combined to give the final forecast index (Fig 5). The index is scaled from -5 to +5 where minus numbers indicate conditions conductive to thermal dissipation or reduction in bleaching risk, and positive numbers thermal accumulation or increase in bleaching risk. The wind values use the current measured wind speeds and the next day forecast wind speeds from the Bureau of Meteorology[17].

Both models were run daily based on the previous days data and so give daily measures of current bleaching risk and potential future risk. The risk index was as a number scaled between 0 (no risk) and 5 (extreme risk) and the forecast risk as a number between -5 (risk strongly decreasing), 0 (risk staying the same) and +5 (risk strongly increasing). The models were built using the Netica™ software (Norsys, 2013).

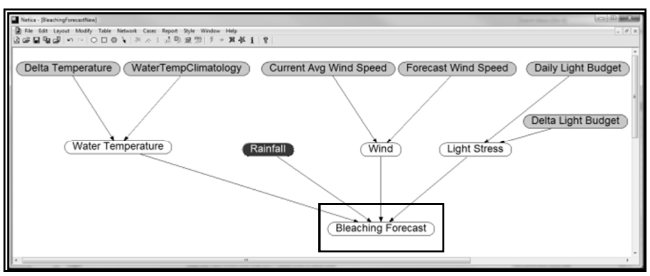

Fig. 5 Bleaching Forecast model, input parameters are grey ovals, calculated parameters are white ovals

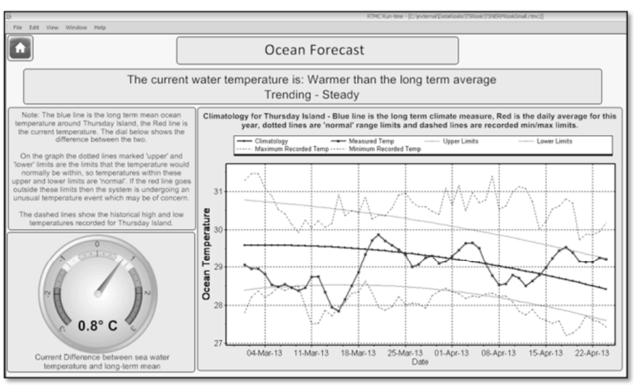

Fig. 6 Technical web site showing the real time temperature data plotted against the climatology data with text interpretations of the current values and a dial plot with the difference between the current and mean temperatures.

Web Sites

Two web sites were developed to display the real time data, the climatology information and to display the results of the two Bayesian models as coral bleaching indices.

The first of these was designed for the environmental management staff of the TSRA (Fig. 6) and was more technical in nature with the real time data presented as raw data as well as graphs.

The climatology was used to display the current difference between the real time and long term average data with the standard deviation values used to display the significance of the variation.

The second web site was developed for the local radio station (4MW) that broadcasts to the Torres Strait region (Fig. 7). For this web site the data were interpreted, via a programmatic interface, into terms more familiar to the listening audience. For example wind directions were converted from directions as degrees to named directions such as 'north-west'. For the bleaching risk and forecasts these were converted into common English terms, again making them easier to understand. In particular the web site was designed to be easy to read and broadcast.

Social Media

A Twitter™ account (@TIClimate) was also used to disseminate the information. A Java™ program was written which took the daily model and temperature / climatology data and reformatted this as a message and 'tweeted' this to the Twitter account. At the moment this happens daily as daily updates but it may be more appropriate to only send messages to Twitter when something of interest occurs (such as conditions being conducive to bleaching).

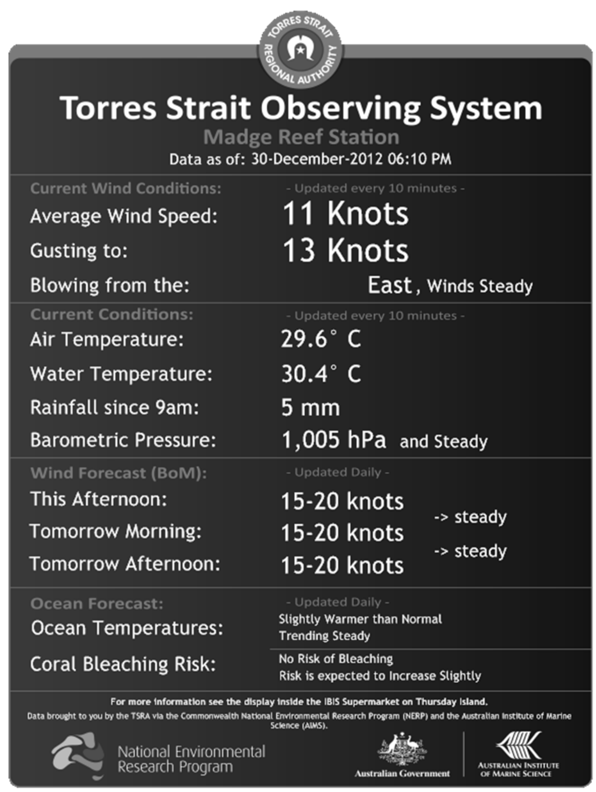

Fig. 7 Community web site showing real time data, forecast wind data and the ocean temperature ('Slightly warmer than Normal / Trending Steady') and coral bleaching ('No Risk of Bleaching / Risk is expected to Increase Slightly') indices.

Results

The system was put into operation in late 2012 for the 2012-13 southern hemisphere summer. There was a failure in the communications equipment due to a lightning strike in late December resulting in no data for an eight-week period. Apart from this, the real time station provided a ten-month, near-continuous ten minute data set on light, water temperature, atmospheric data and salinity.

Data from October to December 2012 show that temperatures were cooler than average with one period in mid-December that equalled the coolest value for that day recorded (Fig 8). While the temperatures were cooler than average, no data points crossed the two standard deviations line and so for this period temperatures were reported as being 'normal' or 'slightly cooler than normal'.

However, in the autumn period from March to May 2013, temperatures fell below the lower two standard deviation limit in mid-March and then rose to above the upper two standard deviation limit in late May (Fig 9).

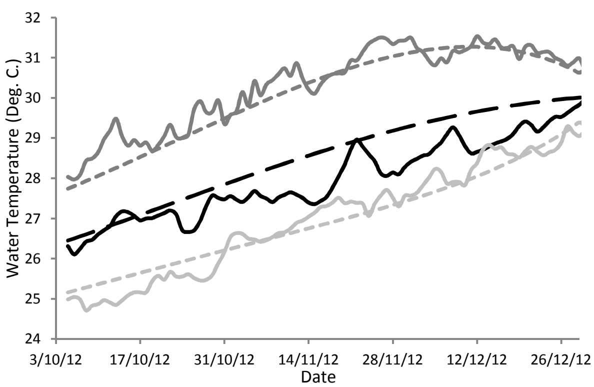

Fig. 8 Measured daily water temperatures for Thursday Island from October to December 2012 (black line) plotted against the long term modelled climatology (black dashed line), the observed climatology min (light grey solid line) and max (dark grey solid line) and the plus or minus two standard deviation climatology (light and dark grey dashed lines).

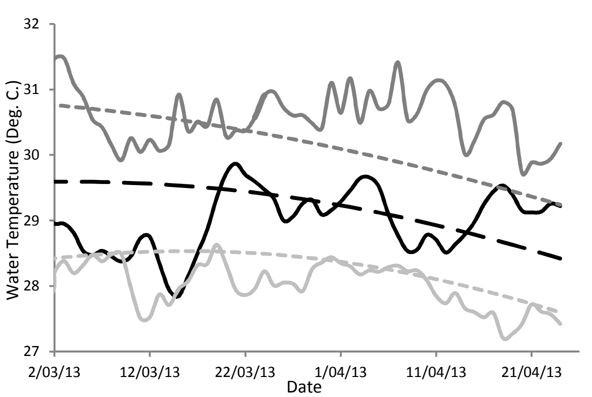

Fig. 9 Measured daily water temperatures for Thursday Island from March to May 2013 (black line) plotted against the long term modelled climatology (black dashed line), the observed climatology min (light grey solid line) and max (dark grey solid line) limits and the plus or minus two standard deviation climatology limits (light and dark grey dashed lines).

As a result the system went from being significantly cooler than normal to significantly warmer than normal over a period of two months. This transition was reported using the position of the temperature within the standard deviation limits to generate wording such as 'normal', 'slightly cooler / warmer than normal' and 'significantly cooler / warmer than normal'.

Overall the real time data showed there was no risk of coral bleaching as most of the summer temperatures were well below the climatology and well below the bleaching threshold. It did however identify brief periods significantly above or below the climatology and as well as periods of temperature and light accumulation and dissipation. As a result there was no coral bleaching predicted for the 2012-13 summer and none observed.

Discussion

A new approach to bleaching risk forecasting

We present here an alternative approach to coral bleaching early warning systems. The system described here uses real time data to give in-situ conditions, climatologies to provide longer term context, and Bayesian models to encapsulate expert knowledge and other data and knowledge inputs. Importantly, it adds a component of weather forecasts to the bleaching risk which effectively turns the system from the 'now-casting' system to a true 'early-warning' system which incorporates near-future weather patterns. The system uses social media and web sites to disseminate the resulting information. In particular the use of climatologies and the variance around these allows for the definition of 'normal', 'unusual' and 'extreme' events and for appropriate response actions to be built around these indicators. The use of Bayesian models allows for expert knowledge about the system to be encapsulated and for other sources of information, such as social science or on the ground observations, to be used.

The work builds on the heuristic modelling approach of Hendee *et al*[36] using Bayesian models to implement a rule based system that is able to deal with conflicting measures of the same parameter, values that may have varying degrees of certainty and parameters that may have complex sensitivities between input values and model outputs. As with the Stimulus / Response index of Hendee *et al*[36] the model gives a simple numeric output that can be translated into real world language representations of the system status. The use of climatologies to provide long-term context and simple thresholds for management action, the use of differing current and future (forecast) risk models and the extensive use of social media, extends the previous work.

The approach is however limited spatially and temporally in that factors used in the model to measure potential heat and light accumulation and dissipation are only known a few days ahead[17] and the real time data is only available from a few points. This makes it different to the larger temporal and spatial scales employed by, for example, satellite-derived bleaching indicators[37-39].

The system does however have some important advantages over satellite-based systems, in particular the fact that it is unaffected by cloud cover, which affects most satellite images for this region in summer. The in-water measurements are also more accurate as data are directly measured, not remotely sensed.

In future, it may be possible to meld this approach with modelling systems[40] to develop longer (temporal) and larger (spatial) range forecasts. A number of other real time stations are planned and this may give an opportunity to increase the spatial component and provide greater linkage to modelling systems. Also planned is the collection of additional variables, such as underwater PAR and turbidity, which may add to the strength of the model.

From Data to Information to Knowledge

The aim of the work was to convert the data collected by the project into information and knowledge that could be taken up and used by both the environmental managers of the TSRA and by the general public, via the local radio station.

The first part of this was to give the data context via the climatology. The climatology indicated if the real time temperatures were warmer or cooler than the long term average, by how much, and if any differences were significant or not. For this study, any data within two standard deviations of the long term mean was considered to be 'normal', between two and three standard deviations as 'significantly warmer/cooler' and if outside the three standard deviation limits as being 'extremely warmer/cooler'.

The provision of context effectively goes from data to information; that is it tells you what the reading means. The conversion from information to knowledge involves looking at what the information means in an even larger context and what response may be appropriate. To achieve this, Bayesian models were used to represent the scientific knowledge of the system / phenomena and to give some idea of what outcomes may come from the current situation. These model outputs were delivered as interpreted text that had meaning to the target audience.

An example of this is shown below (source in italics):

Data:

"The Water Temperature is 29.2˚ C. [*real-time data*]."

Information:

"The Water Temperature is 29.2˚ C [*real-time data*] which is 0.8 degrees warmer than the long term average [*climatology*]. It is just above two standard deviations from the mean making it significantly warmer than normal for this time of year."

Knowledge:

"The Water temperature is significantly warmer than normal [*climatology*] but not warm enough to cause bleaching [*bleaching risk model*], temperatures are trending steady [*real-time data*] but the factors that cause bleaching are declining [*bleaching forecast model*] so that while temperatures are unusually high there is no immediate bleaching risk and in the future any risk will decrease."

Climatologies

The climatology gives a context for the water temperature data; the use of standard deviation limits allows any temperature events to have an associated level of significance. This allows the system to effectively ignore or not respond to 'normal' (within two SD limits) conditions but then to know when an event of significance has occurred at to trigger appropriate responses.

Bayesian Models

Bayesian models have a number of characteristics that make them suitable to this type of application. The first is that they take as input both numeric input (such as the real time data) as well as state data (high | medium | low) or even simple presence absence data (bleaching present | absent). This allows for a range of data types and sources to be utilised by the model.

The second characteristic is that as the model is a matrix of relationships between inputs and responses, the model can deal with uncertain or 'fuzzy' relationships. This more accurately reflects much of the real world knowledge of systems and so in-exact relationships can be used[25]. For example the experimental data shows that daily average water temperatures over 31.5 °C will cause bleaching but in the model this can have a probability associated with it, so that rather than having to be a bleaching | no bleaching point it can have a probability of say 80%. In this way the model can better reflect real world experience where few events are all or nothing. It can also deal with information that has a high level of error or uncertainty and so data from various sources can be utilised, such as community science programs.

The third characteristic is that, via the probability matrices, the relationship between an input and output (response) can be fine-tuned. For example the experimental data shows that water temperatures at 31.0 °C for more than seven days can cause bleaching. It is expected that this is not a magical number but that as the number of days at or over 31.0 °C increases so the probability of bleaching gets higher until at around seven days it is close to 1. The model allows us to not just increase the probability with days in a linear fashion but rather fine tune the relationship so that the response is less intense for days one to four and then more responsive after that.

To illustrate this, Fig 10 shows the response (change in output response probability from changes in input values) for the threshold at 31.0 and 31.1 °C. The 31.0 °C response is tolerant of a small number of days over the threshold (at day three the bleaching probability has only increased to 10%) with a small response early on and a larger response nearer to the final threshold value. The 31.1 °C response is the opposite; in this case we want to get some early warning, given that we would have already gone through the 31.0 °C threshold.

The sensitivity can also be applied to the inputs. In the forecast model real time wind data along with forecast data from the Bureau of Meteorology are used to represent the future wind state. These two inputs form a probability matrix for the output of wind speed. Where the measured and forecast wind speeds agree then this goes directly into the model. Where they disagree we can specify what weight each has, in this case as the two disagree we give more probability to the measured values and less to the forecast wind data (Fig. 11). Where the forecast and measured winds agree the outcome is allocated 100% to that wind speed (such as in the first line of the matrix in Fig. 11). Where they disagree, for example in the fourth line of the matrix in Fig. 11, the probability of the forecast being correct is reduced (in this case to 40%) and the probabilities for other outcomes increased.

We can therefore use multiple measures of the same phenomena and decide, via the probability matrix, the relative weighting of each given their agreement / disagreement. This allows proxy and other data sources to be used, but with their contribution determined by the probability matrix.

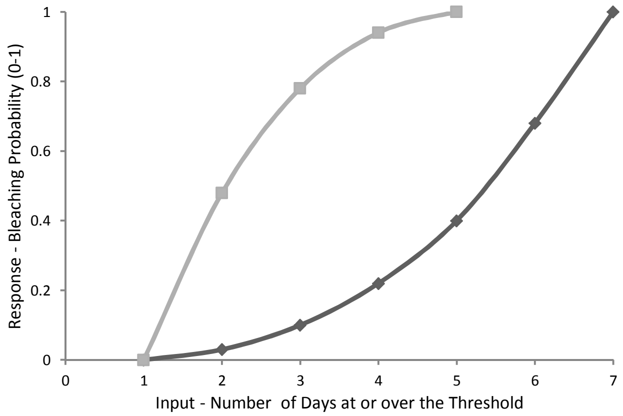

Fig.10 Probability response curves showing differing responses to changes in input values for the 31.0 (black line) and 31.1 (grey line) degree temperature thresholds.

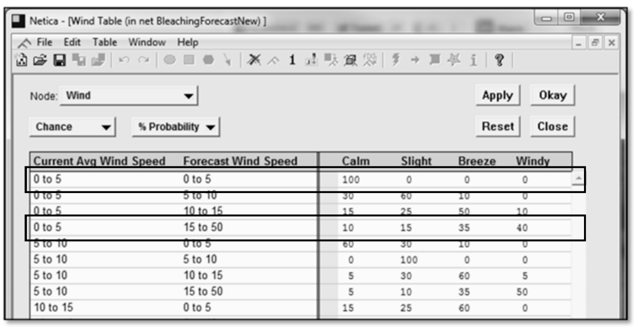

Fig. 11 Bayesian probability matrix between measured and forecast wind values showing how the relative influence of the forecast wind values changes with the agreement between the measured values.

Social Media

The feed to Twitter was updated daily via the program that runs the Bayesian models and so involved no extra work. The uptake or interest in the Twitter feed has been only small with a few followers. This reflects the weak engagement of the local communities with products such as Twitter, unlike the web site.

Links to Management Outcomes

There is a need to link any monitoring or forecast system with resulting management outcomes. This has not been specifically investigated for the Torres Strait but has for the Great Barrier Reef to the immediate south[20, 22, 41, 42].

Marshall and Shuttenberg[20] describe the direct link between early warning systems and management outcomes as: "*to initiate rapid assessments of ecological impacts and increased communication activities which can include senior managers and the media*".

Berkelmans[22] takes this further: "*allows for early management responses to be put in place, including the instigation of formal monitoring programs to assess the extent and severity of bleaching and, where appropriate, take local action to ameliorate the risk of further damage to reefs from such activities as dredging, coastal development and point-source pollution*".

While direct links are valuable there are other more subtle linkages, also of value. This was touched on by Berkelmans[22]: "*reef managers value such warning systems because they allow them to be the source of timely and credible information about bleaching risk for decision makers, stakeholders and the media*".

The ability of management agencies to know of potential issues in advance allows them to take a positive role in raising issues, in asking for and allocating resources, and in communicating their message. It also gives them a position of credibility from which more direct links to potential actions can be forged. The importance of credibility with the general public was repeatedly raised by reef managers at a recent workshop on satellite monitoring of coral reefs in a changing climate[43].

For the work in the Torres Strait the lack of knowledge of, and ability to respond, to the 2009-10 bleaching event was a source of concern within the management agencies. While often there are few practical steps that can be taken to reduce the impact of environmental events at large scales, early warning has an important role to play. It allows for some type of response to occur, for agencies to take a positive role in dealing with the event, in allowing in-situ science to be done to understand the event, and in developing an awareness of larger scale issues that potentially can feed into higher level discussions.

Future Work

For the next summer, a direct-email system will be trialled to deliver warnings to an identified list of key clients and stakeholders. This will be complimented with a RSS (Rich Site Summary) web feed which can be advertised and allow additional interested users to subscribe to the warning feeds. Additional public data kiosks are being installed to increase the exposure to the real time data and forecasts along with direct involvement with the local communities.

An additional real time station is planned for the northern part of the Torres Strait with a further unit under consideration for the eastern part. This network will allow for a broader scale representation of bleaching risk to be developed and allow the system to provide regional information complimentary to the broad scale remote sensing measures.

The Bayesian models are being developed to include more real time parameters, such as water quality, nutrients and underwater light, to include some process based measurements (such as coral / symbiont energetics) and to reflect more of the experimental work being undertaken. This will give more robust models of coral health, rather than just bleaching stress, which can be applied to a wider range of situations including species or system specific responses.

Conclusions

We present here an alternative to the numerically based early warning systems for coral bleaching currently in use[36, 38, 44]. The Bleaching Risk Bayesian model, presented here, provides a way to embody the current level of understanding about what causes bleaching into a single system. The features of this system include the ability to incorporate fuzzy logic and poorly defined relationships as well as the use of probability matrices. The system incorporates both a now-casting component which assesses the risk of bleaching based on current and historical conditions and a forecasting component which modifies the risk if the water column is likely to continue accumulating heat, or reduces the risk if it is likely to lose or dissipate heat. The two models work together to identify potential coral bleaching (risk), and how this risk will change in the near future (forecast).

Future work will see the model incorporate a range of other observing parameters that contribute to bleaching stress. These will include tide level (low tides during the day can increase localised warming), turbidity (which can reduce in-water light levels), underwater light and input from community observations. This model was trialled using real time data for the 2012-13 summer in the Torres Strait, a remote part of northern Australia with a majority indigenous population. Engagement with the local resource managers and communities was by a number of tailored data kiosk displays, web displays and mobile phone apps. The real time weather data was broadcast by a local radio station as part of its scheduled weather service, the issue of coral bleaching was also communicated via a series of interviews and community information programs as well as via social media. Improving community engagement in uptake will be an area of continual improvement.

Notes and references

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‡ This work is funded under the National Environmental Research Program (NERP) Tropical Ecosystems Hub funded under the Australian Federal Government Department of Sustainability, Environment, Water, Population and Communities. The work is supported by the Torres Strait Regional Authority (TSRA) and delivered by the Australian Institute of Marine Science (AIMS). This work is derived from capacity built under the Australian Integrated Marine Observing System (IMOS) project.

Many thanks to Scott Gardner, Shaun Hahn, Geoff Page and Tobias Robinson from AIMS and Frank Loban, John Rainbird, Damien Miley, Stan Lui, Ron Fujii and the crew of the Land and Sea Unit of the TSRA for their help.

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Widespread coral bleaching occurred in the Torres Straits for the first time in 2009-10. Previously equatorial areas were thought immune as the most significant bleaching has been in more southern latitudes. As a result there has been little emphasis on monitoring and responding to coral bleaching in this region. This paper details a new approach to developing indices of current and future bleaching risk using real time ocean data, climatologies and Bayesian models. This information is delivered to local managers and communities via web sites, social media and a local radio station. The work aims to raise awareness of coral bleaching and climate change in the region along with improving our understanding of the causes and impacts of coral bleaching.