Modelling the 2009-2010 Coral Bleaching Event in the Thai-Malay Peninsula with Satellite and In Situ Data:

Optimizing the Usage of Photosynthetic Active Radiation Data.

Master thesis

by

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Declaration

Hiermit versichere ich gemäß § 9 Abs. 5 der Prüfungsordnung für den integrierten binationalen Master-Studiengang Internationaler Naturschutz (engl.: International Nature Conservation) vom 16.08.2006, dass ich die vorliegende Arbeit selbstständig verfasst und keine anderen als die angegebenen Hilfsmittel verwendet habe. Diese Arbeit wurde nicht in der gleichen oder einer ähnlichen Form bereits einem anderen Prüfungsausschuss vorgelegt und wurde bisher noch nicht veröffentlicht.

Hereby I affirm – according to § 9 section 5 of the examination regulations for the integrated bi-national Master programme International Nature Conservation (deutsch: Internationaler Natur-schutz) from 16.08.2006 – that I have penned the present thesis autonomously and that I did not use any other resources than those specified above. This work was not submitted previously in same or similar form to another examination committee and was not yet published.

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Abstract

Mass coral bleaching is a phenomenon that is being recorded more frequently over the last few decades. Changing environmental conditions like temperature cause these coral bleaching events. Several studies have modeled coral bleaching using on environmental data, and more recently some studies modeled coral bleaching using satellite/remotely sensed data. These satellite data provide a constant supply (in time and space) of environmental data and are therefore of particular interest. In this study remotely sensed data were used to assess and predict coral bleaching for the Thai-Malay peninsula during the 2009-2010 bleaching event using binomial generalized linear mixed effect models. The final model explained 78% of the deviance in coral bleaching occurrence, of which 54% was explained by the random effects, time and location, and 24% by the environmental variables; temperature, currents, solar radiation, chromorphic dissolved organic matter and depth of low tide. Solar radiation data strongly affected the model predictions (high estimates) but hardly improved the model (low Likelihood Ratio Test). Additional measures that reduced or increased the effects of solar radiation like turbidity, depth and time of low tide were all much better predictors. Chromorphic dissolved organic matter appeared to be a measure that can very well be used for representing turbidity. Prediction maps showed a higher mean probability in the Andaman Sea in comparison with the Gulf of Thailand. This was most likely due to temperature differences and in smaller degree to turbidity differences.

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Abbreviations

AIC	Aikake Information Criteron
ASCAT	Advanced Scatterometer
BL	Bleached Coral
BODC	British Oceanographic Data Centre
CDOM	Chromorphic Dissolved Organic Matter
CH	Comprimzed Health
CSIRO	Commonwealth Scientific and Industrial Research Organisation
CW	Coral Watch
DHW	Degree Heating Weeks in weeks
DHWdeg	Degree Heating Weeks in degrees
DLOW	Depth of low tide
EMP	Ecological Monitoring Program Koh Tao
GEBCO	General Bathymetric Chart of the Oceans
KNMI	Royal Dutch Meteorological Institute
LRT	Likelyhood ratio Test
NASA	National Aeronautics and Space Administration
NGO	Non Governmental Organization
NOAA	National Oceanic and Atmospheric Administration
OSC	Ocean Surface Currents
PAR	Photosynthetic Active Radiation
RB	ReefBase
SI	Solar Insulation
SSS	Sea Surface Salinity
SST	Sea Surface Temperature
TEMP	Temperature factor
TLOW	Time of low tide

1 Introduction

1.1 Coral Bleaching Models

During the last few decades a large proportion of the world's coral reefs have undergone a major decline or are left heavily degraded (Riegl *et al.* 2009). Many, particularly coastal marine ecosystems are exposed to numerous stressors such as sedimentation (Weber *et al.* 2006), pollution (Green & Bruckner 2000), tourism (Barker & Roberts 2004), over-fishing (Pandolfi *et al.* 2003), diseases (Green & Bruckner 2000) and rising seawater temperatures, which causes coral bleaching (Keller *et al.* 2009). Most of these problems are local and can be prevented with adequate marine and on land conservation management. Seawater temperature and coral bleaching are, on the other hand, not so easily managed.

The frequency and severity of major coral bleaching events has increased over the last 20 years (Riegl *et al.* 2009). For the Thai-Malay peninsula several bleaching events have been reported of which all occurred within the last 20 years. The coral reefs in the Andaman Sea were hit by bleaching events in 1991, 1995, 1998, 2002 (Brown *et al.* 2002) and 2010 (this study). In the Gulf of Thailand bleaching coral bleaching events were reported less frequently (1998, 2002 (Yeemin *et al.* 2006) and 2010 (this study)); however, in 2006 and 2007 large scale bleaching of soft corals (*Sarcophyton* spp.) was reported (Chavanich *et al.* 2009).

Rising seawater temperatures are thought to be a major cause of mass coral bleaching; this is an environemtally-mediated syndrome where the symbiotic interaction between the coral polyp and the zooxanthellae is disrupted. In reaction to this the coral polyp expels or digests its symbionts leaving an uncolored coral polyp with a reduced energy production (Hoegh-Guldberg *et al.* 2009). Bleaching in this scenario occurs because the photosynthetic reaction of the symbiotic algae is altered by increased temperature and solar radiation (West & Salm 2003).

During recent years remotely sensed data have been used more frequently to assess coral bleaching. Early studies mainly focused on detecting bleaching based on changes in spectral reflectance of the benthos (Clark *et al.* 2000, Yamano & Tumara 2004, Hochberg *et al.* 2004, Mumby *et al.* 2004a, 2004b, Hanaizumi *et al.* 2008). Depending on the resolution of these data they could potentially detect bleaching of single colonies (the IKONOS and GeoEye satellite data have a 0.4m resolution). These studies can assess the severity of bleaching but cannot predict bleaching nor unravel the processes involved in bleaching.

More advanced algorithms have been developed over time that allow remote sensing of the environmental conditions or water quality. Some authors suggested the use of those environmental data to model coral bleaching in order to predict or assess coral bleaching (Hatziolos *et al.* 2003, Andréfouët & Riegl 2004,). Subsequently, remotely sensed sea surface temperature data was used for models, mainly based on the National Ocean Atmosphere Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) data (Thompson & Woesik 2009, Boylan & Kleypas 2008, McLeod *et al.* 2010). As a matter of fact synthetic data products based on these models and satellite-derived data are now widely used by many reef managers and conservationists. However, these SST based models are still not able to predict local / regional differences, because data are very coarse (4 km^2) and many other important environmental variables are neglected. Later papers suggested combining these SST data with other remotely sensed environmental variables like PAR or CDOM (Holland *et al.* 2001, Hatziolos *et al.* 2003).

Several studies have modeled environmental variables like seawater temperature and radiation in order to predict or assess coral bleaching. Yee and Barron (2010) used data from 708 coral bleaching surveys, worldwide, over eight years to model coral bleaching. They found that temperature explained most of the variation in coral bleaching and that increased turbidity decreased the probability of bleaching in shallow reefs but increased the probability for deeper reefs. Moreover, high solar radiation seemed to decrease the probability of bleaching which contradicted another modelling study by Yee and her colleagues (2008). This study in the Florida Keys shows not only that solar radiance was an important variable in bleaching, but it also highlighted that 33% of the variability in bleaching could be explained by coral community composition, an effect seen at the species level in empirical studies (Brown *et al.* 2002). The authors suggest that future modelling studies should also include individual species' responses to increase the accuracy of models. Maina *et al*. (2008) built a very similar model to predict coral bleaching in the Western Indian Ocean. This study showed that historical environmental conditions explained 56% of the variation, and when combined with current conditions, 67% was explained. This study combined the predictions with a gap analysis and found that only a small part of the protected zones are within areas that have a low bleaching probability.

The aim of the current study was to model satellite derived environmental data for the 2009 – 2010 coral bleaching event, focusing on the Thai-Malay peninsula. A large front of skepticism exists towards modelling coral bleaching based on satellite derived oceanic environmental data, because data perform bad in coastal region and the accuracy is often unknown (Nahorniak *et al.* 2006, Dunne 2008, Weeks *et al.* 2008, Morel & Gentili 2009). Therefore the focus was on highlighting the possibilities and pitfalls of modelling these datasets in a coral bleaching context. The following research questions were formulated to address these issues:

- Are remotely sensed data sufficient to describe processes that play a role in coral bleaching, within the extent of the 2009 - 2010 bleaching event?
- Can satellite data be used to predict coral bleaching of the 2009 – 2010 coral bleaching event for the Thai-Malay peninsula?

To build a model that can answer these questions several hypotheses were developed. These hypotheses support the selection of variables and interactions within the model.

1.2 Hypotheses

1.2.1 Temperature

Increased seawater temperatures cause coral bleaching as mentioned in the previous paragraph. Seawater temperatures change with depth and this is reflected in the severity of bleaching at different depths. The intensity of solar radiation also decreases with depth as more energy/light is being filtered by the water column. Seawater temperatures can be strongly influenced by upwelling from the deeper regions. In the context of coral bleaching this is beneficial for the coral's resistance and recovery (Salm & West 2003). Seawater temperature is the main driver in coral bleaching regardless of the different pathogens that can also cause bleaching (Rosenberg & Ben-Haim 2002), which are thought to be partially driven by thermal stress themselves (Bruno *et al.* 2007). With increasing temperatures and the longer duration of these increased temperatures the severity of bleaching should increase as well.

H_0: *Increased sea water temperatures do not increase the percentage of bleached coral.*

H_1: *Increased sea water temperatures increase the percentage of bleached coral.*

Both wind speed and seawater velocity mix seawater and this mixing of seawater influences the effect sea water temperature has on coral bleaching. Wind velocity also influences water velocity, so it is possible that these variables exhibit collinearity.

H_0: *Increased wind/seawater velocity does not reduce the effects that the temperature variable has on the percentage of bleached coral.*

H_1: *Increased wind/seawater velocity does reduce the effects that the temperature variable has on the percentage of bleached coral.*

Temperatures decrease with depth in open ocean system; therefore, corals that are situated deeper are less susceptible to coral bleaching. However, most coral reefs are not located in the open ocean but in coastal areas. Here the temperature gradient at different depths is much smaller as the water column is better mixed. Moreover, corals that have been exposed to environmental extremes prior to the bleaching event are likely to be more resistant to bleaching. Shallow corals are therefore less susceptible. The complexity of this interaction between temperature and depth makes it difficult to make a single statement regarding the effects.

H_0: *There is no interaction in the effects of depth and the variable representing temperature on the percentage of bleached coral.*

H_1: *There is an interaction in the effects of depth and the variable representing temperature on the percentage of bleached coral.*

1.2.2 Solar Radiation

Several studies have investigated the various effects of radiation apart from temperature on corals. Dunne and Brown (2001) studied shallow coral reefs in Phuket (Thailand) and discovered that radiation history can make corals more resistant to bleaching and more recent studies confirm these results (Torregiani & Lesser 2007, Thompson & Woesik 2009). The study by Torregiani and Lesser (2007) also showed that sandy substrates adjacent to corals increase the radiation on the corals by means of reflection. Certain suspended solids (silicates) have similar effects, whereas Colored Dissolved Organic Matter (CDOM) absorbs the radiation and decreases the stress (West & Salm 2003). In another study Brown, Dunne and colleagues (2000) found that west facing sides of corals are more susceptible to bleaching, because the afternoon sun that directly lightens the west side is stronger than the morning sun that lightens the east side. A recent experimental study that involved shading of corals by Piggot *et al.* (2009) showed that shading decreased zooxanthellae densities in the coral polyp, which suggests reduced health. Thus, radiation fluctuations can be both beneficial and dangerous for the persistence of the coral holobiont depending on duration and intensity.

H_0: Increased solar radiation does not increase the percentage of bleached coral.

H_1: Increased solar radiation increases the percentage of bleached coral.

The effects of solar radiation are dependent on the turbidity of the water. CDOM absorbs solar radiation and therefore reduces the effect solar radiation has on coral bleaching.

H_0: There is no interaction between the effects of CDOM and the variable representing solar radiation on the percentage of bleached coral

H_1: There is an interaction between the effects of CDOM and the variable representing solar radiation in which the effect of solar radiation on the percentage bleached coral decreases under an increase of CDOM.

The effect of solar radiation on corals is dependent on the depth. The PAR data have already been corrected for depth; however, this does not include tidal differences. Therefore, an interaction between solar radiation and the depth of the lowest tide at day *x* can be expected.

H_0: There is no interaction between the effects of depth of the lowest tide and solar radiation on the percentage of bleached coral.

H_1: *There is an interaction between the effects of depth of the lowest tide and solar radiation in which the effects of solar radiation increase with lower sea water levels.*

Solar radiation is most intense during midday. Low tides that occur during the solar radiation peaks are more likely to affect bleaching by increased radiation.

H_0: *There is no interaction between the effects of time of low tide and solar radiation.*

H_1: *There is an interaction between the effects of time of low tide and solar radiation in which the effect of solar radiation increases with times closer to noon.*

1.2.3 Salinity

Reduced salinity can also cause coral bleaching. However, this is more a local problem (Brown 1997). Rivers, run-off and storms are in general the causes of a reduced salinity in coastal areas (Brown 1997, Castro & Huber 2007).

H_0: *Salinity does not affect the percentage of bleached coral.*

H_1: *Reduced salinity increases the percentage of bleached coral.*

1.2.4 Growth Forms

Figure 1 summarizes the main environmental variables and their relation to coral bleaching but also includes coral characteristics and factors that can affect either the environmental variables or the corals directly. Different coral species/ growth forms/ compositions are responding differently to environmental stressors. Therefore, community composition should affect the severity of bleaching.

H_0: *There is no difference in the percentage of bleached coral in different coral growth forms.*

H_1: *There is a difference in the percentage of bleached coral in different coral growth forms. Certain growth forms are more susceptible to bleaching than others.*

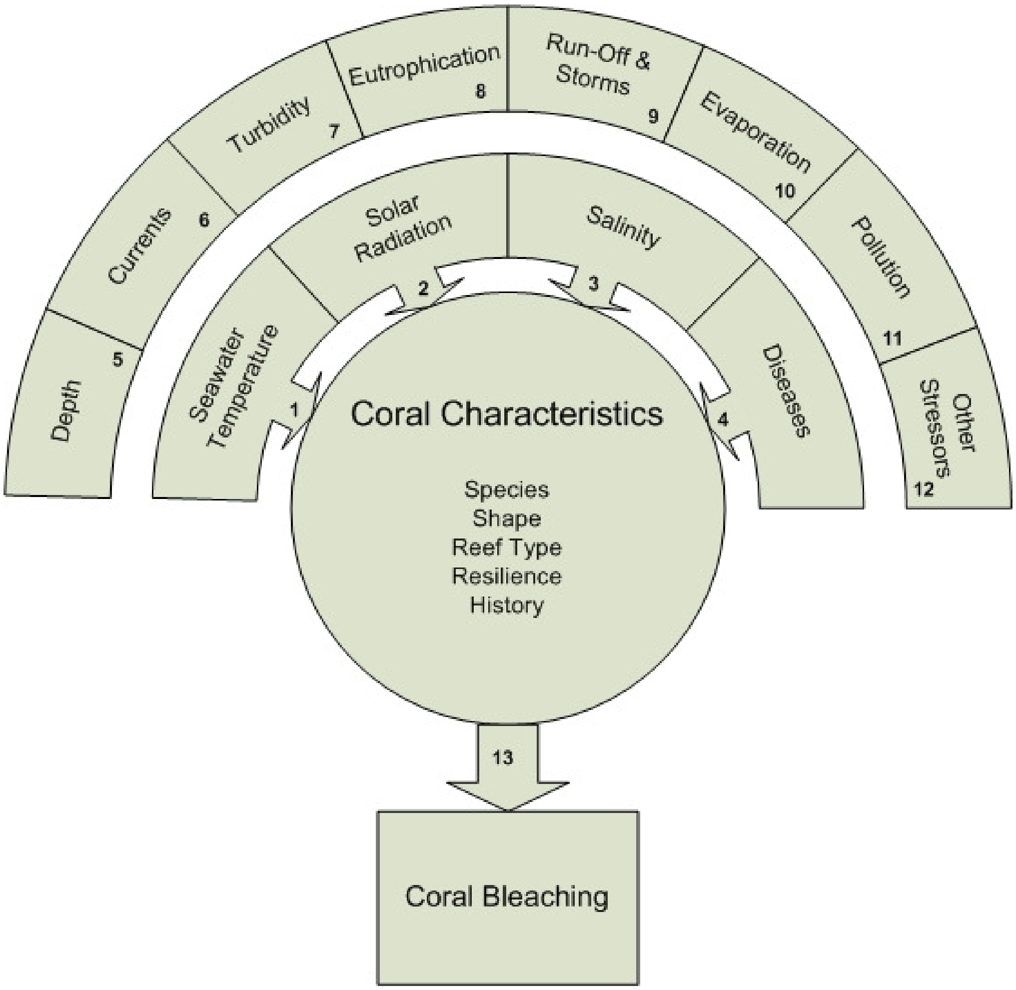


*Figure 1. Scheme of different factors that affect coral bleaching. The numbers in the figure refer to numbers in the text: Increased seawater temperatures[1], increased solar radiation[2], decreased salinity[3] and diseases[4] are the main factors that cause coral bleaching. Factors that influence the seawater temperature are depth[5], currents[6] and run-off[9]. **1** Deeper coral reefs are less affected by a temperature increase. Shallow reefs with little currents are more likely to bleach because the heat accumulates. **2** Solar radiation is directly dependent on the atmospheric conditions like thickness of the ozone layer or cloud cover. Other factors that influence the solar radiation are depth[5], surrounding substrate[12] and turbidity[7]. Deeper reefs receive less radiation because this has been filtered out by the water column. Turbidity can both increase or decrease the radiation that reaches the coral polyps, particles that reflect or absorb sunlight (silicates or CDOM) increase the radiation. Sandy substrates that are adjacent or within a coral reef increase the radiation as well by means of reflection. Turbidity is heavily affected by activities on land like deforestation, waste water disposal or development[12]. **3** Reduced salinity is generally caused by run-off, storms[9] and rivers. Evaporation[10] can increase the salinity which easily happens in shallow reefs with little exchange with the open ocean. **4** Bleaching diseases are often triggered by temperature stress but do not occur on the massive extent as pure climatological bleaching. Pollution[11] and Eutrophication[8] can decrease the resilience or even introduce a pathogen. Other factors[12] that can decrease the resilience like over-fishing can make reefs more susceptible for diseases and bleaching. **13** All these variables trigger the coral bleaching process, but it is dependent on the characteristics of the corals whether or not they bleach. Certain species react different to temperature and radiation changes than other species. Moreover, the shape of coral colonies is also influencing the process. Species with a higher surface-volume ratio are more susceptible as well as east facing corals. Individual corals that have had previous high exposure to sunlight are less susceptible to bleaching, like corals that have survived a previous bleaching event.*

2 Methodology

2.1 Study area

This study encompasses the coral reefs of peninsular Thailand and Malaysia, on the west coast the Andaman Sea and Strait of Malacca and on the east coast the Gulf of Thailand (Top Left Corner: N 16.04999, E 92.0000, Bottom Right Corner: E 110.79166, N -2.95000, coordinate system: WGS 1984) (figure 2.1). These seas are divided by the peninsular, a land strip with a varying width of approximately 150 to 400km. The closed character of the Gulf causes a different environmental regime in comparison with the west coast, which is more directly influenced by the open ocean (Indian Ocean). Therefore, bleaching response to the environment might be very different in space and over time.

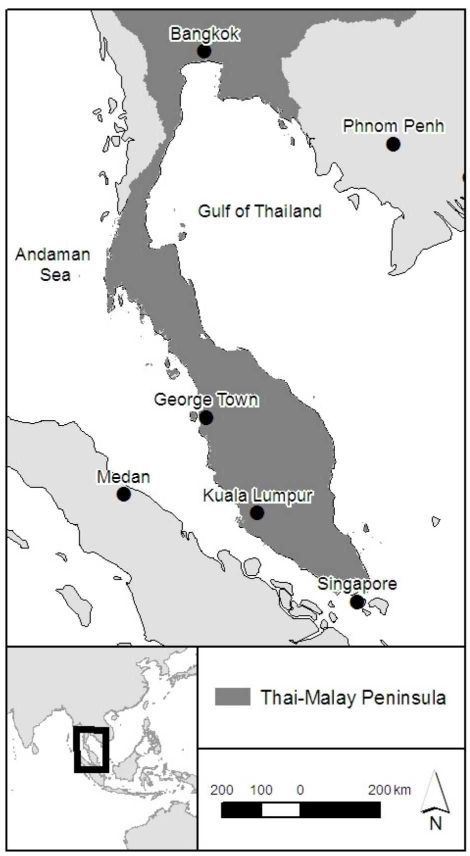


Figure 2.1. study area with the main cities (data from DIVA GIS)

Table 2.1. Characteristics of in situ data from 4/5 different sources

	Reef Base	CSIRO	Coral Watch	EMP
Bleaching parameter	Categorical: no/low/high	General Impression (in percentage bleached)	Color Codes: multiple observations	Percentage cover: 120 obs. at a transect.
Number of Transects	35	13	46	174
Date	Inaccurate	Accurate	Accurate	Accurate
Location (GPS)	Inaccurate	Inaccurate	Inaccurate	Accurate
Growth form data	Not available	Not available	Available	Available
Species data	Not available	Not available	Not available	Available for 34 transects
Method	Mixed	General impression of surveyor	Haphazardly distributed samples	120 samples at 0.5m intervals along 14 fixed transects.

Moreover, due to the differences in connectivity with the open ocean, the coral reefs in the Gulf of Thailand are expected to be influenced to a greater extent by on-land activities (sedimentation/erosion, eutrophication, pollution, etc.). Thereby, seawater circulates in the Gulf of Thailand which causes a slow exchange with the South China Sea (Latypov 2003, Aschariyaphotha et al. 2008)

2.2 In Situ Data

During the period April to June 2010 South East Asia was hit by a major coral bleaching event. Scientists and non-scientists from varying organizations (governments, universities, NGO's and businesses) monitored this event for various reasons. These data were obtained from ReefBase (http://www.reefbase.org), CSIRO (The Commonwealth Scientific and Industrial Research Organisation), Coral Watch (www.coralwatch.org) and the Koh Tao Ecological Monitoring Program (www.marineconservationkohtao.com). In total 252 records were collected and used for further processing. For all different sources, different sampling techniques were used, this made the data rather hard to use for analysis. Table 2.1 gives an overview of the different datasets.

To create a single consistent dataset the data were converted to percentage cover. The ReefBase data which are categorical, mainly contained surveys without bleaching therefore 0% bleached could be entered for all records. Two ReefBase observations were categorized as highly bleached and were set at 100% bleached. The CSIRO data already consisted of percentages and did not need any conversion.

The CW data were more difficult to convert to percent cover data because the data were presented in color codes (figure 2.2). For every sample of a survey two codes were given; the lightest and darkest color of a colony. The average value of a colony was used to determine whether it was bleached or not. Averaged values ranging from 2.5 to 6 indicated healthy coral and values from 1 to 2 were considered bleached. This was repeated with values from 1 to 2.5 being considered as bleached. The presence-absence of bleaching for each sample was used to calculate the percentage bleached coral for that survey.

The percentage cover in combination with the number of trials gave a standard binomial response variable as the percentages represent the amount of trials that were

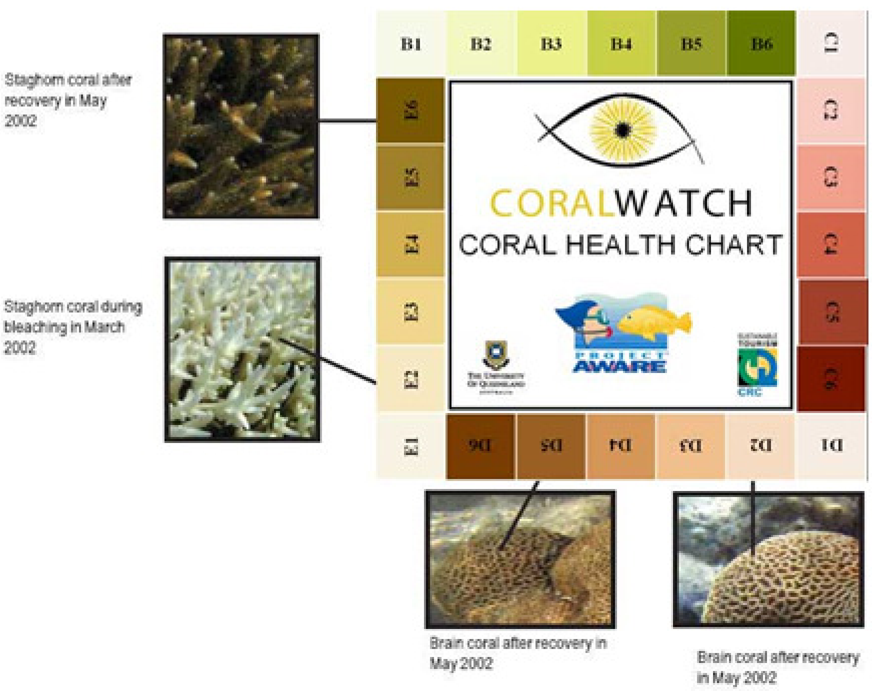


Figure 2.2. Coral health chart, displaying the color codes used for the Coral Watch data. (source: www.coralwatch.com)

observed with presence as response. For ReefBase and CSIRO data there were no number of trials as these data were based on a general impression by the observer. For this reason the number of trials for these data was set to one.

Data concerning growth forms had to be simplified because not all data sources used the same format or contained this information at all. Only the dominant growth form recorded by a survey was used as a measure for community composition. It was judged that more elaborate measures would create too many categories which are not practical in statistical analysis. If a growth form covered 50% or more of the samples in a survey it was considered as dominant. If 50% was not reached by any growth form the data were treated as a mixed community. The categories that were created were: Table, Massive (Boulder), Branching and Mixed (Other). The EMP data contained more detailed information on growth forms than the Coral Watch data and had to be simplified. Figure 2.3 displays the reclassification of the EMP growth forms to the Coral Watch format.

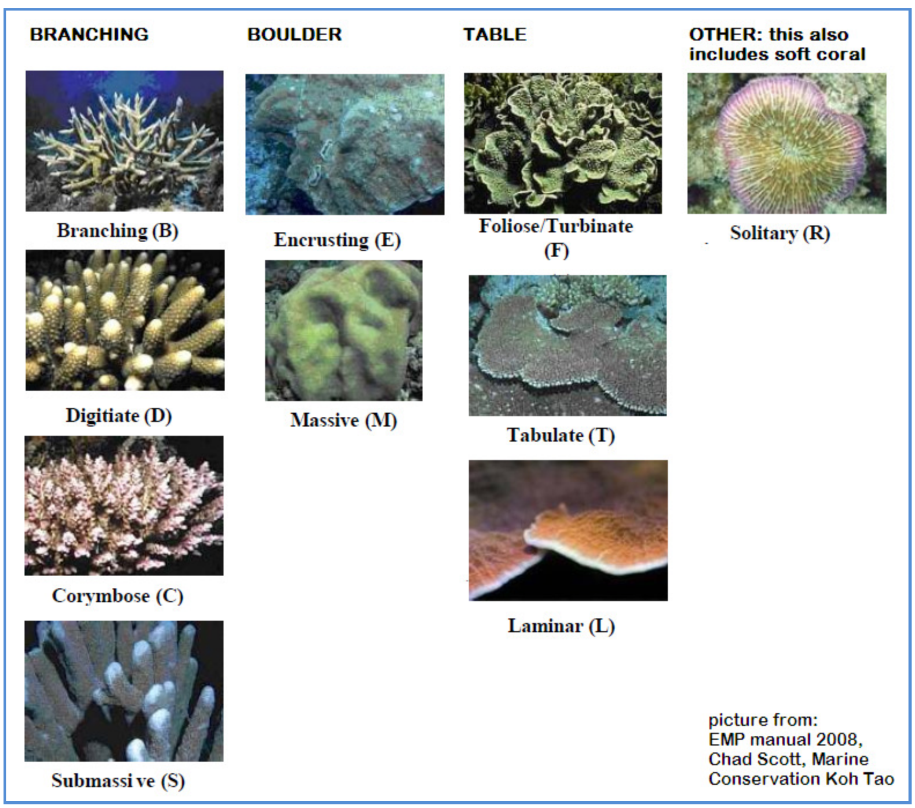


Figure 2.3. Reclassification of EMP growth form data to the more simple Coral Watch growth forms. The pictures represent the growth forms in the EMP data. The growth forms that can be found in the same column are grouped together in the simplified growth forms: Branching, Boulder, Table and Other.

Missing values (for ReefBase and CSIRO data) were also given the mixed category. This created a bias towards the mixed category which was tolerated because the effects of the mixed category are not of interest because this category does not represent a certain/consistent community composition. Moreover, the CSIRO and ReefBase data covered areas with low sample densities therefore it was not desirable to exclude them from the data/analysis even though this caused some loss of detail.

Depths were available for almost all in situ data. The depth data were very approximate so standardizing to lowest or mean sea level was not likely to increase the quality of these data. For that reason these values were used as they were provided.

2.3 Raster Data

Bleaching surveys did not contain environmental variables like temperature or turbidity, hence, remotely sensed data were used. Remotely sensed data were available for many environmental variables that could be used as model input. These data were evaluated and converted before they were used.

Environmental data were downloaded from several websites and servers these included sea surface temperature, PAR, KD490, CDOM, cloud fraction, currents, wind, elevation and bathymetry. Most explanatory variables that were included in the model were derived from raster dataset; in most cases these were satellite data and in others modelling data based on both satellite and in situ data. All raster files were reprojected to one uniform coordinate system (UTM WGS 1984) (if files were not already projected in this particular coordinate system). Subsequently these files were clipped to the extent of the study area, renamed and exported as geotiff file. Values representing no data were all reclassed to the ESRI ArcGIS “NoData” notation; this avoided mistakes in further geoprocessing.

Bleaching is a process over time; therefore, time had to be incorporated in the model. This was done by converting the environmental variables to measures that include time like: maximum temperature over a certain period, heating weeks or variability in temperature. Incorporating temperature variability in models would increase the accuracy of the model (Boylan & Kleypas 2008 , Maina *et al.* 2008, Yee *et al.* 2008). More details on these data are given in textbox 1.

2.3.1 Sea Surface Temperature

From Nasa's Ocean Color website (http://oceancolor.gsfc.nasa.gov/), Aqua-Modis mapped (level 3) Sea Surface Temperature (SST) data were downloaded. These data contained eight day mean SST for the period 1-1-2009 to 1-10-2010 at a 4km resolution. The data performed bad in coastal areas but were the only data available with a high temporal resolution and a relative high spatial resolution covering all in situ sites; other remote sensors like NOAA's Pathfinder or NASA's Seawifs perform similar and have the same problems. This low quality in coastal zone problem was found for all of the following variables; SST, PAR, KD490 and CDOM (more on these data in the following paragraphs) (Desa *et al.* 2001, Kilpatrick *et al.* 2001). The SST data were converted to several new parameters that represent SST over a longer period of time, as bleaching is not a short time process. New parameters that were calculated are displayed in table 2.2.

Textbox 1 Details on the Aqua-MODIS data and other datasets

Some of the raster datasets could not deal with non-integer values and needed to be rescaled to obtain geo-physical values. The (linear) functions that were needed to rescale these data were provided in the meta-data of the specific files.
The data came with a meta-data raster layer of which every pixel refers to the quality of each pixel in the SST layer; these are called "quality flags". Quality flags were available for different categories (o.a. good, bad, cloud contamination or mixed pixel). All Aqua-Modis data contained quality flags. These quality flags generally indicated bad quality pixels in coastal zones, in which most in situ samples could be found (Nahorniak *et al.* 2005). Distinguishing between good or bad quality was rather pointless, as all data were of low quality.

Table 2.2. Framework for calculating variables that incorporate variability in time based on Maina et al. (2009) and Yee et al. 2008.

	Variables	Formula	Comments
Mean	2 week: SI / DLOW 6 week: SST / PAR / OSC / WIND / CDOM 12 week: SST / PAR	$\frac{\sum_{i=1}^{n_d} Xd_i}{n_d}$	Mean of a two, six or 12 week period before a certain moment.
Degree Heating Weeks	SST	$\sum x_{1...12} - x_{\max}$	Sum of the differences of weekly averaged values and the climatological maximum.
Heating Weeks	SST	Count if: $x_{1...12} - x_{\max} > 1$	Number of weeks that a variable is exceeding the climatological maximum during a 12 week period.
Standard Deviation	SST / OSC / WIND	$\sigma = \sqrt{\frac{\sum (x - \bar{x})^2}{N}}$	Standard deviation in which x is the value of each 8 week mean
Coefficient of Variance	SST	$\frac{\sigma \cdot 100}{LtM}$	Standard deviation of six week periods devided by the long term mean (LtM).
Maximum	OSC / WIND	Not Available	The maximum value during a 6 week period before a certain moment.
6 and 12 week difference	SST	$\left(\frac{\sum_{i=1}^{n_{2010}} X2010_i}{n_d}\right) - \left(\frac{\sum_{i=1}^{n_{2009}} X2009_i}{n_d}\right)$	6 or 12 week mean from a certain period minus the 6 or 12 week mean from the same period one year earlier.

2.3.2 Ocean Surface Currents

Ocean surface current data (OSC) were downloaded from NOAA's NODC website. The OSC data are modeled values based on satellite imagery and in situ data like buoys and other measurement devices. These data are very coarse (1 deg resolution), therefore, wind speed data were also used which have a much higher spatial resolution (next paragraph) (Lagerhoef *et al.* 2009). The OSC data were downloaded as 5 day averaged, NetCDF files. These data could easily be imported to ArcGIS after which they were saved as Geotiff files. The OSC data are given as two layers: the zonal velocity and the meridional velocity. To calculate the total velocity the Pythagorean Theorem was applied. These total velocity values were used to calculate the parameters as presented in table 2.2.

2.3.3 Wind Speed

Wind speed data were ordered and downloaded with help from the European Space Agency (ESA) Eumetsat web application. These data are recorded with a scatterometer device on board of the Meteosat 8 satellite. The data consist of single swath NetCDF files (level 2 data) with approximately 5 swaths per day and a spatial resolution of 25km (KNMI 2010) (swaths are individual pictures from single satellite orbits). The data were binned at 25km raster cells for swaths within eight day periods, creating a similar data format as the Aqua-MODIS level 3 data (Textbox 2). These binned raster files were then used for calculating the parameters as displayed in table 2.2.

Textbox 2 Processing of Swath Data

NetCDF swath files can be loaded into ArcGis but cannot be projected as the extent of the swaths is not rectangular. The BEAM 4.8 software package (ESA 2010) can deal with these files. With the binning processor in this software it is possible to create level 3 mapped data.

2.3.4 Solar Radiation - PAR

Sunlight consists of a very broad wavelength of which most has no effect on coral bleaching. For coral bleaching the important wavelengths are within the Ultraviolet Radiaton (UVR) (290 – 400nm) and the so called Photosynthetic Active Radiation (PAR) (400 - 700nm) range (Basti *et al.* 2009, Brown & Dunne 2008, Dunne & Brown 2001). UVR and PAR are highly correlated variables; therefore it was unnecessary to use both variables. Moreover, PAR is thought to have a more significant role in the bleaching process than UVR (Brown *et al.* 1994, Hoegh-Guldberg 1999), therefore PAR values were used for this study.

Data for sea surface PAR were downloaded from NASA's Ocean Color website for the Aqua-MODIS satellite. The data have a 4km spatial resolution and consist of 8 day mean PAR. The data are partially cloud corrected and averaged for an eight day period based on data from several swaths (Nahorniak *et al.* 2005). Partially cloud corrected refers to the fact that intense cloud cover returns “No Data”. This will cause a bias, resulting in an overestimate of sea surface PAR values. Moreover, coral bleaching does not occur at the ocean surface; radiation is strongly affected by water turbidity and depth. Therefore it is important to correct these data before they can be used for analysis (Dunne 2008).

Correcting PAR for depth and turbidity was easily done with Beer's Law (formula 1) (Li 2005, Lee 2009). All that was needed to solve this equation is; PAR, a light attenuation coefficient (KD490 (Textbox 3)) and depth. These KD490 data were

Textbox 3 Light attenuation coefficient

The Ocean Color website also offered a light attenuation coefficient (Aqua- MODIS, 4km resolution, 8 day mean) for PAR (kPAR). These data were only available for a restricted time period and could therefore not be used. An alternative option was the use of the light attenuation coefficient at 490nm (KD490) (Lee2009) as has been proposed in other bleaching modelling studies (Yee *et al.* 2009). Note that using KD490 instead of kPAR creates a bias; not all light is attenuated similar, values of kPAR and KD490 could differ significantly.

also available at the Ocean Color website for Aqua-MODIS (4km, 8day), combined with the in situ depths (z) a more realistic PAR value was calculated. Eventually these corrected values were used for calculating the parameters as displayed in table 2.2 using the models mentioned in the previous paragraph (Model Builder).

$$PAR = PAR_0 \cdot e^{-KD490 \cdot z}$$

Formula 1. Beer's Law applied for underwater light attenuation of PAR (Li 2005, Lee 2009).

2.3.5 Solar Insolation

Solar Insolation (SI) values were calculated with the ArcGis 9.3 solar radiation toolbox, which bases it's calculations on a Digital Elevation Model (DEM). DEM data are available at the SRTM website at a 90m resolution. SI calculated with this model is always for a *uniform* sky; in this case a clear sky. Furthermore, the model demands an input called "size of sky map". This is a value that represents how many pixels of the DEM are used to calculate the horizon, which the sun passes in specific angle at a specific day. The size of the sky map was set at 2000 pixels, as this value is higher than the minimum required size and small enough to not create extreme computation times (Harlow *et al.* 2008).

To correct the assumption of a uniform clear sky several methods were available. Kumar, Kumar and Mathew (1991) tested several of these methods that can correct these SI values for cloud cover. The method that scored best in their paper assumes an average cloud thickness for their study area, the Arabian Sea. In this study their best scoring method was used. The average cloud thickness value was copied and in combination with cloud fraction data (Textbox 4) the following equation was solved to correct SI data for cloud cover:

$$SI_c = SI_0 \cdot 1 - 0.6 \cdot CL^3$$

Formula 2. Cloud correction of SI data. SI_0 = SI output from ArcGIS solar radiation toolbox. CL = Cloud fraction (Laevastu 1960).

Textbox 4 Cloud Fraction Data

Cloud fraction data were downloaded from the MODIS level 1 and Atmospheric LAAD website. These data consisted of irregularly averaged cloud fraction (%) at a 25km resolution. The LAAD website allows preprocessing so downloaded data could immediately be used (Nahorniak *et al.* 2005).

The advantage of these corrected SI data over PAR data is that corrected SI data have more spatial variability. This is also the major disadvantage since GPS locations of in situ data need to be rather accurate (45m). This sounds reasonable, however, in fact most in situ data are poorly geo-referenced. The corrected data were used to calculate a two week mean kWh per day.

2.3.6 Depth

Apart from the in situ data, depths were also downloaded as a raster dataset. This dataset (the General Bathymetric Chart of the Oceans (GEBCO) is available at the British Oceanographic Data Center (BODC) as a NetCDF file with a +/- 0.9 km resolution. These data are modeled data based on mixed techniques; remote sensing, sonar (multibeam) and interpolation (Goodwillie 2008). These data were converted to GeoTIFF files using the methods described in Appendix 1

2.3.7 Salinity

The HYbrid Coordinate Ocean Model (HYCOM) is a project developed by the Miami University (US). This project offers modeled salinity data, which are based on interpolated values derived from buoys, remote sensing and other techniques in an elaborate ocean circulation model. Salinity data are available for different depths as a 1/12 degree spatial resolution NetCDF file. From a practical point of view data for sea surface trends were used only. These data do not show the actual salinity but the change in salinity. As a reduction in salinity causes bleaching and not the actual levels of salinity, these data were used without any further processing. Moreover, the variable already regarded time as it concerns a trend (Canuto 2000).

2.3.8 Chromorphic\ Coloured Dissolved Organic Matter

Chromorphic Dissolved Organic Matter (CDOM) does not influence the coral bleaching process directly but alters the solar radiation intensity as mentioned in the introduction (West & Salm 2003). CDOM data were downloaded from the NASA Ocean Color website. This Aqua-MODIS level3 data product has a 4km spatial resolution and was downloaded as eight day mean CDOM concentration. The data were further processed as other Aqua-MODIS data (SST, PAR and KD490) to calculate the variables displayed in table 2.2.

2.4 Non Raster Data - Tides

Depth data are available as in situ data and in mapped bathymetry from the GEBCO digital atlas (http://www.gebco.net/). In situ depths are used for model input, but these depths vary during a day because of tides. The variability in depth during time is thought to have a significant impact on coral bleaching. Having low tides at midday can have a detrimental effect on the coral.

Tidal data were obtained from two sources; the Thai Royal Hydrological Department (TRHD) and the JTides software (Flater 2008). For every bleaching survey the tide table of the nearest location was used (textbox 5), preferably from the TRHD as these data are more accurate. The time of the lowest tide (TLOW) and the highest tide were noted for the specific day of a survey. The depths of both the lowest and highest tide were also noted (DLOW, DHIGH), as depth to lowest sea level.

For these tidal variables there was no coverage data and it was impossible to integrate this variable to GIS. However, part of this study was to build a model that described the bleaching event, so it was unwise to exclude this variable from the analysis. Moreover, the peak of coral bleaching appeared to be overlapping the lowest tides of the year (at least for Koh Tao) (Cook 2010 *unpubished*) and therefore a significant effect was expected.

Because bleaching showed a non linear response to time of low tide (see Results), this variable was linearised by mirroring the data at the peak of bleaching (time is 0.45). This was done by applying the following equations:

$$T_{cor} = T_{original} - 0.45$$

$$TLOW = 1 - \sqrt{T_{cor}{}^{2}}$$

Formula 3 & 4. The first equation places the peak of bleaching at time is 0. In the second equation the negative values are transformed to their positive equivalent.

Textbox 5 Tide table selection

For every data point the nearest tide table was selected. In case the nearest location was near a major river, or even up stream from a river, and the bleaching data came from an off-shore location, the second nearest location was chosen. For example: the data for Koh Tao are closer to Chumphon than to Koh Samui. It is more likely that the tide regime on Koh Tao is more similar to that of Koh Samui than that of Chumphon. This is because the Chumphon tide table predicts for a location one to two kilometer upstream a river, whereas Koh Samui is the second nearest island.

2.5 Analysis

The final dataset contained 222 records (based on 16401 trials) and 27 variables. This large number of variables had to be reduced because many variables were highly correlated and, in some cases, represented different aspects of the same environmental factor, for example, six week mean SST and 12 week mean SST. A pre-selection of the dataset was made by examination of scatterplots and boxplots of the explanatory variables against the response variables. The records that contained no data for these pre-selected variables were removed. The variables were standardized to avoid unwanted correlations among variables and the intercept in the model using the following equation:

$$(x - mean\ (x)\ )\ /\ std\ (x)$$

Formula 5: standardizing data. x = variable, std = standard deviation (Zuur et al. 2009).

For this dataset the Variance Inflation Factors (VIF) were calculated. High VIF values indicate that variables are collinear. A cut off value of 3 was used to remove collinear variables (Zuur *et al.* 2009). This value was chosen because it fully minimized variables to one for those that were based on the exact same dataset (like for example the temperature based variables). This way the number of variables was further reduced. Moreover correlating variables also violated the independence assumption.

Because the data were in most cases clustered and repeated measures it was quite clear that they were not independent. Therefore, simple generalized linear models were not appropriate. Generalized linear mixed models account for the lack of independence by adding a dependence structure. To understand GLMMs it is important to first understand GLMs. A GLM is not much more than an expansion of linear regression, the difference is the possibility of a non-normally distributed response variable (Zuur *et al.* 2009). It can simply be written as:

$$x = \alpha + \beta_1 \cdot y_1 + \beta_2 \cdot y_2 + \ \dots$$

Formula 6: Generalized Linear Model. Where x is the response variable, α is the intercept, β is the slope of a particular variable, and y is the value of the explanatory variable.

GLMMs work similarly to GLMs in terms of the so-called "fixed effects", but in GLMMs a random intercept or slope can be specified that accounts for clustering in the data. This means that the model will be fitted with different intercepts or intercepts and slopes for every value of a random effect (Zuur *et al.* 2009). In this study, due to the repeated measures, time was added as a random effect, as well as location. As fixed effects all the other environmental variables could be used. The time variable was based on the dates of the survey that were categorized into four, half year periods starting in January 2009. A GLMM gives estimates for a typical situation, of which values can differ based on the random effects (Zuur *et al.* 2009). Several models were built with different dependence structures (Textbox 6). In these models the response variable (x) was fitted against value 1 (y) plus a random effect, in order to assess which random effect structure performed best.

The response variable is binomial therefore linear regression is not directly possible. The `glmer` function in R (Pinheiro *et al.* 2011) can deal with binomial data because it uses a logit link. This link converts probabilities (binomial data) to odds. The difference between probabilities and odds is that odds are continuous and can therefore be modeled with linear regression. The logit link that the glmer function uses can be written as: (Zuur *et al.* 2009)

$$\frac{\exp{(x)}}{1+\exp{(x)}}$$

Formula 7: Logit link for converting probabilities to odds(Zuur et al. 2009),

Textbox 6: Dependence structures

```
-     glm (BL ~ 1, family = binomial)
-     glmer (BL ~ 1 + (1|timecat), family = binomial)
-     glmer (BL ~ 1 + (1|location), family = binomial)
-     glmer (BL ~ 1 + (timecat|location, family = binomial)
-     glmer (BL ~ timecat + (1|location), family =
      binomial)
```

2.5.1 Modelling Approach 1

The variables that remained after removal based on the VIFs were used to build the optimal model structure with the best-performing random effect structure (based on the AIC score *see next paragraph*). This means a model that contains all variables and interaction terms specified in the hypotheses, if the variable had not already been removed. Based on all variables the fixed effect part looked like this:

$$Bleaching = SST * OSC + SST * wind + SST * depth + PAR * CDOM + PAR * TLOW + PAR * DLOW + SSS + Growth\ Form$$

The optimal model structure was fitted with the glmer function from the lme4 package (Pinheiro *et al.* 2011) after which variables were stepwise removed. The anova function with Chi-square Likelihood Ratio Test (LRT) was used to assess whether removing a variable improved the model (Zuur *et al.* 2009). Observations that were earlier removed because some variables contained no data were added back into the dataset if this variable was excluded from the model. This more complete dataset was used for refitting the model. This dataset was used to perform the likelihood ratio test on all variables and interaction in the model. After the model was refitted, the percentages of certain growth forms were added as fixed effects to see how this would affect the model. The main focus in this study was on coral bleaching in general and not specific species or growth forms. Therefore starting with an optimal model that already contains very specific growth form information was avoided.

2.5.2 Modelling Approach 2

In a second approach to modelling the data, all variables that were left after removal were modeled separately as models with a single fixed effect and in all possible interactions that theoretically made sense. The AIC and LRT were noted and the best scoring single effect models were combined after which the AIC and LRT were noted again.

The AIC score (Akaike Information Criterion) is a measure of the goodness of fit of a model (Akaike 1974). It is based on both the accuracy and simplicity of a model and allows comparing different models (as long as they are fitted on the same dataset). Models with lower AIC scores are better than models with higher scores (Akaike 1974, Zuur *et al.* 2009).

The likelihood ratio test is based on the difference in deviance explained between the final model and a null model that only contains the random effects. Significance was determined using a chi square test. In this modelling approach the best model was the model with the best scores without having high correlations in the explanatory variables. The final model was refitted and analyzed as described for approach 1.

2.5.3 Modelling Approach 3.

In a third approach, all variables that were present before removal with VIF were modeled in a factor analysis. In a factor analysis, correlated variables are combined as a single variable, the so called ‘underlying factor’. The most important assumption is that the mean of the specific factors is equal to zero. Factors that made theoretical sense were used to create artificial variables (Borkenau & Ostendorf 1990). Non graphical solutions to the Cattell’s Scree Test were used to determine the number of factors needed (Raîche *et al.* 2006).

Modelling these factors individually and comparing them to models with the original variable gave insight into whether these factors improved the model. If this was the case, these simple models were then used for further modelling following approach 1 and 2. Approach 1 was conducted twice where collinearity among variables was fully ignored once. In the modelling study by Maina *et al.* (2008) variables were removed if the VIFs exceeded ten (three in this study). This causes variables that are regarded to be non-collinear in their study to be collinear in the current study. If collinearity is ignored strong correlations among variables in the model are expected, but it allows to model certain environmental factors for which no variables where included in the modelling study so far. However this also causes estimates in the model to be incorrect as the effect of one variable might also be caused by it's collinear variable (Graham 2003, O'Brein 2007, Zuur *et al.* 2009).

2.5.4 Model Validation

To validate the final models, the normalized residuals and observed values were plotted against the fitted values. Relationships for the produced models were visualized using scatterplots and interactions were visualized using 3-D plots (`lmerPlotInt.fnc` function from the LanguageR package (Baayen 2010). Variables that were removed due to collinearity were further investigated by assessing correlation coefficients and scatterplots.

The model that scored best was used for creating prediction maps. The growth form variables are not available as raster data so the model variant without this variable was used. The predicted values from this model were plotted against the observed values. Note that predicted and fitted values are not the same in GLMM. Fitted values take the fixed and the random effects into account whereas the predicted values are only based on the fixed effects. It is therefore not strange if observed values do not fit the predicted values very closely (Zuur *et al.* 2009). For this reason the final model was reconstructed in which time was added as a fixed effect. In the original model time was a random slope. Simply adding time as a fixed effect was not appropriate for this caused time to be a fixed intercept instead of slope (Zuur *et al.* 2009). Therefore time was added in an interaction with the main explanatory variable.

Not enough data were available to calibrate the final model with cross validation. Twenty-seven records contained no data for PAR because depth data were absent. These data were removed from the analysis. These removed observations were used for creating semi-control observations to assess the accuracy of the predictions. Based on the GEBCO bathymetry data, depths were added to these observations after which the values for PAR were calculated. These data were not as accurate as the in situ depth data because the GEBCO data gave averaged depths for 0.9 grid cells. Therefore, sites close to shore could get positive values and sites close to drop-offs extreme low values.

The percentage of correctly classified observations and the average error of these classifications give an estimate of the accuracy of the model. This will most likely underestimate the quality of the model, because no real control sites were used.

3 Results

3.1 In situ data

The response variable (% bleached coral) was composed from five different datasets. Figure 3.1 displays the response variable versus 12 week mean SST per data source. The data from the different sources seem to respond similarly to SST, except for the Reef Base data. For this reason the Reef Base data was not used for further modelling efforts. This caused a loss of 23 records from a total of 222 records.

As mentioned in the methodology two different methods were used to convert the Coral Health Watch data to presence – absence data. Figure 3.3 displays the

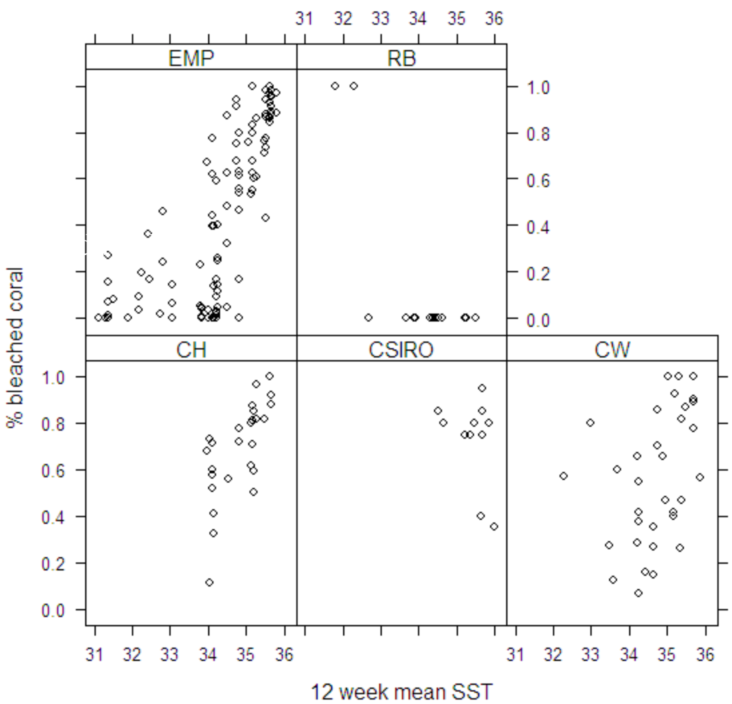


Figure 3.1. Response variable versus 12 week mean SST per data source. The Reefbase (RB) data did not respond similar to data from other sources: Ecological Monitoring Program (EMP) and Compromised Health (CH) for Koh Tao, Coral Watch (CW) and the Commonwealth Scientific and Industrial Research Organisation (CSIRO)

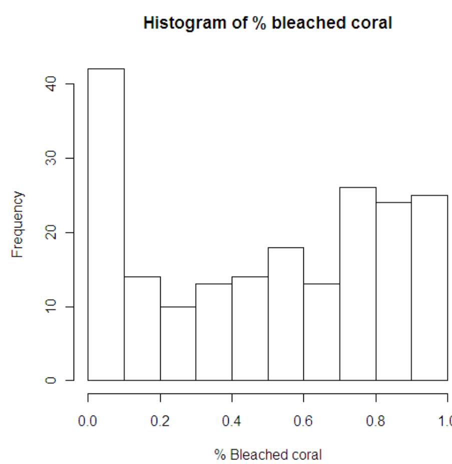


Figure 3.2. Frequency histogram of the response variable; % bleached coral.

response variable versus 12 week mean SST for both coral watch datasets. The figure clearly shows that coral watch data converted with method 2 fits much better to the other datasets. Therefore the Coral Health Watch data that were composed with method 2 were used for further processing.

A frequency histogram of the response variable seems to reveal a zero-inflated dataset. However, the opposite is true, for the data have a very low representation of non bleached observations. Further problems concerning over dispersion were not encountered (Figure 3.2).

3.2 Reducing the Number of Environmental Variables

All explanatory variables were plotted versus the response variable to visually asses their relationships. The most interesting of these plots are displayed in figure 3.4 with some additional figures in Appendix II. *!! We must be very careful at this point with making any conclusions about patterns, as the data are in many cases clustered repeated measures that are unequally weighted (variety of trials per transect lays between 1 and 208)!!*

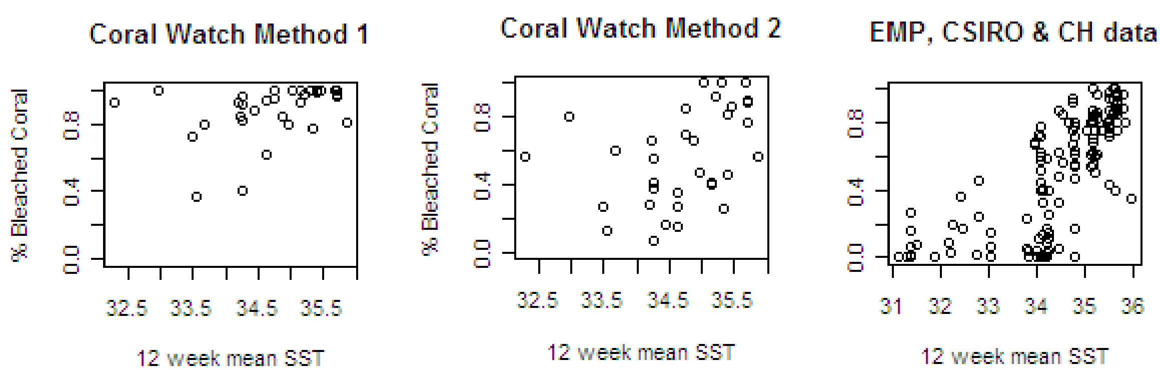


Figure 3.3. % bleached coral versus 12 week mean SST for : 1. The coral watch data transformed with method 1. 2. The coral watch data transformed with method 2. and 3. The untransformed EMP, CH and CSIRO data.

The SST and DHW graphs show a clear relation with the response variable (% bleached coral). For SST this relation appears to be non linear, as there is a clear tipping point from where coral bleaching starts to increase rapidly (+/- 34˚C). Other SST based variables like "six week mean SST" or "coefficient of variation" did not show such clear patterns.

The DLOW plot shows some clustering of no bleaching at very low depths. The tlow plot shows a very strong relation, in which bleaching increases as the time of low tide gets closer to the hottest time of day. Alternative measures like the corrected time of low tide also showed clear patterns. These data are linear; therefore the corrected

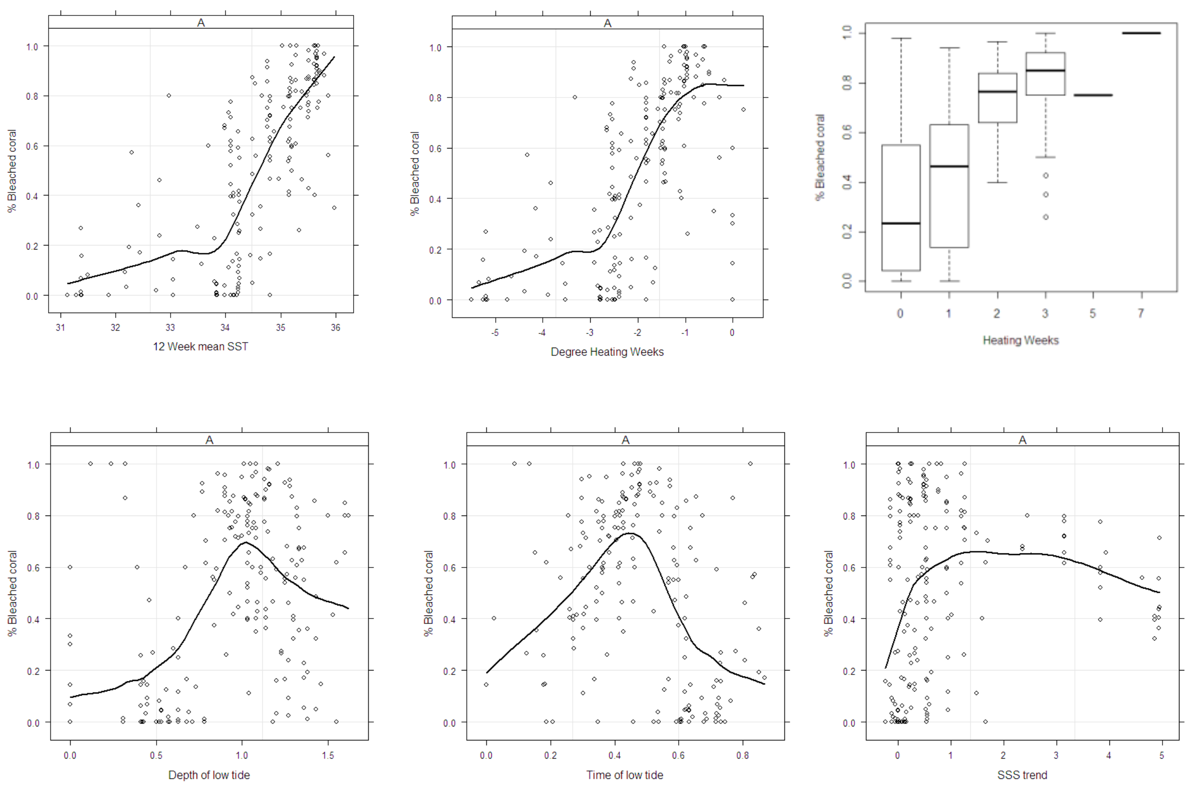


Figure 3.4. A set of plots for those variables which showed the least random patterns with response variables. In the upper row the three SST variables: 12 week mean, Degree Heating Weeks and Heating Weeks. In the lower row: Depth of low tide, Time of low tide (uncorrected 0.5 = noon) and the trend in SSS.

version was preferred.

The bleaching data seemed to respond linearly to CDOM; bleaching decreases as CDOM increased. However, CDOM itself does not reduce bleaching; this only occurs when it interacts with PAR. When looking at the PAR data there seemed to be no relation to bleaching at all. Several simple GLMs were built with the different PAR measures to investigate which variable to choose. This did not give any satisfying results. To not exclude PAR from further analysis, the variable that was most likely to respond best was selected (12 week mean PAR). This was based on previous modelling studies (Maina *et al.* 2008, Yee *et al.* 2008, Yee & Barron 2009).

OSC, Depth and Wind did not show any apparent patterns except for some clustering of low bleaching at extreme wind speeds. As mentioned for the CDOM data these variables are mainly involved in interactions and are not expected to have a large direct effect. Moreover, as mentioned earlier care is needed with interpretation of these plots at this point. As there were no alternative variables available these data were not removed.

The SSS data did show a rather strange pattern in which an increasing trend in SSS seems to go with an increase in bleaching. Whereas the literature suggests that reduced SSS should increase bleaching (Brown 1997). Increased evaporation caused by heat and radiation could cause this effect. As there were no alternative variables available these data were not removed at this stage.

The dominant growth forms all appeared to respond similarly except that Massive corals had less variation (Appendix II) and seemed to bleach less than other growth forms. Even though it is not very clear, growth forms could explain some more variance (mainly Massive growth forms), this becomes more apparent when looking at figure 3 in the appendix. This figure displays the peak of bleaching for tlow per dominant growth form. It seems that massive corals bleach less.

Table 3.1. Variance Inflation Factors before removing variables from the dataset and after removal. A cut-off value of 3 was used.

Variable	VIF at start	VIF<3
dhwdeg	42.9	*Dropped*
dhw	3.8	2.3
SST12	41.6	*Dropped*
tlow	4.8	*Dropped*
dlow	2.2	1.6
PAR12	1.3	1.1
sss	1.8	1.6
osc	1.5	1.4
wind6	1.8	1.8
cdom	3.5	2.6
depth	1.1	1.1

Eventually the selected variables (Table 3.1) were used to calculate variance inflation factors (VIF). Table 3.1 displays the VIFs of the dataset before and after removing variables with VIFs higher than 3. As the table shows SST, DHW, DHWdeg, TLOW and CDOM all show high collinearity. After finishing this procedure DHWdeg, SST and TLOW were removed resulting in the dataset displayed in the right column of table 3.1. VIFs cannot detect non-linear relationships. Further interpretation of scatterplots revealed that all variables that related non-linear among each other and to the response variable had been removed like for example TLOW versus 12 week mean SST (figure 3.5).

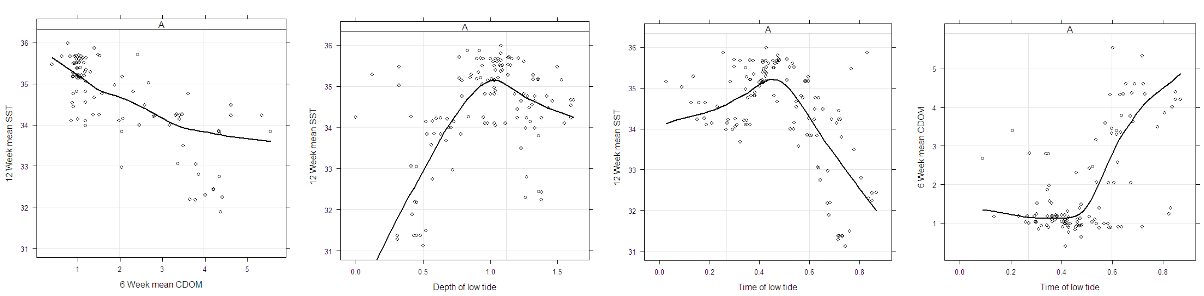


Figure 3.5. Examples of collinearity among variables. From left to right: SST vs. CDOM, SST vs. dlow, SST vs tlow, CDOM vs. tlow

Table 3.2. AIC scores of models with different dependence structures. 0 is a model with no variables specified. DF are the degrees of freedom.

Model	AIC	DF
0	7747.5	1
(1|timecat)	4180.9	2
(1|location)	6251.3	2
(timecat|location)	3356.5	11
timecat + (1|location)	3468.9	5

3.3 Building a dependence structure

The residual plots (figure 3.6) of the models with different dependence structures (random effects) confirm the earlier statements that the data were violating the assumption of independence. The null model showed patterns in the residuals for both location and time. The graphs of the other models display a lot of improvement, especially the models that include both location and time. Table 3.2 gives the different AIC scores of these models as well as the degrees of freedom. Both models with time and location scored better than other models. Note how the effect of time had a greater effect than location. The structure with both time and location as a random effect was used for further modelling for it had the best AIC score and shows the least patterns in the residual plots.

Models with fixed variables were also showing patterns in the variance when residuals were plotted against fitted values. This violates the assumption of homogenous variance on which GLMMs rely. For this reason time had to be added in the model. Adding time in these models took care of these patterns and already explained more than 30% of the deviance in a model without any fixed effects.

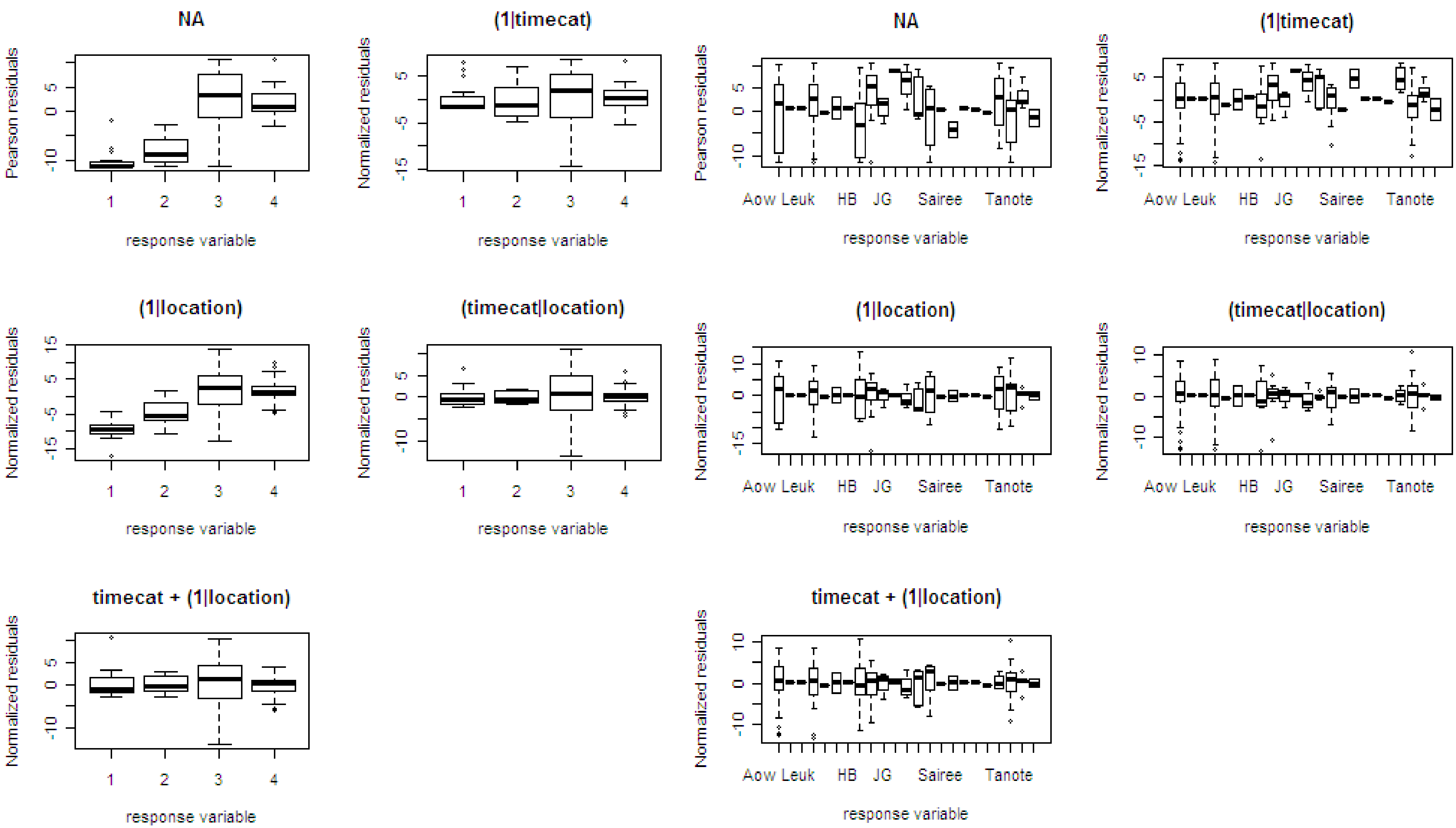


Figure 3.6. residual plots of the 5 models versus time and location. Both NA plots indicate a violation of independence. This violation is taken care of in the other models. The two models that contain both location and time show no patterns in their residuals anymore.

Table 3.4 Output of the both models built with approach 2. Model 3 is without Massive growth forms and model 4 with.

	Model 1				Model 2				Model 3				Model 4			
	Est	std	LRT	p	Est	std	LRT	p	Est	std	LRT	p	Est	Std	LRT	p
DHW	1.04	0.04	600.85	<0.001	1.00	0.04	588.75	<0.001	1.19	0.04	1111.80	<0.001	1.22	0.04	1141.60	<0.001
PAR	1.98	0.33	18.31	<0.001	1.55	0.33	9.31	0.002	-	-	-	-	-	-	-	-
DLOW	-0.27	0.08	9.76	0.002	-0.19	0.07	4.95	0.026	-	-	-	-	-	-	-	-
OSC	-0.07	0.03	4.75	0.029	-0.08	0.03	6.43	0.011	-0.32	0.05	42.32	<0.001	-0.32	0.04	35.79	<0.001
WIND	-	-	-	-	-	-	-	-	-0.17	0.07	0.76	0.382	-0.20	0.07	6.89	0.009
DHW:OSC	0.38	0.04	111.18	<0.001	0.33	0.03	90.61	<0.001	0.57	0.04	209.58	<0.001	0.53	0.04	190.76	<0.001
PAR:DLOW	-1.86	0.28	21.72	<0.001	-1.41	0.27	11.94	0.001	-	-	-	-	-	-	-	-
WIND:OSC	-	-	-	-	-	-	-	-	-0.48	0.05	80.85	<0.001	-0.54	0.04	93.03	<0.001
DM	-	-	-	-	-0.22	0.03	54.46	<0.001	-	-	-	-	-0.26	0.03	77.98	<0.001
	Model 5				Model 6				Model 7				Model 8			
	Est	std	LRT	p	Est	Std	LRT	p	Est	std	LRT	p	Est	Std	LRT	p
PAR	-	-	-	-	-	-	-	-	3.96	0.47	54.00	<0.001	2.69	0.53	20.55	<0.001
DLOW	-0.38	0.07	27.71	<0.001	-0.34	0.07	21.73	<0.001	-0.87	0.09	85.16	<0.001	-0.79	0.09	69.84	<0.001
OSC	-	-	-	-	-	-	-	-	-0.11	0.05	4.45	0.035	-0.09	0.05	3.08	0.079
WIND	0.18	0.05	13.28	<0.001	0.20	0.05	15.56	<0.001	-0.07	0.07	0.82	0.366	-0.03	0.08	0.14	0.706
CDOM	-0.24	0.05	20.88	<0.001	-0.24	0.05	17.09	<0.001	-0.77	0.07	91.89	<0.001	-0.66	0.08	64.86	<0.001
SSS	0.18	0.05	11.12	0.001	0.15	0.05	7.17	0.007	-	-	-	-	-	-	-	-
TLOW	-	-	-	-	-	-	-	-	-0.62	0.08	56.41	<0.001	-0.62	0.08	56.43	<0.001
TEMP	0.79	0.07	148.01	<0.001	0.78	0.07	146.03	<0.001	1.15	0.08	223.83	<0.001	1.11	0.08	205.60	<0.001
TEMP:OSC	-	-	-	-	-	-	-	-	0.20	0.05	14.74	<0.001	0.20	0.05	15.06	<0.001
TEMP:WIND	-	-	-	-	-	-	-	-	0.24	0.07	11.03	0.001	0.17	0.07	5.82	0.016
PAR:CDOM	-	-	-	-	-	-	-	-	-2.63	0.31	56.15	<0.001	-1.81	0.34	21.87	<0.001
DM	-	-	-	-	-0.21	0.03	47.85	<0.001	-	-	-	-	-0.16	0.03	21.92	<0.001

3.4 Model: approach 1

With the selected variables the following optimal GLMM was created:

```
Optimal model <- glmer (BL ~ dhw * wind + dhw * osc + dhw * depth
                 + dhw * dlow + PAR * tlow + PAR * CDOM + PAR *
                 dlow + domin + sss + (timecat|location), family =
                 binomial, weights = trials)
```

Stepwise selection of this optimal model resulted in the following model:

```
Model 1    <-    glmer   (BL   ~   dhw   *   osc   +   PAR   *   dlow   +
           (timecat|location),   family   =   binomial,   weights   =
           trials)
```

This model was refitted on a more complete dataset after which the likelihood ratio test was performed on all variables and interaction in the model. The output of the likelihood ratio tests are given in table 3.4. Only massive corals seemed to improve the model (AIC: model 1 = 1722.4, model 2 = 1669.9, model with random effects only = 3572). In model 1 the variable PAR has a strong correlation with the intercept (0.577) and DLOW had a strong correlation with dhw (0.528). In model 2 the correlation of PAR and the intercept had slightly been reduced (0.453), but DLOW and dhw still had a high correlation (0.552).

3.5 Model: approach 2

In the second approach to model coral bleaching, all variables and interactions were modeled separately and in all possible combinations that made sense theoretically. The output of all these models are given in Appendix III. Table 3.5 is a condensed form of the appendix with only the single fixed effect models and best scoring combinations. An assessment of the correlation coefficients revealed that from the best scoring models, the

Table 3.5 Condensed form of Appendix III. AIC and LRT output of models with different variables and combinations that were used for approach 2. The base model is a model that only has random effects. App. 1 is the winning model for approach 1 and app. 2 is the winning model for approach 2. All models were significant better than a model with only random variables as all LRT values were highly significant (p < 0.001) except for a model with Depth only (p = 0.03526)

Variables	**AIC**	**LRT**
Base	3356.5	NA
DHW	1904.7	1453.9
TLOW	2080.7	1277.8
CDOM	2113.1	1245.4
DLOW	2329.2	966.2
WIND	3122.7	235.9
Dominant	3139.5	223.1
PAR	3235.3	123.7
SSS	3259.8	98.8
OSC	3316.2	42.4
Depth	3354.1	4.4
Base Model Interactions		
DHW x OSC + DLOW + PAR x CDOM	1609.6	1760.9
DHW x OSC + PAR x CDOM	1620.2	1748.3
DHW x OSC + CDOM + PAR x DLOW	1620.2	1748.3
DHW + DLOW + PAR x CDOM	1641.1	1725.4
DHW x OSC + OSC x WIND (app. 2)	**1663.5**	**1703.1**
DHW x OSC x WIND	1665.5	1705
DHW x OSC + PAR x DLOW (app. 1)	**1667.2**	**1701.3**
DHW + PAR x CDOM	1687.2	1677.4
DHW + CDOM + PAR x DLOW	1692.4	1674.1
DHW x OSC	1761.8	1600.7
PAR x CDOM x DLOW	1834	1536.5

model `"dhw * osc + wind *osc"` did not show any strong correlation (> 0.5) among variables. Table x also gives the scores of the model created with the previous step. The model created with approach 2 (AIC 1663.5) scored better than the model created with approach 1 (AIC 1667.2) (AIC for the null model was 3356.5). The models with only single fixed effects also showed some interesting results. DHW, TLOW, CDOM and DLOW created significantly better models than WIND, DOMIN, PAR, SSS, OSC and DEPTH. Combining these variables in a single model caused the model to improve but not as much as would be expected from the variable's individual effects.

The final model was refitted on a more complete dataset after which the likelihood ratio test was performed on all variables and interaction in the model. The output of the likelihood ratio tests are given in table 3.4. After the model was refitted, the percentage of a certain growth form was added to see whether this improved the model. As before, only massive corals improved the model (AIC: model 1 = 1781, model 2 = 1705).

3.6 Model: approach 3

The Scree test revealed that four factors were adequate for a factor analysis based on the variables in the first column of table 3.1. Of these 4 factors the first factor explained 42% of the variance and contained all temperature data as well as time of low tide, CDOM and PAR. The second factor explained 15% of the variance and contained wind, currents and depth of low tide. These first two factors were used to create artificial variables that were used for further modelling. The following factors were created based on the output in table 3.6:

- Factor 1: the Aqua-MODIS factor
    - DHW + DHWdeg + SST12 + CDOM + PAR12
- Factor 2: the Temperature factor
    - DHW + DHWdeg + SST12
- Factor 3: the Flow factor
    - OSC + WIND + DLOW

Table 3.6. Output of the factor analysis. The lower a uniqueness values the more similar is the variance of a variable compared to other the other variables. Note how SST, DHWdeg and Tlow have a similar variance as the uniquenesses are very low and all three variables correlate strongest with the first factor. Test of the hypothesis that 4 factors are sufficient. The chi square statistic is 45.27 on 11 degrees of freedom. The p-value is 4.35e-06 (Values below 0.25 are not displayed)

	Uniquenesses	**Factor 1 (42%)**	**Factor 2 (15%)**	**Factor 3 (12%)**	**Factor 4 (5%)**
DHW weeks	0.32	0.82	-	-	-
SST	0.03	0.98	-	-	-
DHW degrees	0	0.99	-	-	-
CDOM	0.23	-0.74	-	-.043	-
TLOW	0	0.84	-	-	-0.53
PAR	0.57	-0.54	-	-	-
OSC	0.63	-	0.54	-0.27	-
WIND	0	-	0.85	0.51	-
DLOW	0.38	-	-0.62	-	0.46

Table 3.7 AIC, BIC LRT and LogLikelihood scores of the factors and variables used to create the factors modeled against bleaching with random effects. Scores are comparable with table 3.4 (same dataset was used). LRT is based on a comparison to a model with random effects only (p < 0.001 for all models).

Variable	**AIC**	**LRT**
Aqua MODIS	1810.7	1547.8
Flow	2992.0	366.5
Temperature	1802.4	1556.2
DHW + DHWDEG +SST12 + CDOM + PAR	1742.0	1622.5
DHW + DHWDEG + SST12	1753.4	1609.2
OSC + WIND + DLOW	2444.1	918.5

Table 3.7 gives a comparison of the different factors versus the variables used to build the factor. The temperature factor indeed improved the model when comparing it with a model that contained dhw, sst or dhwdeg only (Table 3.5 and Appendix III). The other factors did not show any improvement in the model. The flow factor for example scored much lower than DLOW did individually.

The temperature factor was then used to model the data following approach 1 and 2. Approach 1 was conducted twice in which collinearity among variables was fully ignored once. This resulted in the following models:

```
Optimal model <- glmer (BL ~ temp * wind + temp * osc + temp *
                dlow + PAR * tlow + PAR * CDOM + PAR * dlow +
                domin + sss + (timecat|location), family =
                binomial, weights = trials)

Final model 5 <- glmer (BL ~ temp + CDOM + wind + dlow + sss +
                (timecat|location), weights=trials, family =
                binomial)

Final model 7 <- glmer (BL ~ temp * sosc + sPAR11 * scdom + temp
                * swind6 + sdlow + stlowcor + (timecat|location),
                weights = trials, family = binomial)
```

These two models were not refitted as no extra data was acquired. The percentages of certain growth forms were added. Again, only massive growth forms seemed to improve the models (AIC for the first model from 1683.9 to 1637.2 (start 3353) and for the second model from 1595.0 to 1575.1). The LRT outputs of these models are given in table 3.8.

The models that were created with second approach are given in Appendix IV. This time the model with the highest AIC did not show any strong correlations among variables and was the best model. This model was refitted and improved with adding massive growth forms (AIC from 1649.8 to 1628.5, null AIC was 3353). The output is given in table 3.8

Table 3.8 Output of model 9 and 10, Likelihood Ratio Test was performed on the full model and the full model minus the specific variable or interaction.

Model 9	**LRT**	**p**	**est**	**std**
intercept	-	-	0.37	0.11
temp	168.9	0.00	0.77	0.06
osc	1.4	0.23	0.04	0.04
dlow	59.4	0.00	-0.56	0.07
PAR	41.0	0.00	2.97	0.42
CDOM	65.7	0.00	-0.51	0.06
temp : OSC	4.7	0.03	0.10	0.05
PAR : CDOM	42.2	0.00	-1.97	0.28
Model 10				
intercept	-	-	0.29	0.12
temp	151.8	0.00	0.73	0.06
osc	3.5	0.06	0.07	0.04
dlow	45.3	0.00	-0.50	0.07
PAR	15.2	0.00	1.98	0.46
CDOM	46.4	0.00	-0.44	0.06
dm	23.3	0.00	-0.16	0.03
temp : OSC	3.5	0.06	0.09	0.05
PAR : CDOM	15.9	0.00	-1.33	0.30

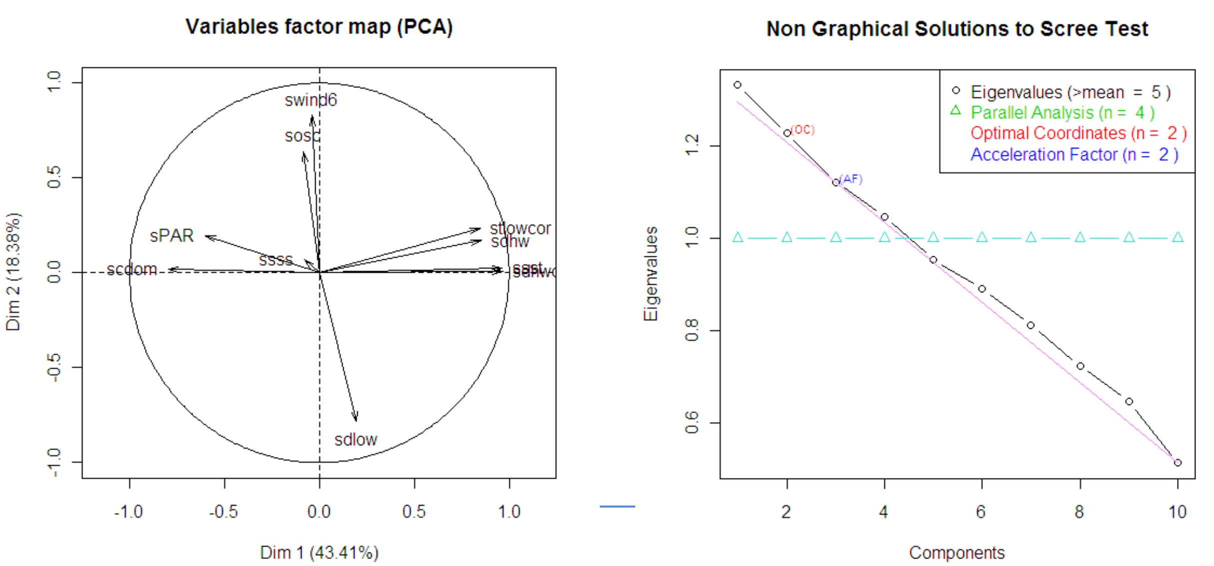


Figure 3.7 Plots for validating the number of factors needed for the analysis (Non Graphical Solutions to Scree test)

3.5 All models together

To validate the ten final models the normalized residuals and observed values were plotted versus the fitted values. These plots are displayed in appendix V. The models that scored best were those with the temperature factor. Table 3.10 displays several parameters that were interpreted for the different model. The models that were constructed by approach 2 generally scored better. The best model was model 10, which showed the least patterns in the residuals and gives the straightest line for the plots of observed versus fitted values. Moreover, this model did not have any strong correlations among its variables. On other parameters most models scored similarly. None of the models explained significantly more deviance than any of the other models.

Model 9 was subsequently used for predicting coral bleaching from raster data. As the variable Massive growth form is not available as raster data the model without this variable was used. The predicted values from this model were plotted against the observed values (figure 3.8). Looking back at table 3.2, one can see that most of this deviance is taken up by time; this causes the bad predictions for model 9. For this reason the model was reconstructed in which time was a fixed effect. In the original model time

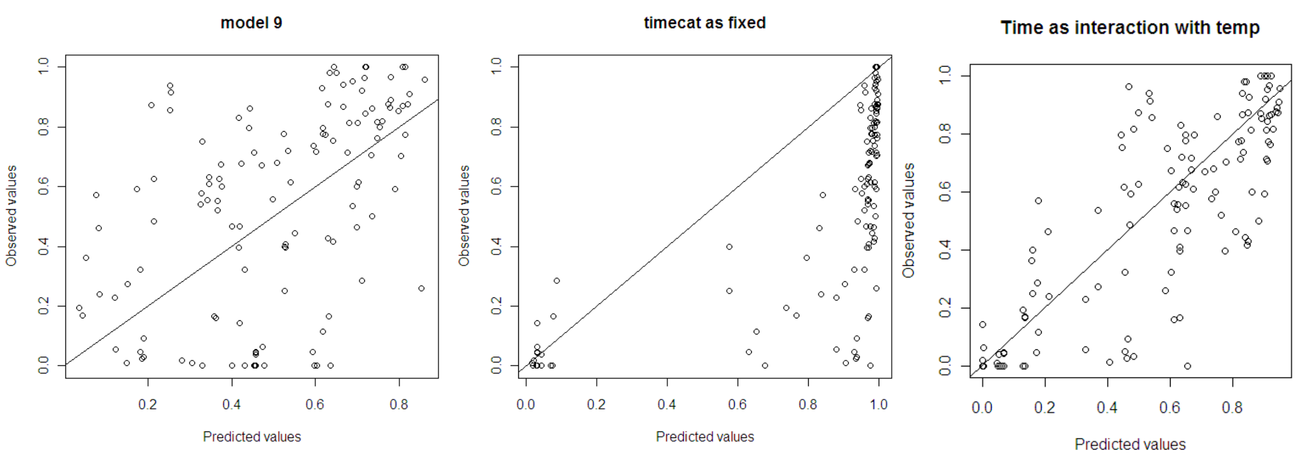


Figure 3.8 Predicted values versus the Observed values for 3 models. Left: Model 9 predicted values. Middle: Model 9 with time as a fixed effect (intercept).Right: Model 9 with time in an interaction with temperature (slope).

is a random slope. Therefore, time was added in an interaction with temperature. Because temperature was the most important variable in the model (Table 3.8), it is likely to have accounted for most of the variance corrected by time in the original model. Figure 3.9 displays the residuals of this model versus the predicted values. There is no clear violation of the assumption of homogeneous variance. The predicted values of this model matched the observed values much better than the other models (figure 3.8) this did not count for the fitted values because these also accounted for the random effects. The AIC of this model was considerably higher (from 1650 to 1703) and the percentage of explained deviance was also lower (from 77.8% to 76.5%). Therefore the model was not as good as model 9. However, more deviance was explained by the fixed effects, which made the model more appropriate for predictions (from 23.7% to 62.63%). The output of this model showed that all the estimates for the time categories when time was included in the model in an interaction with temperature were highly significant ($p = >0.001$) except for the second time period. Therefore predictions showed higher errors in this period than the original model 9. During other periods model 9 was expected to predict better (Figure 3.10). The following three equations were used to create bleaching probability maps from the raster data:

```
Equation 1: Model 9 with DLOW set to zero

    Bleaching =  0.371 + (0.768 * temp) + (0.043 * sosc) + (-
    0.56 * sdlow(0)) + (2.971 * sPAR11) + (-0.514 * scdom) +
    (temp * sosc * 4.743) + (sPAR11 * scdom * -1.972)


Equation 2: Model 9 with both DLOW and OSC set to zero

    Bleaching =  0.370 + (0.769 * temp) + (0.043 * 0) + (-0.560
    * sdlow(0)) + (2.971 * sPAR11) + (-0.514 * scdom) + (temp *
    sosc * 4.743) + (sPAR11 * scdom * -1.972)
```

```
Equation 3: Time as fixed effect

    Bleaching = - 1.185 + 0.102 * sosc + sdlow (0) * -0.518 +
    0.888 * sPAR11 + scdom * -0.196 + sPAR11 * scdom * -0.602 +
    temp * timecat(Y) + temp * sosc  * timecat (Y)
```

The first equation is the fixed part of the original model 9 (depth of low tide is set at 0), the second equation is the fixed part of model 9 without OSC data and the third equation is based on model 9 but has time added as an interaction with temperature.

Table 3.9 gives an overview of the predictive ability of these 3 models and the unaltered version of model 9 and 10. Model 10 was predicting much better than model 9 (error is more than 10% smaller). The model with time as an fixed effect also predicted better than model 9. For model ten 48.15% of the predicted values were within a 25% range from the observed values for the time as fixed effect model this is 44.44%. The time model generally underestimated bleaching, as figure 3.10 displays. The other models did not show any pattern in the predicted values.

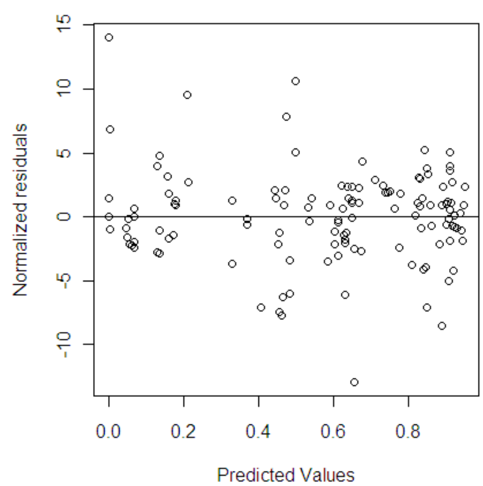


Figure 3.9 Normalized residuals versus predicted values for the model with time in an interaction with temperature. Except for a few outlier there seem to be no patterns in the residuals

Table 3.9. Comparison of predictive ability of several models. These values are very approximate as no real control sites were available. The control observations differ from normal observations in the origin of depth data. Which has a major effect on PAR.

	Model 9	**Model 9 - dlow**	**Model 9 – dlow osc**	**Time as fixed**	**Model 10**
Average Error	44.09 %	44.09 %	31.59 %	36.28 %	29.99 %
Average Error in time period 1 and 2	54.28 %	54.28 %	39.34 %	33.28 %	40.17 %
Average Error in time period 3 and 4	41.03 %	41.03 %	29.27 %	37.19 %	26.94 %
Control within 25% of predicted values	37.04 %	37.04 %	48.15 %	44.44 %	48.15 %
Weighted Average Error	54.95 %	55.19 %	40.80 %	41.30 %	39.61 %
Weighted Average Error in time period 1 and 2	53.60 %	52.11 %	40.11 %	33.57 %	40.27 %
Weighted Average Error in time period 3 and 4	55.17 %	55.70 %	40.92 %	42.56 %	39.51 %

Figure 3.11 and 3.12 give an impression of prediction maps based on the earlier given equations. In the first row the maps of model 9 with DLOW and OSC set to zero are displayed. The second row shows the maps in which currents were not set to zero. The last row displays the predictions of the time model. The second image of (26/6/10 – 14/9/10) is from the second time period, it heavily overestimates bleaching. In figure 3.12 the images of this model are more realistic than of the other models due to the higher percentage of deviance explained by the time model. Figure 3.12 displays some summarizing images based on this model. What the images show is the average probability for coral bleaching during the period 1/1/10 to 14/9/10 of which we can

assume that this is an underestimate (Figure 3.10) with an averaged error of 41.3 % (Table 3.9).

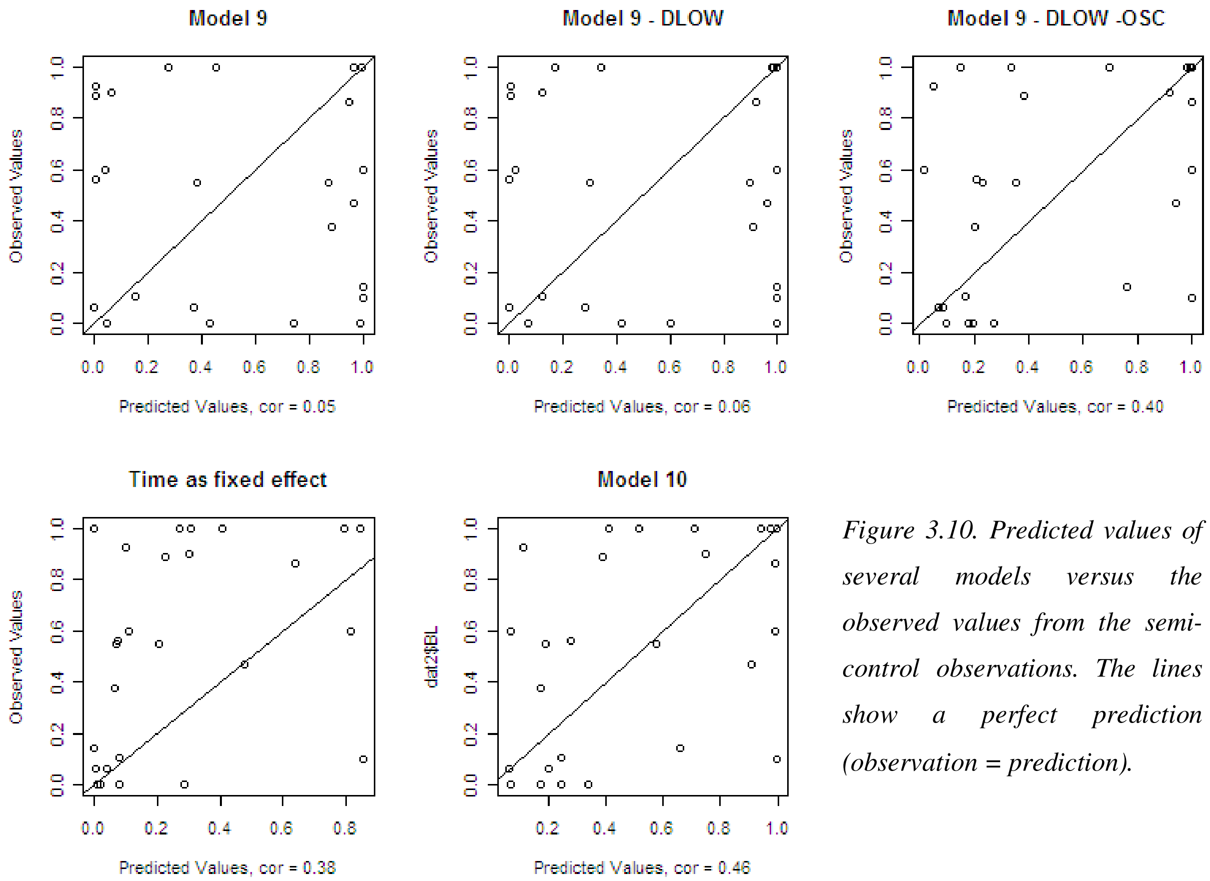


Figure 3.10. Predicted values of several models versus the observed values from the semi-control observations. The lines show a perfect prediction (observation = prediction).

Table 3.10 Comparison of all models. The AIC Scores are only comparable within a column and among those models for which the scores are similarly colored. "Dev" = Deviance, "0" = model with no parameters, "R" = model with random effects only, "DF" = Degrees of Freedom, "Correlation" = Variables that had strong correlations in the model."Res vs Fit" = Residuals versus fitted values, "Fit vs Obs" = Pearson's correlation coefficient of fitted and observed values."(F)" = Fixed effects, "(R)"= Random effects, "(T)" = Total, "Transect" = Number of transects used in analysis.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Dev 0	7665.2	7661.1	7901.7	7901.7	7247.9	7247.9	7247.9	7247.9	7247.9	7247.9
Dev R	3554	3550	3589	3589	3331	3331	3331	3331	3331	3331
Dev E	1691	1634	1749	1671	1651	1603	1553	1531	1614	1590
DF	17	18	16	17	16	17	21	22	18	19
Correlation	par vs int, dlow vs dhw	dlow vs dhw slightly	NON	NON	cdom vs temp, sss vs temp	cdom vs temp, sss vs temp	tlow vs temp, tlow vs dlow,osc vs wind, par vs cdom	tlow vs temp, tlow vs dlow,osc vs wind, par vs cdom	NON	NON
Res vs Fit	BAD	BAD	OK	OK	GOOD	GOOD	BAD	BAD	GOOD	GOOD
Fit vs Obs	0.886	0.889	0.898	0.897	0.901	0.899	0.906	0.905	0.905	0.903
Transects	146	135	145	145	127	127	127	127	127	127
AIC (R)	3576	3572	3611	3611	3353	3353	3353	3353	3353	3353
AIC (E)	1725	1670	1781	1705	1683	1637	1595	1575	1650	1628
Dev (R) %	53.6%	53.6%	54.6%	54.6%	54.0%	54.0%	54.0%	54.0%	54.0%	54.0%
Dev (F) %	24.3%	25.0%	23.3%	24.3%	23.2%	23.8%	24.5%	24.8%	23.7%	24.0%
Dev (T) %	77.9%	78.7%	77.9%	78.9%	77.2%	77.9%	78.6%	78.9%	77.7%	78.1%

Figure 3.11 Probability maps based on equation 1, 2 and 3. The model output for the model with time in an interaction with temperature showed that during the second time category the results are highly insignificant. This results in the misclassification of bleaching during this period for this model (the red colored map). For other periods this model is probably more accurate than the other models as approximately 40% more deviance is explained by fixed effects of this model.

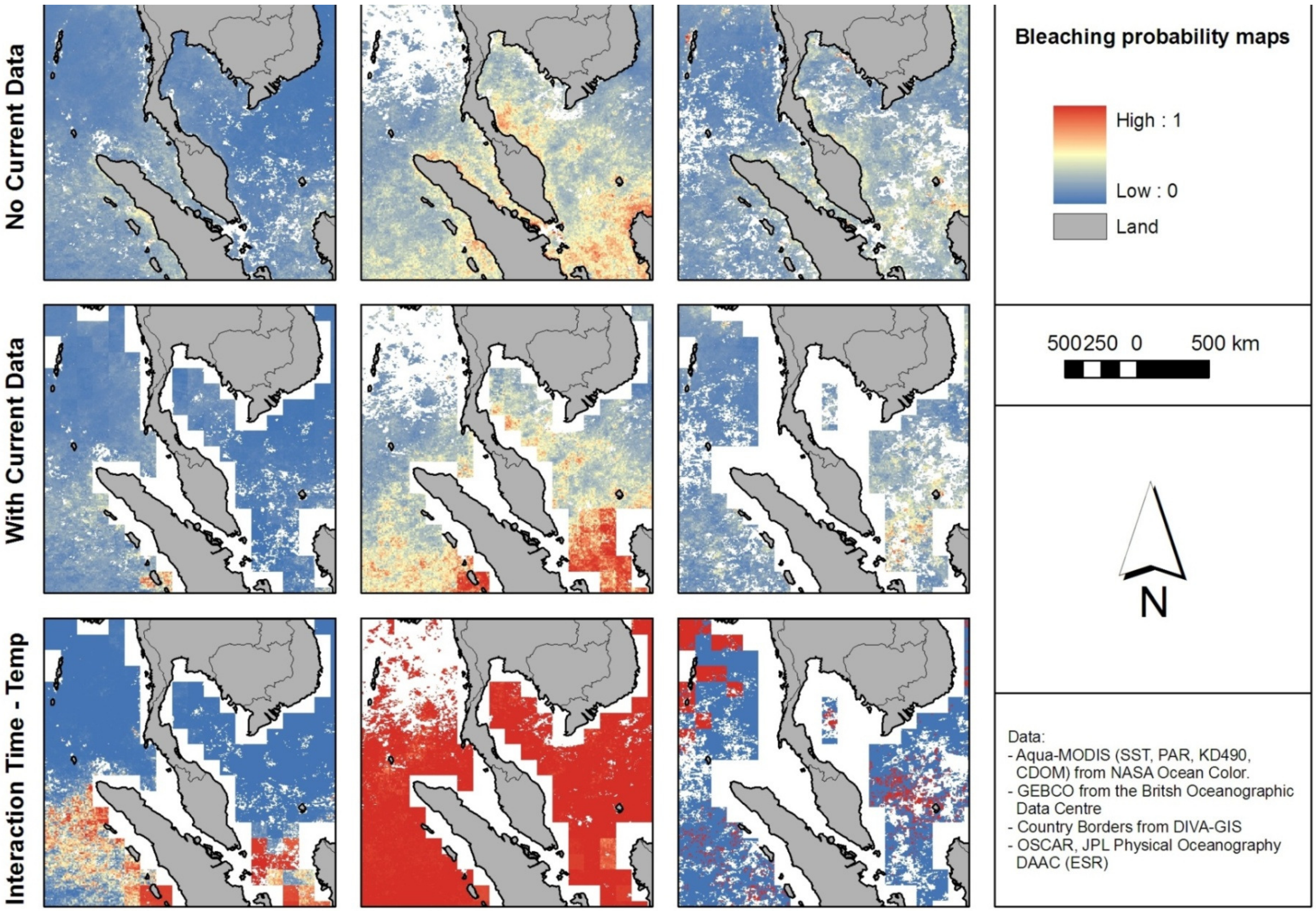


Figure 3.12 Probability maps based on equation 1, 2 and 3. Note how the maps that do not include OSC, show much lower bleaching than the maps with OSC. Setting variables at zero appears to have a big effect on the maps. Remember that the depth of low tide was also set to zero for all models.

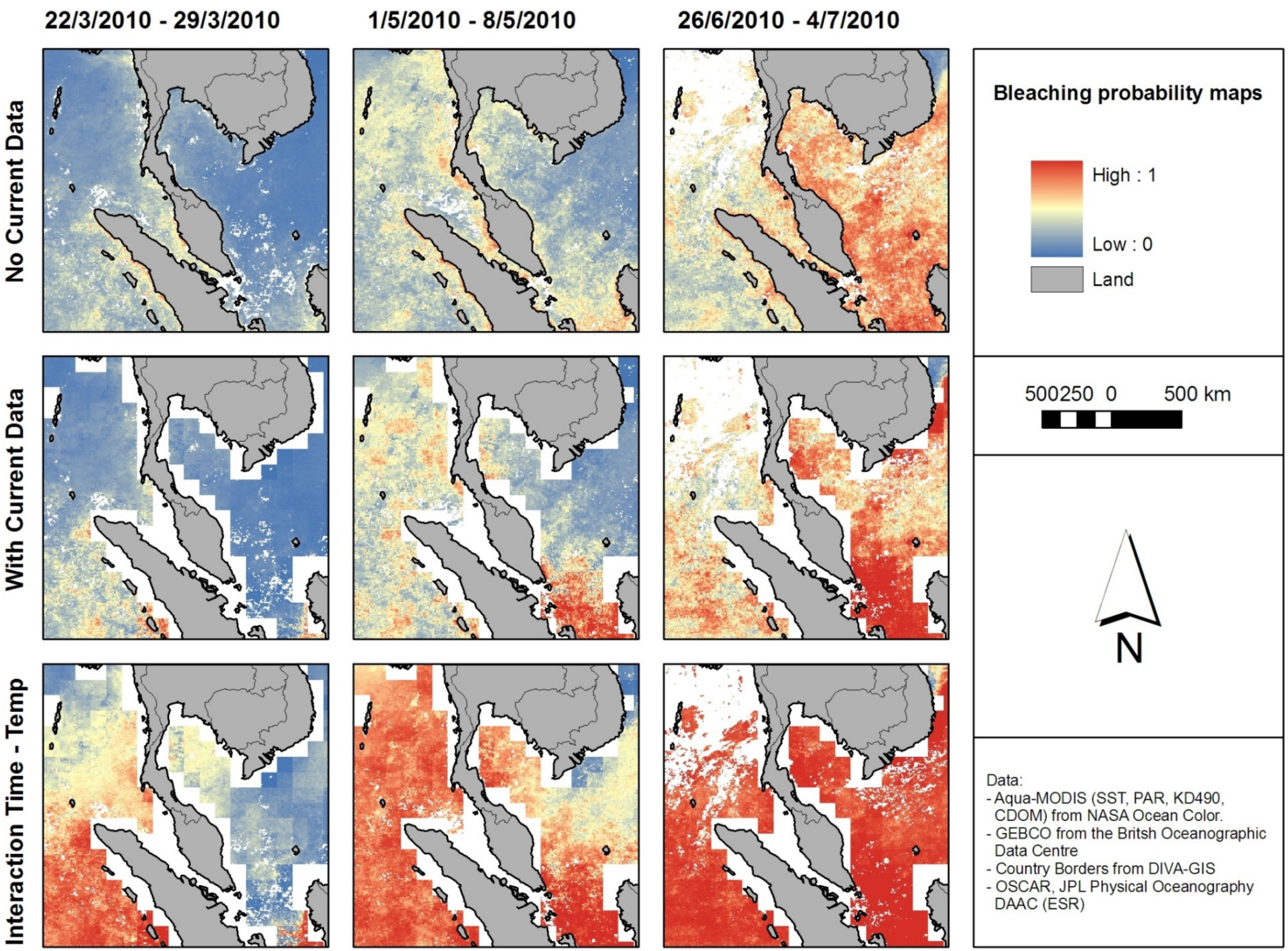
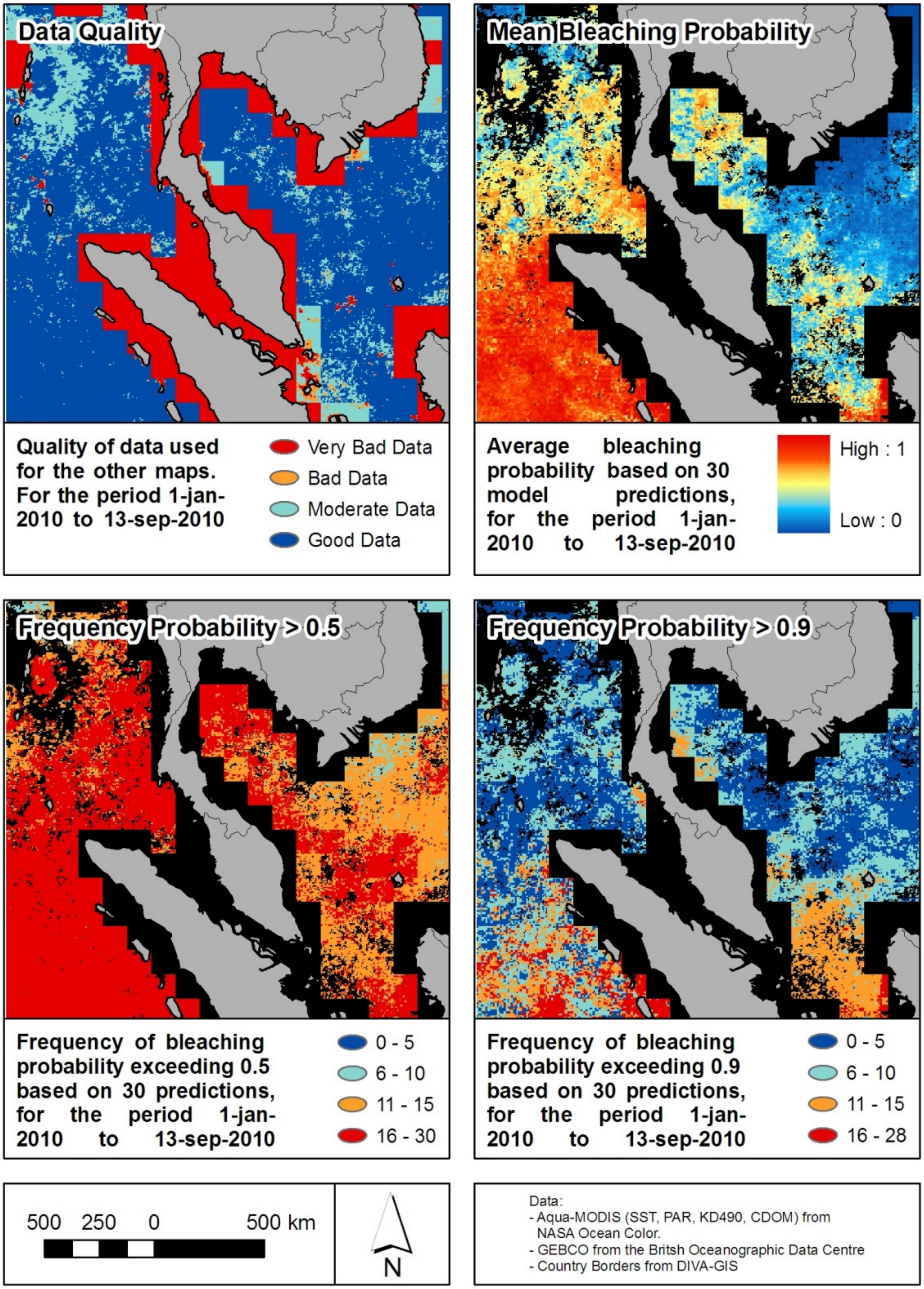


Figure 3.13 Summarizing figures for the prediction maps based on the model with time in an interaction with temperature for the period 1/1/2010 to 14/9/2010. The first map gives a general idea about data availability. Data that did not score well are masked (black) in the other figures.



4 Discussion

Seventy-eight percent of the deviance was explained by the final model. Regarding the fixed effects only, most of the deviance was explained by temperature followed by CDOM, depth of low tide, massive growth forms, PAR and OSC. Even though, PAR itself was not very strongly related to bleaching, parameters that influenced PAR like CDOM and depth of low tide did show strong relationships. This showed that after temperature solar radiation did affect bleaching most strongly, but that PAR data without correcting measures did not represent this.

The model that ignored collinearity among variables showed more significant relationships and interactions (a temperature and wind interaction and time of low tide effect). Moreover, a factor analysis on the environmental variables showed that temperature, CDOM, PAR and time of low tide are very closely related. This indicates that the deviance explained by temperature could also partially be accounted for by these closely related variables (especially time of low tide). The probability maps that were based on the best predicting model showed that reefs in the Gulf of Thailand bleached less than reefs in the Andaman Sea and Strait of Malacca.

In the following paragraphs the results will be discussed and compared with other modelling studies. First a detailed interpretation of the final model will be given in which all included variables and interactions are described. This is followed by the interpretation of the probability maps. In the last section of this chapter the accuracy of the prediction maps, the input data and the final model are discussed.

4.2 Model Interpretation

Model ten was the best model; therefore this model was selected for an interpretation of the environmental variables. This model included temperature, OSC, depth of low tide, PAR, CDOM and interactions between temperature and OSC and between PAR and

CDOM. The model in which collinearity was ignored had a much better AIC score and involved more variables. Time of low tide was highly significant in this model and also created the best single effect model after temperature. Moreover, the factor analysis showed that temperature and time of low tide were highly correlated. For this reason it is not clear whether all the effects ascribed to one of the collinear variable are caused by that particular variable. Removing collinear variables as was done for the final model causes the same issues, because now it is unclear whether all deviance explained by temperature was actually caused by temperature and not by one of the removed collinear variables (Graham 2003, Obrein 2007).

The final model explained 78% of the deviance. Beside fixed effects the model also contained a random slope for time with a random intercept for location. These random effects take up 54% of the deviance explained and the fixed effects 24%. Without these random effects the model shows very strong patterns in the residuals. Most of the deviance explained by the random effects came from the time variable (37%). The percentage explained by the random effects is rather high. In the study by Yee *et al.* (2008) time also explained a lot of deviance and location explained less deviance; however, the deviance explained by the environmental variables is much higher. The current study only regards a single bleaching event whereas the study by Yee *et al.* (2008) concerns an eight year time span with 287 surveys. The influential role of time could be explained by the fact that only a single bleaching event was modeled. The spatial distribution of the data was not optimal as they were clustered around Koh Tao (the semi control sites were more equally distributed). This is a good explanation for why so much deviance is explained by the random effect location. A more homogeneous spatial distribution of the in situ data addressing several bleaching events could have avoided the strong influence of the random effects time and location. However, in the study by Yee and Barron (2009) which regarded a global dataset, time and space were also found to explain much more deviance than the actual environmental variables. In their study 708 surveys were used over a time span of eight years suggesting that using more widely distributed data including several bleaching events may not solve this problem. Moreover, this study concludes that the model is suitable for predicting bleaching; based on cross validating the model on subsets of the data (this could not be done for the current study as only 127 surveys were available instead of 708). However, regarding time as a variable only allows predicting within the period of observations that were used for fitting the models. Removing this variable will reduce the accuracy of their predictions significantly, as is observed in the current study.

Clearly temperature was the most significant variable (LRT = 151.8, p = 0) as expected. The modelling studies by Maina *et al.* (2008) and Yee *et al.* (2008) show similar results, as displayed in table 4.1. Yee *et al.* (2008) used clustered binomial regression for their analysis and reported an estimate of 0.67 (std 0.07) for their temperature variable; degree heating weeks. Temperature in the final model of this study had an estimate of 0.73 (std 0.06). Even though the temperature data are not similar (DHW vs. Temperature Factor) they still seem to affect the model similarly. Maina *et al.* (2008) used a combination of several temperature parameters as individual effects, which created better results than using a single temperature variable at least from a predictive point of view; this is in agreement with use of the temperature factor in the current study.

The interaction between temperature and currents was not significant in the model (LRT = 3.5, p = 0.062) but removing the interaction from the model increased the AIC. The same could be said for the OSC data as an individual effect. The study by Maina and his colleagues (2008) used velocity data from the same source, but modeled the meridional and zonal currents as two separate variables. The two variables did not respond similarly; with increased meridional currents the bleaching probability was reduced and with increased zonal currents the probability of bleaching also increased. The fact that a combined variable was used in this study could possibly explain why currents do not show a strong relation with bleaching. Another explanation could be the fact that corals respond different to currents depending on the environmental situation. Where some studies suggest that currents are tempering the effect of increased

Table 4.1 Comparison of the final model with model results from Maina et al. 2008, Yee et al. 2008, Yee & Barron 2009.The values given are the estimates in the final models.

Variables for which hypotheses where tested	**This Study**	**Maina *et al.* (2008)**	**Yee *et al.* (2008) (all taxa model)**	**Yee & Barron (2009) (moderate bleaching model)**
Temp	0.734	Max SST, DHW, SST, slope SST	0.67 (DHW)	0.93 (DHW)
Temp * Depth	NA	NA	0.014 (DHW * depth)	0.1
Temp * wind/current	0.085	Wind, OSC	NA	NA
PAR	1.987	UV, PAR	6.12 ln(PAR)	-6.64 ln(PAR)
PAR * CDOM	-1.329	not tested	not tested	not tested
PAR * dlow	NA (collinear temp)	not tested	not tested	not tested
PAR * tlow	NA (collinear temp)	not tested	not tested	not tested
Salinity	NA	not tested	not tested	not tested
Community	-0.158 for massive	not tested	Massive corals bleach less	not tested

temperatures by mixing and cooling seawater (West & Salm 2003) other studies suggest that cool upwelling with low oxygen levels can also induce bleaching (Phongsuwan 2010). Some studies even suggest that high water flow creates a narrow environment which makes corals in these areas more susceptible (Maina 2007).

The effect of PAR in the model was much stronger than temperature but it was less important as the LRT only scored a tenth of the score for temperature (15.2, $p < 0.0001$). Increased PAR did increase the probability of bleaching. The estimate of 1.97 (std 0.46) for PAR was much higher than that of temperature so small changes in PAR more strongly influenced the model output than changes in temperature. In the study by Yee *et al.* (2008) the natural logarithm of PAR was modeled instead of the actual values. They reported an estimate of 6.12 (std 2.17) but the variable ln(PAR) was part of an interaction with DHW, this makes it difficult to compare these results. However, the shared high estimates suggest similarity. In another study by Yee and Barron (2009) high estimates for ln(PAR) were found as well, and only a small percentage of additional deviance was explained. In this model the estimate was negative however, suggesting that bleaching decreases with increased ln(PAR). This is similar to an increase of bleaching with an increase of unconverted PAR data (without the natural logarithm).

PAR was also involved in an interaction with CDOM. CDOM which absorbs radiation, reduces the effect of PAR on bleaching (estimate = - 1.329, std = 0.3). This interaction was slightly more important in the model than PAR itself. This is consistent with Dunne's (2008) comments on Maina et al's (2008) study in which PAR data are stated to be inaccurate if not corrected for depth and turbidity/water type. It seemed that CDOM strongly alleviated the effects of a high estimate for PAR. These CDOM data are not taking care of all the effects of a turbid water column like for example scattering (West & Salm 2003, Vassilkov *et al.* 2005, Li 2005, Veal *et al.* 2009), but it indicates that turbidity is indeed very important to efficiently use these PAR data. When regarding CDOM apart from the interaction with PAR it was three times more important in the model than PAR (LRT 46.4, $p < 0.001$). Yee and Barron (2009) mentioned in their study that turbidity did not play a significant role, but also that models with variables other than temperature did not improve their model in the Asian region. Turbidity appears to have a very significant role, at least for the Thai-Malay peninsula, and this may explain why their model performed worse in this region.

The variable massive growth form showed that if the coral community is composed of more massive corals the probability of bleaching is reduced. In other words there is a different response to bleaching among different growth forms, in which massive growth forms are less likely to bleach. Other growth forms did not significantly improve the model so this effect can fully be ascribed to massive corals. Yee and her colleagues also modeled individual species, of which those that correspond more or less to massive growth forms are less susceptible (like for example *Montastraea sp.*). This is also seen in an experimental study by Schloder and D'Croz (2004). Massive growth forms are often more abundant in shallower waters and in areas with higher sedimentation rates (as they are least susceptible to getting covered by sediment) (Dunne *et al.* 2002). Due to this more hostile environment the corals build a natural resistance to environmental extremes.

The depth of low tide also played a highly significant role in the model (LRT = 45.3, $p < 0.001$) in which lower tides increased the probability of bleaching. In this model these data were not part of an interaction with PAR as proposed in the hypotheses. This interaction did not improve this model. However, other models (with strong correlations and collinearity among variables) did show a significant interaction between PAR and the depth of low tide. This suggests that there is an interaction with tidal data and PAR, but the importance of the effects of this interaction could not be detected in the current study. Models based on single fixed effects (Appendix III and IV) showed similar results; after degree heating weeks (AIC 1904.7 start AIC = 3356.5), the time of low tide (AIC 2080.7) created the best model. This means that there is strong evidence that tidal data can improve bleaching predictions significantly, which is supported by many studies (Brown *et al.* 2000, Dunne & Brown 2001, West & Salm 2003, Anthony & Kerswell 2007, Chavanich *et al.* 2009)

4.3 Interpretation probability maps

Figure 3.11 and 3.13 display bleaching probability maps for the three equations based on model 9 for eight day periods. The mean bleaching probability map is based on the outputs of the time model. Only data are visualized for which 22 or more predictions were available, otherwise means would be based on too few predictions. This rough estimate is an indication for the bleaching severity during the 1/1/2010 to 14/09/2010. There was a clear difference between the Gulf of Thailand and the Andaman Sea, the average probability was much higher in the Andaman Sea. The frequency of bleaching probability exceeding 90% showed that especially the areas near Koh Phuket/Koh Phi Phi and Koh Samui had extended periods in which the bleaching probability reached 90% or higher. The probability of bleaching appeared highest on the west coast of Sumatra (Indonesia) and lowest in the South China Sea. It is most likely that the appearance of these two fronts have caused the differences in bleaching severity between the Gulf of Thailand and The Andaman Sea. Cooler water from the South China Sea kept the environmental condition under relative control for the Gulf of Thailand. The hotter water from the Indian Ocean resulted in the opposite in environmental conditions in the Andaman Sea and Strait of Malacca. However, detailed OSC data were not available so this is difficult to conclude. OSC are of high interest as these are not only helpful for coral bleaching modelling but also for coral restoration in the focus of coral spawning and recruitment (Oliver *et al.* 1992, Galindo *et al.* 2006). Moreover CDOM data had generally higher values in the Gulf of Thailand which indicates that radiation related bleaching was also causing these differences.

4.1 Accuracy

4.3 The Data

PAR, KD490 and CDOM contained many missing values in the original data. Calculated averages were therefore not based on the same number of pixels, this was unavoidable with the size and region of the current dataset. The region consists of many islands and irregular shaped coastlines, causing a high coast-sea ratio.

The raster data generally performed poorly in coastal areas. Looking at Aqua MODIS in particular, there are hardly any pixels used for fitting and validating the model that were of good quality. The exact error is unknown for Aqua-MODIS data (Nahorniak *et al.* 2005). One could choose to use pixels that are at least 4km off shore to avoid this problem, but do these values represent the actual situation at the reefs near shore? These reefs are often exposed to fewer currents, more turbidity (erosion/deforestation) and more heating (shallow and still waters) than off shore reefs (Brown *et al.* 2002, Thompson & Dolman 2009, Thompson & Woesik 2010).

The in situ data on bleaching were collected with standardized methods that do not leave room for subjectivity or at least for the EMP and Coral Watch data. The ReefBase data were rejected as the data seemed inaccurate. The inaccuracy of the

ReefBase data can have several causes like inaccurate dates, inaccurate GPS location or missing variables in the dataset of this study.

The Model

As there were no mapped tidal data available, this variable was set to zero. The question remains, how did this influence the results of the output maps? Removing DLOW did not influence the predictive ability a great deal. Table 3.9 showed that the errors are the same. Setting currents at zero actually reduced the errors from the semi-control observations. From this we can conclude that setting DLOW at zero for the time model does not substantially change the predictions.

The PAR data used for fitting the model were based on in situ depths whereas the semi control sites used averaged depths for 0.9 km squares. The error resulting from this may have been large because some sites close to shore are now situated above sea level. This causes extremely high PAR values, which in turn, has a rather large effect on the accuracy of the prediction because of the high estimate. This is very well displayed in figure 3.8 and 3.10. It shows how the predictions made on data with GEBCO depths were less accurate than for those with in situ depth. This could also be ascribed to the fact that the later set was used to calibrate the model, so it will be more accurate in the first place. However, the prediction would be much more accurate if detailed bathymetry data was available. The GEBCO bathymetry data gives positive depths for many sites close to shore. Therefore, PAR values increase instead of decrease when they are corrected for depth, this gives absurd values. Take for example an uncorrected PAR value of 1.5 einstein/m^2/d with a KD490 of 0.05 and a depth of 8m. Using Beer's Law this results in a corrected PAR value of 1.006. If the depth was for example 6 meters above sea level because GEBCO data was used, the corrected PAR value would be 2.238 einstein/m^2/d. This does create a very rough error estimate for the coastal areas.

As example, bathymetry data were manually digitized for Koh Tao to display the strong effects of using more detailed bathymetry data. This clearly gave a lot more detail and accuracy and highlights the importance of using detailed bathymetry data for correcting PAR (Figure 4.1). The map shows high probabilities close to the coast and much lower probabilities of shore. All the reefs on Koh Tao are situated close to shore (Weterings 2010 *in press*) and had an average probability of 84% in the period 24/5/10 to 1/6/10. The average probability for the remaining area was 75%. Bleaching probability for the whole area based on the GEBCO data was 76%. This clearly displays the additional error of 8% caused by using less detailed bathymetry data and highlights the importance of correcting PAR data in predictions models.

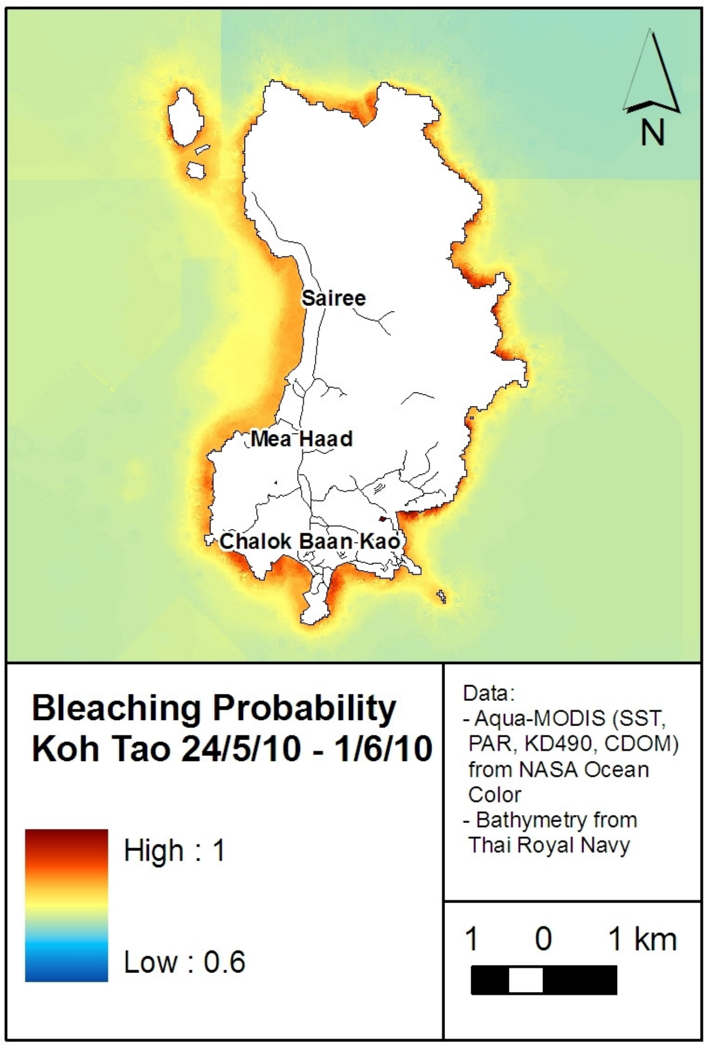


Figure 4.1 Prediction map for Koh Tao based on properly corrected PAR data. The hotter colors indicate the highest probability these areas are also the locations of the reefs.

5 Conclusions

This study showed that temperature, PAR, location, time, CDOM, DLOW and OSC were important for coral bleaching in the 2009/2010 event for the Thai-Malay peninsula. Moreover there are very strong indications that time of low tide was also important for this event, but the exact effects remained unknown due to very strong collinearity with temperature. Collinearity among environmental variables made it also difficult to assign the entire temperature effect to the temperature variable (Graham 2003, Obrein 2007) which is a very common but not acknowledged problem in coral bleaching models.

Accurate predictions are difficult as time and location are variables that explain much deviance in some of the few modelling studies. Therefore, predictions with these models are only accurate within the period and area of the study. This requires constant refitting on new in situ data if these models are supposed to predict the near future. This can be realized by combining bleaching detection techniques (Clark *et al.* 2000, Yamano & Tumara 2004, Hochberg *et al.* 2004, Mumby *et al.* 2004a, 2004b, Hanaizumi *et al.* 2008) with the environmental data. This will give response variables in raster format that allow more detailed modelling, with very large sample sizes.

The current study also showed that the effects of PAR data are very strongly mediated by turbidity. Moreover, variables that influence the effects of PAR like turbidity, depth of low tide and time of low tide all related much stronger to the response variable than the actual PAR variables. Therefore, PAR data should only be included in coral bleaching models if these data can properly be corrected for depth and turbidity. CDOM appears to be a measure that could be used for representing turbidity. However, its validity should be tested with in situ measurements like for example Secchi depth (Rongas *et al.* 2006).

Probability maps showed higher bleaching in the Andaman Sea and Strait of Malacca in comparison with the Gulf of Thailand. This is most likely caused by different water regimes, in which the Andaman Sea was more influenced by the Indian Ocean and the Gulf of Thailand by the much cooler South China Sea or by differences in turbidity.

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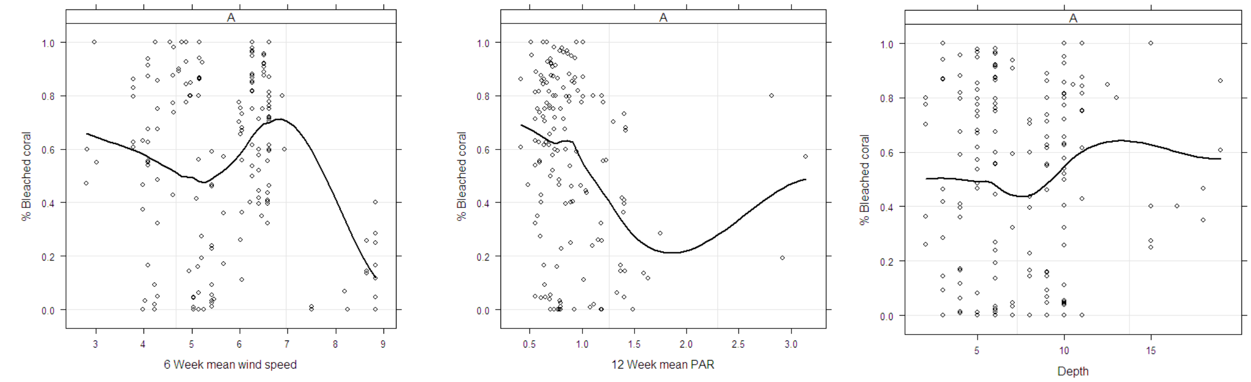
Appendix I: Preparing depth rasters

Generally, raster datasets are built up from columns and rows where each cell represents a value for a certain coverage of space (in this case 0.9 * 0.9 km). The GEBCO dataset consists of a single column therefore this data cannot be read with ordinary GIS software. The website offers a software package that can read and export these data to GeoTIFF file (GEBCO Grid display (BODC 2011). To run this software the full dataset is required, which is problematic as downloading these large files cannot be interrupted and / or continued. An alternative method was used for converting these data. First the NetCDF file was imported into HDFview 2.6, where the individual data sheet can be exported as HDF files. These HDF files were converted to txt files after which they were imported in R commander 2.12. Based on the information on number of rows and columns in the metadata sheet the original data was written as an ASCII style text file using the `split` and `write.table` commands. After this the column names were removed and the six lines in Textbox 1 were added in a text editor which created a real ASCII file. This file can be read by most GIS packages.

Textbox X

```
ncols 2421
nrows 2318
xllcorner 90.98333333333335
yllcorner -2.950000000000003
cellsize 0.008333333333333333
NODATA_value -9999
```

Appendix II: Additional figures from the data exploration



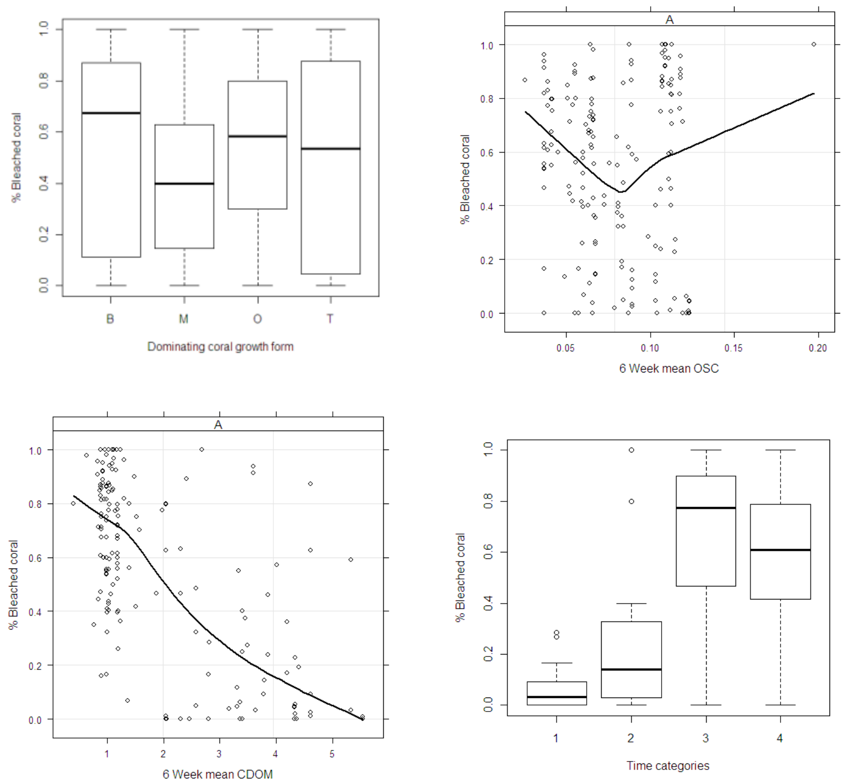


Figure 1. Scatterplots and a boxplot of a selection from the environmental variables versus the percentage bleached coral. A LOESS smoother was added for the ease of visual interpretation

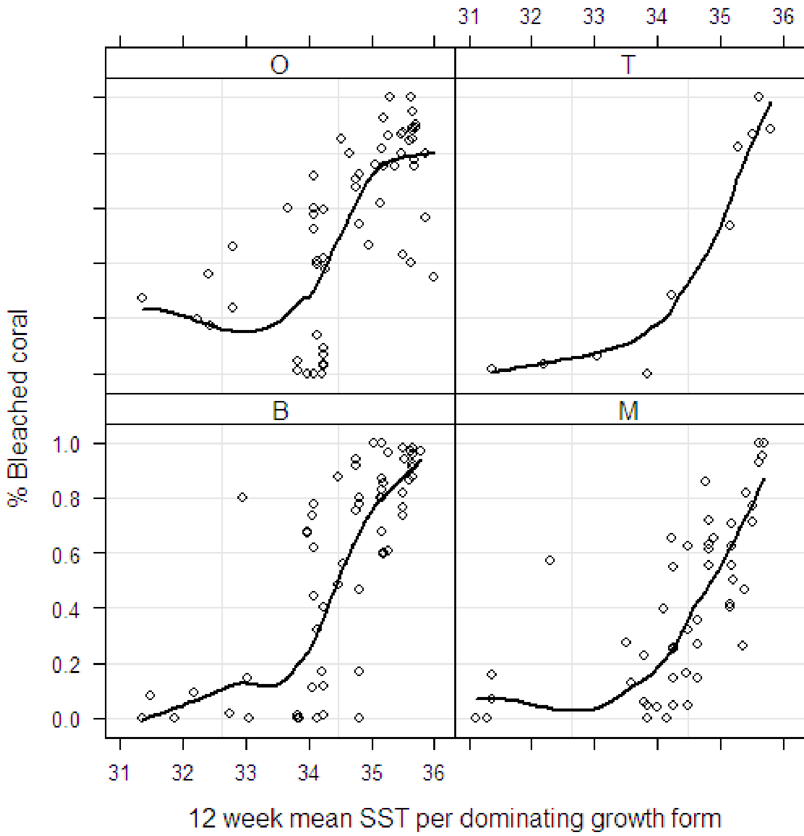


Figure 2. Coral bleaching against 12 week mean sea surface temperature for different growth forms (B) Branching, (M) Massive, (T) Tabulate, (O) Other

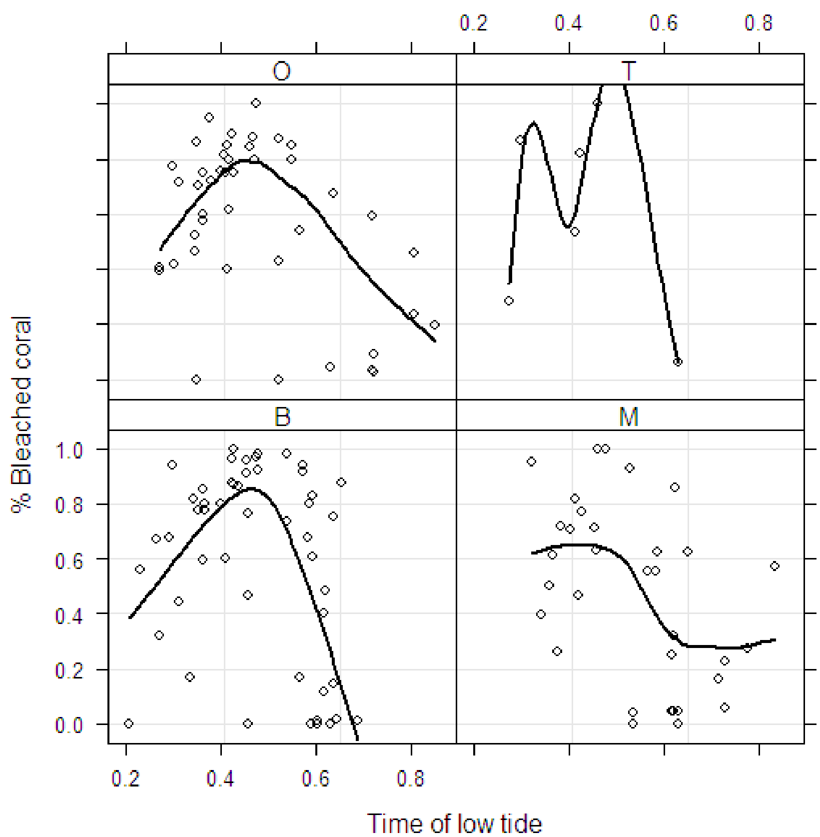


Figure 3. Coral bleaching against the time of low tide for different growth forms (B) Branching, (M) Massive, (T) Tabulate, (O) Other. On the X axis 0 represent 00:00 and 0.5 represents 12:00.

Appendix III: All possible models for approach 2.

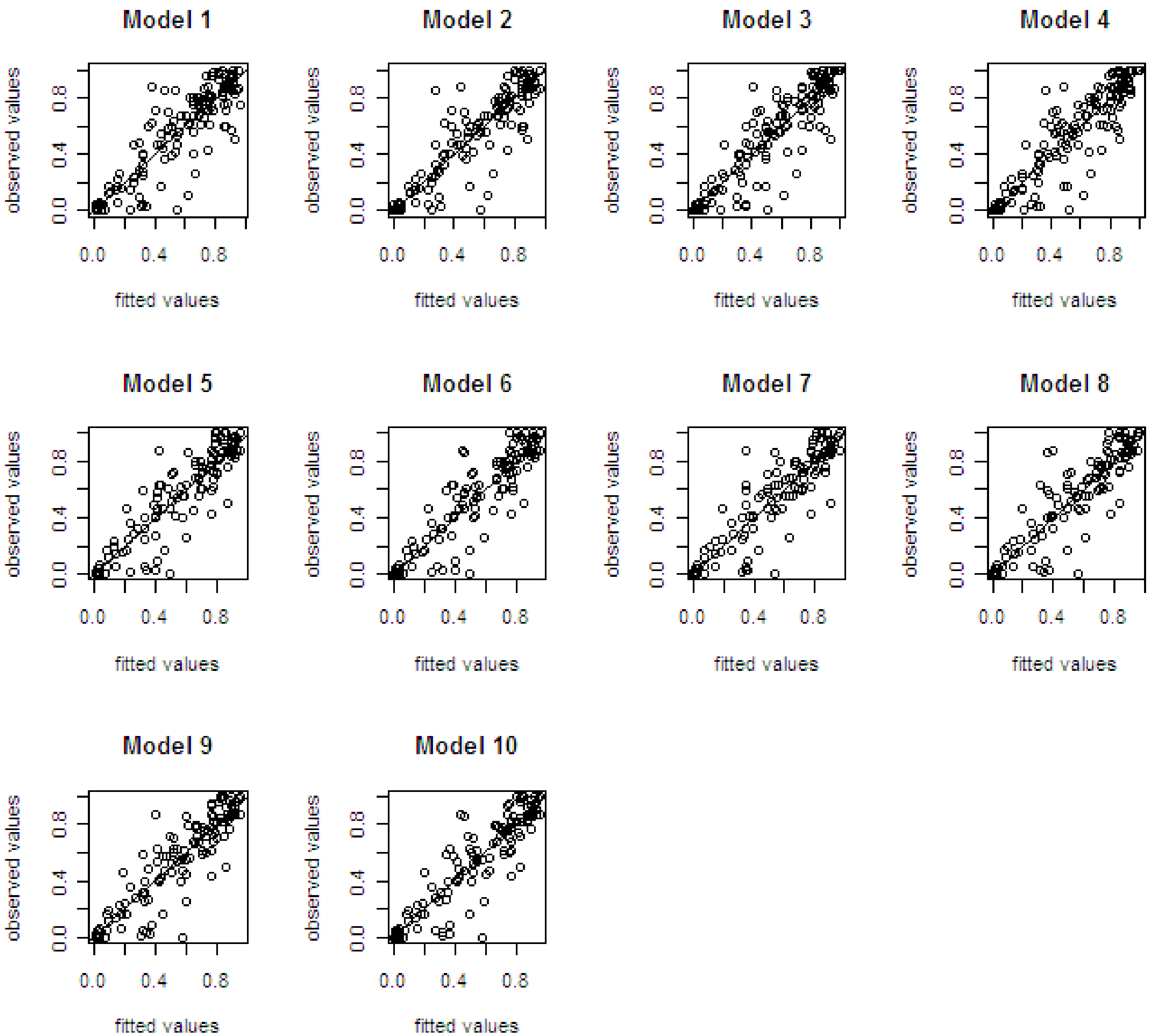
Variables	**AIC**	**BIC**	**Log**	**LRT**
Base model elements				
Base	3356.5	3388.6	-1667.27	NA
DHW	1904.7	1939.7	-940.34	1453.9
CDOM	2113.1	2148.2	-1044.6	1245.4
DLOW	2329.2	2427.4	-1184.2	966.2
WIND	3122.7	3157.7	-1549.3	235.85
Dominant	3139.5	3180.3	-1555.7	223.07
PAR	3235.3	3270.4	-1605.7	123.69
SSS	3259.8	3294.8	-1617.9	98.767
OSC	3316.2	3351.2	-1646.1	42.35
TLOW	2080.7	2115.8	-1028.4	1277.8
Depth	3354.1	3389.1	-1665	4.43
Base model interactions				
DHW x OSC x WIND	1665.5	1718.1	-814.77	1705
DHW x OSC	1761.8	1802.7	-866.9	1600.7
PAR x CDOM x DLOW	1834	1886.6	-899.02	1536.5
CDOM x DLOW	1855.1	1896	-913.54	1507.5
DHW x Depth	1888.8	1929.7	-930.41	1473.7
DHW x WIND	1898.4	1939.2	-935.18	1464.2
PAR x CDOM	2098.3	2139.2	-1035.2	1264.2
PAR x DLOW	2292.4	2333.3	-1132.2	1070.1
OSC x WIND	2945.2	2986.1	-1458.6	417.32

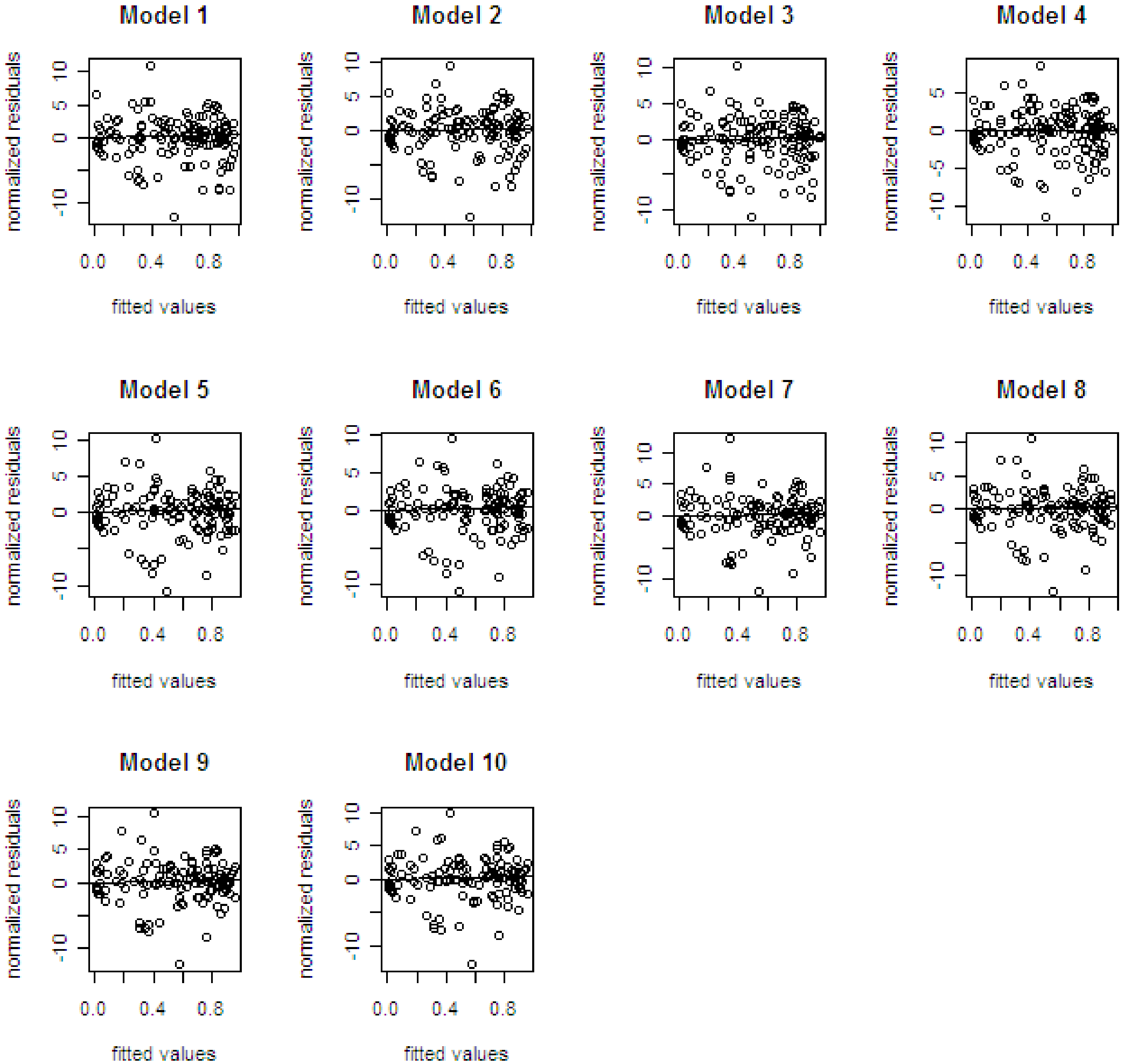
Variables	AIC	BIC	Log	LRT
Combinations with 3 parts				
DHW x OSC + DLOW + PAR x CDOM	1609.6	1662.2	-786.82	1760.9
DHW x OSC + CDOM + PAR x DLOW	1620.2	1669.8	-793.1	1748.3
DHW + DLOW + PAR x CDOM	1641.1	1687.9	-804.57	1725.4
DHW + CDOM + PAR x DLOW	1692.4	1739.1	-830.21	1674.1
DHW x OSC + CDOM x DLOW	1704.2	1753.9	-835.12	1664.3
DHW x OSC + CDOM + DLOW	1702.8	1749.5	-835.39	1663.7
DHW + CDOM + DLOW	1731	1771.9	-851.52	1631.5
Combinations with 2 parts				
DHW x OSC + PAR x CDOM	1620.2	1669.8	-793.1	1748.3
DHW x OSC + OSC x WIND	1663.5	1710.2	-815.73	1703.1
DHW x OSC + PAR x DLOW	1667.2	1716.9	-816.61	1701.3
DHW + PAR x CDOM	1687.2	1731	-828.59	1677.4
DHW x OSC + CDOM	1709.9	1753.7	-839.94	1654.6
DHW + CDOM x DLOW	1732.9	1776.7	-851.44	1631.7
DHW x OSC + DLOW	1761.3	1805.1	-865.64	1603.2
DHW + PAR x DLOW	1762.9	1806.7	-866.43	1601.7
DHW + CDOM	1767	1805	-870.51	1593.5
DLOW + PAR x CDOM	1841.6	1885.4	-905.82	1522.9
CDOM + PAR x DLOW	1848.9	1892.7	-909.44	1515.6
DHW + DLOW	1972.8	1910.8	-923.42	1487.7

Appendix IV: All models for approach 2 with the Temperature factor.

Variables	AIC	BIC	log	LRT
0 model	3356.5	3388.6	-1667.27	1556.2
temp * OSC + dlow + PAR * CDOM	1655.3	1707.9	-809.65	1679.8
temp + dlow+ PAR * CDOM	1663.4	1710.2	-815.72	1671.7
temp * OSC + wind * OSC + dlow	1674	1723.4	-819.88	1694.8
temp * OSC + wind * OSC	1686.7	1722.4	-827.36	1695.4
temp * OSC + CDOM + PAR * dlow	1687.6	1740.1	-825.79	1715.2
temp * Wind * OSC	1691.1	1742.7	-827.57	1589.5
temp * OSC + dlow + CDOM	1694.9	1741.6	-831.43	1683
temp * OSC + CDOM * dlow	1695.4	1745	-830.69	1651.4
temp + CDOM * dlow	1706.7	1750.5	-838.33	1635.8
temp + CDOM + PAR * dlow	1708.7	1755.4	-838.35	1703.1
temp + dlow + CDOM	1711.2	1752.1	841.59	1657.8
temp * OSC + PAR * CDOM	1711.3	1760.9	-838.63	1673.2
temp * OSC + PAR * dlow	1711.9	1761.6	-838.96	1657.3
temp * OSC + dlow	1720.5	1764.3	-845.23	1656.6
temp * OSC + CDOM	1728.7	1772.5	-849.36	1644.1
temp + PAR * dlow	1742.8	1786.6	-856.42	1615.9
temp * OSC	1747.5	1788.4	-859.75	599.8
temp + dlow	1748.6	1786.6	-861.32	1621.7
temp + PAR * CDOM	1748.6	1792.4	-859.31	1657.9
temp * Wind	1762.7	1803.6	-867.36	1679.4
temp + cdom	1771.4	1809.3	-872.69	1611.9
temp * depth	1773.1	1813.9	-872.53	1589.1
temp	1802.4	1837.4	-889.18	1615

Appendix V: Validation Plots




Model 1
Model 2
Model 3
Model 4
Model 5
Model 6
Model 7
Model 8
Model 9
Model 10
normalized residuals
fitted values
0.0
0.4
0.8
-10
0
5
10