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Coral Bleaching in the Red Sea: An investigation into the environmental causes of bleaching

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Coral Bleaching in the Red Sea: An investigation into the environmental causes of bleaching

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Fintan Griffin

Bachelor thesis, 15 credits, in *Physical Geography and Ecosystem Science*

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Abstract:

This report aims to investigate the links between various environmental factors and coral bleaching in the Red Sea. Corals in the Red Sea have seen less bleaching than in other coral regions. Researchers point to a higher thermal tolerance among coral reefs in this sea. However, bleaching is beginning to occur here with increasing frequency as oceans warm and acidify. Taking monthly data of sea surface temperatures, pH, wind speed, salinity, chlorophyll a concentration, and sea surface currents from *MODIS* and *Copernicus*. Processing was then carried out in *ArcGIS Pro* on 474 records of coral bleaching from the *Global Coral Bleaching Database* between 2007-2023. Correlations analyses and Principal component analyses were performed to identify links between the parameters and bleaching. Random forest, decision tree and k-nearest neighbours regressions were also used to investigate how coral reef bleaching may change under RCP 8.5. Significant correlations were found between bleaching and SST, chlorophyll a, pH, wind speed, & salinity. All regressions predicted increases in bleaching by 2050, 2070, & 2100, with a threefold increase predicted by 2100.

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1. Introduction

Coral reefs are often referred to as the "rainforests of the sea", due to their incredible productivity and biodiversity. Despite covering less than 1% of the ocean floor, they support one quarter of all discovered marine species (Numa et al., 2023). They also provide ecosystem services to nearly 1 billion people (Burke et al., 2011). These services range from providing seafood, to protection from coastal erosion, to, the often hard to quantify, recreational services.

Reef building corals are a symbiosis of coral polyps, which are animals closely related to jellyfish and sea anemones, with algal photosynthetic zooxanthellae. The evolutionary success of modern corals is linked to this symbiotic relationship with their dinoflagellate endosymbionts (Lesser, 2021). This relationship provides the zooxanthellae with shelter in exchange they provide the coral polyps with between 60-85% of total nutrients, while also giving them their distinctive colour. It is, therefore, ironic that this symbiotic relationship is also leading to its mortality through the mechanism known as bleaching.

Bleaching occurs when corals expel their endosymbionts. This causes the white colour of the coral skeleton to be exposed and leads to the term "bleaching". The loss of their nutrient-providing endosymbiont can result in the death of the corals if they are not promptly recolonised. Bleaching has been shown to occur due to several different environmental triggers, for example, salinity stress, disease and, arguably most importantly elevated sea temperatures (Fujise et al., 2014). However, given uncertainties and regional resistance to some environmental factors, namely SST, it is therefore, it is important to fully understand the complex mechanisms that underly and cause coral reef bleaching.

Numerous studies have shown that elevated sea surface temperatures cause coral bleaching though it is the magnitude and duration of elevated sea surface temperatures that is thought to affect the susceptibility of corals to bleaching (Lesser, 2011). For this reason, Degree Heating Weeks (DHWs) are often used as an indicator of bleaching susceptibility. A DHW is when the temperatures >1°C of the maximum monthly average of the hottest month. This is totalled over a running 12-week period. Thus, if the temperature is 2 degrees hotter than the monthly max for 14 days then it would get a value of 4 °C-weeks.

A time during which coral bleaching risk increases is during the El Nino Southern Oscillation (ENSO) warm phase. Incidences of ENSO events are occurring with increasing frequency and magnitude (Wang et al., 2016). The 2010-11 La Nina and 2015-16 El Nino events saw sea surface temperatures 4 °C lower and more than 3 °C higher than average temperatures respectively, for more than 3 weeks (Cruz-Garcia et al., 2020). Recent El Nino events and the subsequent rise in sea surface temperature led to mass bleaching on a global scale, with 99% of corals bleached at some sites in the Central Mexican Pacific (Cruz-Garcia et al., 2020). Worryingly, these bleaching events aren't restricted to just El Nino events; during the summer of 2021-22 La Nina, 60% of live corals in the Central Great Barrier Reef saw some degree of bleaching (McGowan & Theobald, 2023). This implies that bleaching events will likely increase regardless of ENSO phase as SSTs (Sea Surface Temperatures) are expected to rise over the coming century.

Studies have also shown that minor changes in the salinity of seawater may also negatively impact coral physiology (Van der Merwe et al., 2014). Ocean acidification has also been shown to negatively affect coral physiology. Antony et al. (2008) showed in a series of experiments that coral reef productivity was reduced when exposed to higher CO_2 stresses. Increases in ocean acidification can slow down carbonate production in corals. Calcification rates are slowed by a more acidic ocean as it can erode the calcium carbonate skeletons of the corals (Cornwall et al., 2021).

It is possible that areas with higher wind speed and surface currents may counteract the effects of sea surface temperatures on coral bleaching. In such conditions mixing of the water column would be enhanced and therefore act to regulate temperatures. However, where surface currents are high, there could be more upwelling bringing nutrients up from depths. This may lead to the eutrophication of the water column and could potentially increase bleaching susceptibility.

Chlorophyll a concentrations can also affect coral physiology. Studies have shown a negative relationship between bleaching and chlorophyll a concentration. Suggesting that areas with higher concentrations of chlorophyll will be more resistant to bleaching. It is the combination of additional nutrients and the chlorophyll effectively shading corals by reducing incoming radiation (Keighan et al., 2023)

One area that has seen less bleaching than other areas is the Red Sea. Studies have shown that the corals here have higher thermal tolerance than corals in other areas (Osman et. al 2017). However, bleaching is beginning to occur with increasing and severity (National Centers for Environmental Information (NCEI), 2024). As bleaching seems to be most correlated with marine heatwaves and despite the Red Sea reaching temperatures considered by experts to cause mass coral bleaching and even mortality, fewer bleaching events have occurred here than in other areas. Therefore, it is likely that SST is not the only contributor to bleaching and other parameters may act to reduce the effects of elevated SSTs. Given fewer bleaching events in recent time in the Red Sea, it was chosen as the study area for the project and the research questions were formulated to investigate the contributing environmental factors leading to coral reef bleaching:

1.2 Research Questions

What are the key environmental factors influencing coral bleaching in the Red Sea?

What is the current relationship between sea surface temperatures and coral reef bleaching in the Red Sea and how might this relationship be influenced by projected increases in sea surface temperatures under RCP 8.5?

The environmental factors chosen for this study are sea surface temperatures, pH, wind speed, surface currents velocity, salinity, photosynthetically active radiation (PAR), and chlorophyll a concentration. It is hypothesized that increases in SST, salinity, and chlorophyll a concentration would act to amplify coral bleaching while increases in sea surface currents, PAR, and wind speed would act to reduce it. It is also hypothesised that decreases in pH will also be linked to coral bleaching. These will be investigated using several correlation analyses. Projections in bleaching will also be investigated under expected increases in SSTs in climate warming scenario RCP 8.5, using several regression models.

2. Background

2.1 Thermal tolerance in the Red Sea

Present thermal conditions in the Red Sea often exceed thermal projections for other areas over the next 50 years under various climate scenarios e.g. RCP 8.5, however few bleaching events have been recorded in the region. With temperatures reaching 34 °C in parts, it is apparent that corals here have a higher thermal threshold than corals in other tropical regions. This thermal tolerance could be because the Red Sea has been nearly cut off throughout history from the greater Indian Ocean, during periods of low sea levels, like those seen during the Last Glacial Maximum. Najeeb et al. (2019), discovered that sea depth at Hanish Hill, near the outflow into the Indian Ocean was as low as 25m which would have had significant effects on both ecology and ocean circulation. Nowadays it has a maximum depth of 137m which promotes more mixing with the Indian Ocean, thus reducing temperature. This reduction of inflow and outflow may have caused temperatures and salinity to increase possibly above levels we see today. This, in turn may have led to the evolutionary selection of corals and their endosymbionts with higher thermal thresholds (Osman et al., 2018).

2.2 Related Works

Many studies have attempted to quantify the link between the various environmental factors and coral bleaching. The study done by Osman et al. (2018), investigated the link between sea surface temperatures and coral bleaching. They compared incidences of bleaching with Degree Heating Weeks (DHWs). They found that no coral bleaching occurred in the gulf of Agaba in 2010 or Hurghada in 2012, despite seeing DHWs of 11 °C-weeks and 15.1 °C-weeks respectively. *Coral Reef Watch* claim that once the accumulated heat stress reaches 4 °C-weeks, widespread coral reef bleaching is expected to occur, while at 8 °C-weeks reef-wide coral mortality is expected. Even with values of 18.9 °C-weeks as seen in Wadi El Gemal (2012) only 8-20% of reefs were bleached.

Another study carried out by (Maina et al., 2008) in the Western Indian Ocean showed, through a PCA (Principal Component Analysis) that UV irradiance, SST variability, and temperature as the variables that were best at predicting coral bleaching. They then used this statistical analysis to assign weights to each variable. Based upon similar relevant studies, the parameters were fuzzified based on their link to coral bleaching, and a fuzzy logic analysis was done creating maps showing coral reef bleaching susceptibility across the study area.

Salinity stress induced by changes in salinity has been shown to affect the metabolic rates and photophysiology of coral polyps or their endosymbiont counterparts (Chartrand et al., 2009). Many studies have been done documenting the link between salinity stress and coral bleaching. However, most of these studies have been done on hyposalinity rather than hypersalinity. Moberg et al. (2009) indicated that in lower salinity conditions (10-20 mg g^{-1}), photosynthetic rates were lowered proportionately to the reduction in salinity. Hoegh- Gudberg & Smith (1989), conducted an experiment which exposed two coral species found in the Red Sea, Stylophora pistillata and Seriatopora hystrix at salinity levels of 30 mg g^{-1} for 4–10-day periods at several different temperatures. No bleaching was recorded during this experiment. However, when they were exposed to 23 mg g^{-1}coral mortality was observed within 48 hours. The proximity of reefs to desalination plants can cause increased salinity in nearby waters (Van der Merwe et al., 2014). However, extreme high and low salinity events are rarely recorded in the Red Sea, though the presence of desalination plants along the coast of Saudi Arabia could cause hyposalinity. At present there is little research on the salinity in the eastern red sea.

Photosynthetically Active Radiation (PAR) is a measure of how much light can be used in photosynthetic processes. Therefore, a reduction in PAR may act to increase coral bleaching, while PAR values of higher than 118.05 W $m^{-2}day^{-1}$. alongside temperatures of 30 °C may cause the expulsion of zooxanthellae and cause bleaching. (Sridhat et al., 2012). While this concerns an increase in the amount of PAR, a reduction may also be detrimental to the zooxanthellae's ability to photosynthesize. A reduction of PAR due to heavy cloud cover has also been observed, with up to a 12-time reduction in the amount of incoming PAR compared with a clear day (Jyothibabu et al., 2018). With more extreme weather events forecasted as climate changes over the coming century, it may lead to more cloud cover in tropical oceans, Liu et al. (2023), though given the proximity of the

Red Sea to the Sahara Desert, and the subsequent low levels of precipitation, it may be exempt from this.

Regarding wind speed, Paparellea et al. (2019), showed that wind speeds of <4 m/ s^{-1} were correlated with increases in SST in the next days, while faster speeds resulted in cooling. This shows how wind speed can act to regulate SSTs and potentially reduce the risk of bleaching. Surface currents too can be a factor regarding coral bleaching. DeCarlo et al. (2020) showed that upwelling of nutrients from depth, driven by sea surface currents can exacerbate the negative effects of heat stress. They point to 2015, when widespread bleaching was reported in Farasan despite it not being the warmest summer on record. This is further validated by the differential bleaching in the east versus the west of the red sea. During the same bleaching event in 2015, the west, which has lower upwelling and thus lower nutrient levels experienced insignificant bleaching while the opposite was true in the east where nutrient levels and upwelling are higher.

Keighan et al. (2023) noticed a negative correlation between chlorophyll a concentrations and bleaching prevalence. Areas with higher chlorophyll a concentration saw lower bleaching. They suggest two reasons as to why this may be the case, firstly during times of coral stress some corals utilise a heterotrophic diet. This can alleviate some of the stresses associated with elevated temperatures. Secondly the elevated chlorophyll a concentration may also act to shade the corals, effectively reducing irradiance and temperatures. However, too much shading could have adverse effects and in high enough concentrations could result in detrimental effects to the coral.

The study done by Antony et al. (2008) exposed three species of corals, Porolithon onkodes (*Po*) Acrropoa intermeidea (*Ai*) and Porites lobalta (*Pl*) to differing CO2 levels for an 8-week period. They set up 30, 20 litre tanks keeping light levels constant. pH was set to between 7.85-7.95 to correspond to CO2 levels of 520.705ppmV, and 7.60 - 7.7 for 100-1300ppmV, to deal with medium and high C=2 concentrations, respectively. A control tank of 8.0-8.4 was also set up to simulate current conditions. Each CO2 treatment was set up with low (25-26 °C) and high (28-29 °C) summer temperatures for the region, (Great Barrier Reef).

They found that in the high CO2 scenarios the calcification was reduced for all 3 species with *Po* seeing declines in total biomass at around 4% in the high CO2 high temperature scenario. They also found that bleaching increased in all scenarios and among all species though the magnitude differed, approximately 20% bleaching occurred with *Pl* while *Po* saw almost 60% bleaching in the high CO2 high temperature scenario. Again, net productivity was reduced in all scenarios and species. Interestingly, however, Ai saw an increase in productivity in the intermediate scenario with elevated temperatures. but at lower pH this was reduced significantly and much lower than at the base level.

Cornwall et al. (2021) showed that carbonate production in corals may slow or even cease with increasingly more acidic ocean. They estimate that by 2100 under RCP 4.5

and RCP 8.5 that declines in carbonate production will be so severe that reef accretion will cease by 2100. This is even with optimistic estimates that don't factor in physical erosion. Under RCP 2.6 it is estimated that global net carbonate production will be reduced by 71% and 77% by 2050 and 2100, respectively. Though they attribute bleaching events rather than the direct impact of ocean acidification or elevated SSTs as the responsible factors in this scenario. They do conclude, however, that the capacity of coral reefs to acclimatise to more frequent heatwaves and reductions in pH is not well understood. Thus, their projections are sensitive to changes in thermal and acidic tolerance.

3. Materials and Methods

3.1 Study area

The Red Sea is one of the hottest and saltiest seas in tropical regions. It is located between 12N and 30N with average temperatures (1982-2012) ranging from 21.7 °C in the northern regions in the Gulf of Suez, to 29 °C in Farasan in the south (Osman et al., 2017). Salinity levels in the Red Sea are around 41 mg g^{-1}. pH sits at around 8.3 but with increased $CO2$ in the atmosphere from anthropogenic sources and its subsequent dissolution into seawater, this value is likely to decrease. The Red Sea covers approximately 445,000km^2 from around 30 ° N, 33 °E to 13 °N, 44 ° E. The corals here are the northernmost of all Indian Ocean Reefs extending along approximately 2000km of shoreline, covering approximately 2% of the sea floor here. Fringing reefs are the most dominant type and are characterised by the proximity to the shoreline, with Acropora and Porites, two highly branched species of coral are the dominant species here. Though some are found further offshore around small islands in the sea. It is estimated that some of these fringing reef complexes are over 5000 years old (Coral Reef Info, 2024).

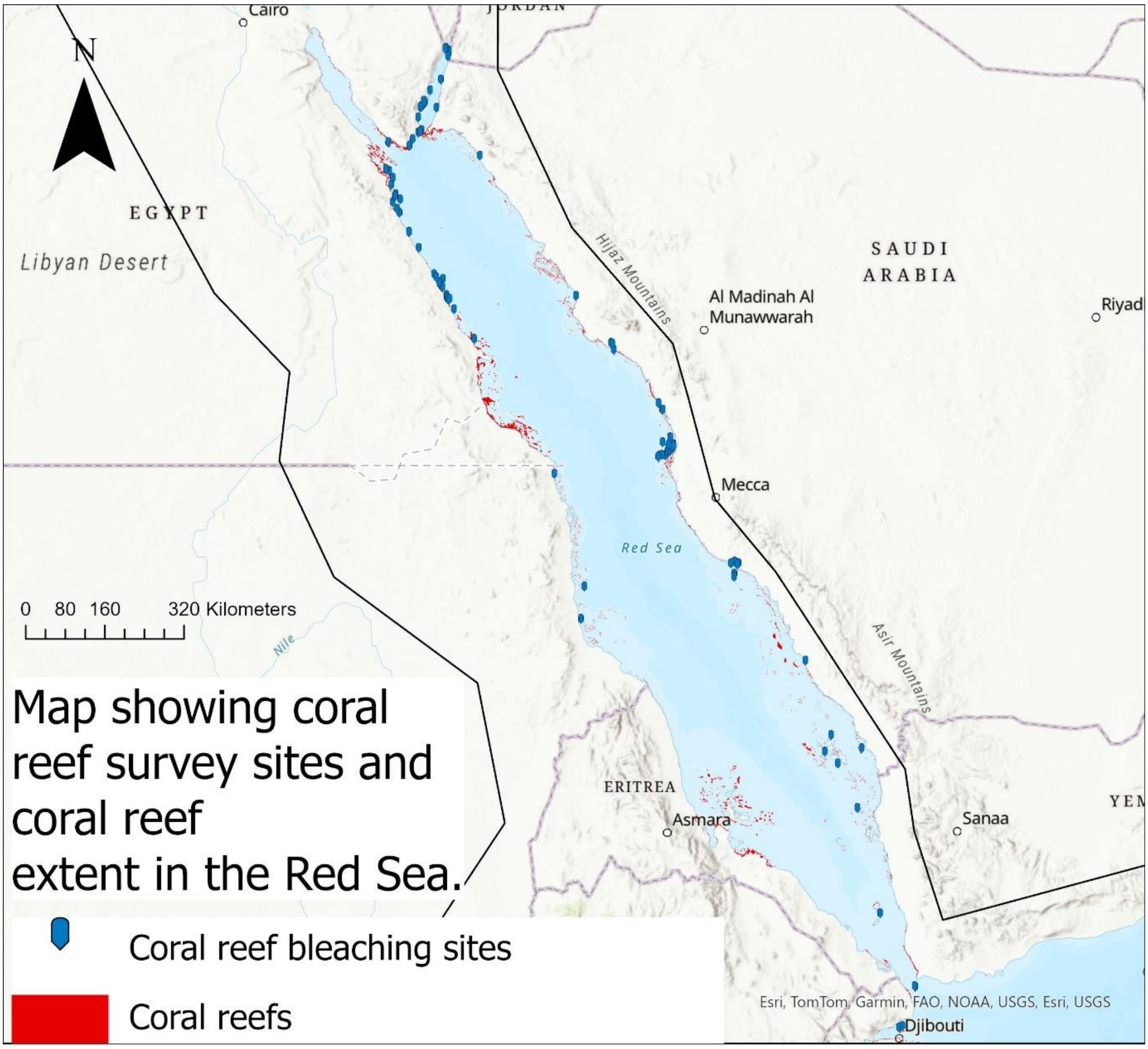

Figure 1: Coral reefs of the Red Sea, with bleaching survey sites.

3.2 Bleaching data collection

In order to investigate which environmental factors cause bleaching, records for coral bleaching were required. The *Global Coral Bleaching Database* is a database consisting of 35054 records of coral bleaching from 1963 to 2024. With records across the world, spanning from the Caribbean to the Banda Sea. The data comes from numerous sources; from, the non-profit organisation, Reef *Check,* to individual surveys carried out during scientific expeditions. The database was compiled by the *National Centres for Environmental Information* (NCEI) which is a part of the *National Oceanic and Atmospheric Administration* (NOAA).

The database consists of over 700 records for the Red Sea between the years 1980-2022. Due to the time constraints of the thesis and the temporal data availability of some environmental parameters, the period of 2007 – 2023 was chosen for the analysis. The database had records indicating the latitude & longitude of each measurement, the depth at which the measurement was taken, the day, month, and year in which it was taken, and the percent of coral bleached and coral mortality, amongst some other records. Some records displayed "N/A" in the "Percent_bleached" category and were thus removed. After which there were 477 records of bleaching spread across the temporal range and spatial extent of the Red Sea from the Gulf of Aqaba in the north to the Bab al-Mandeb strait in the south by the outlet near Djibouti into the greater Indian Ocean.

This data was then saved into a CSV file and imported into ArcGIS Pro as point data, using the tool *Coordinate table to point*. Next, the data had to be overlain over each of the environmental factors. While daily resolution of many of the parameters were available, it was decided to use monthly data for the analysis. This was due to time constraints and keeping the project size to a manageable level. Therefore, the monthly data for each parameter was overlaid with the reef data points for each given month.

3.3 Environmental factors

3.3.1 Sea Surface Temperatures, chlorophyll a concentration & PAR (Photosynthetically Active Radiation)

SST data was downloaded from *MODIS* (or *Moderate Resolution Imaging Spectroradiometer*), an advanced instrument which is aboard both the NASA Aqua and Terra satellites, also known respectively as EOS PM-1 and EOS AM-1. With an orbital altitude of 705km and a 55-degree scanning pattern, it provides global coverage every day or two. To correct atmospheric disturbances, radiative transfer theory is used. It makes observations through "windows", where there is little atmospheric absorption. They are then compared to in-situ radiometer measurements and adjustments are made. The data was in monthly and global 4km resolution between January 2007 and March 2024. All the months in the period were available here except for June 2023. This was downloaded in a *GEOTIFF (float)* format and was in 9km resolution. However, as no coral bleaching record existed in June 2023 it was not used.

The MODIS sensor is also responsible for estimating chlorophyll a concentration. It measures ocean colour, and it is from this that chlorophyll a concentration can be derived. It is calculated by using an empirical relationship combining remote sensing reflectance in the blue-green wavelength with in-situ measurements of chlorophyll. It had a global resolution of 4km. The full temporal range for the time was available and was downloaded for each month.

PAR data was obtained from the *MODIS Daily Mean Photosynthetically Available Radiation* algorithm. It was in 4km resolution and the option to clip the data to the study area was available and was chosen. It is defined as the proportion of radiation received from the sun that is usable by plants in photosynthesis and is thus a common input when attempting to model the primary productivity in a marine environment. This algorithm requires observations of radiances at the top-of-atmosphere in the range of 400-700nm, the visible spectrum (*NASA Ocean Color*, n.d.).

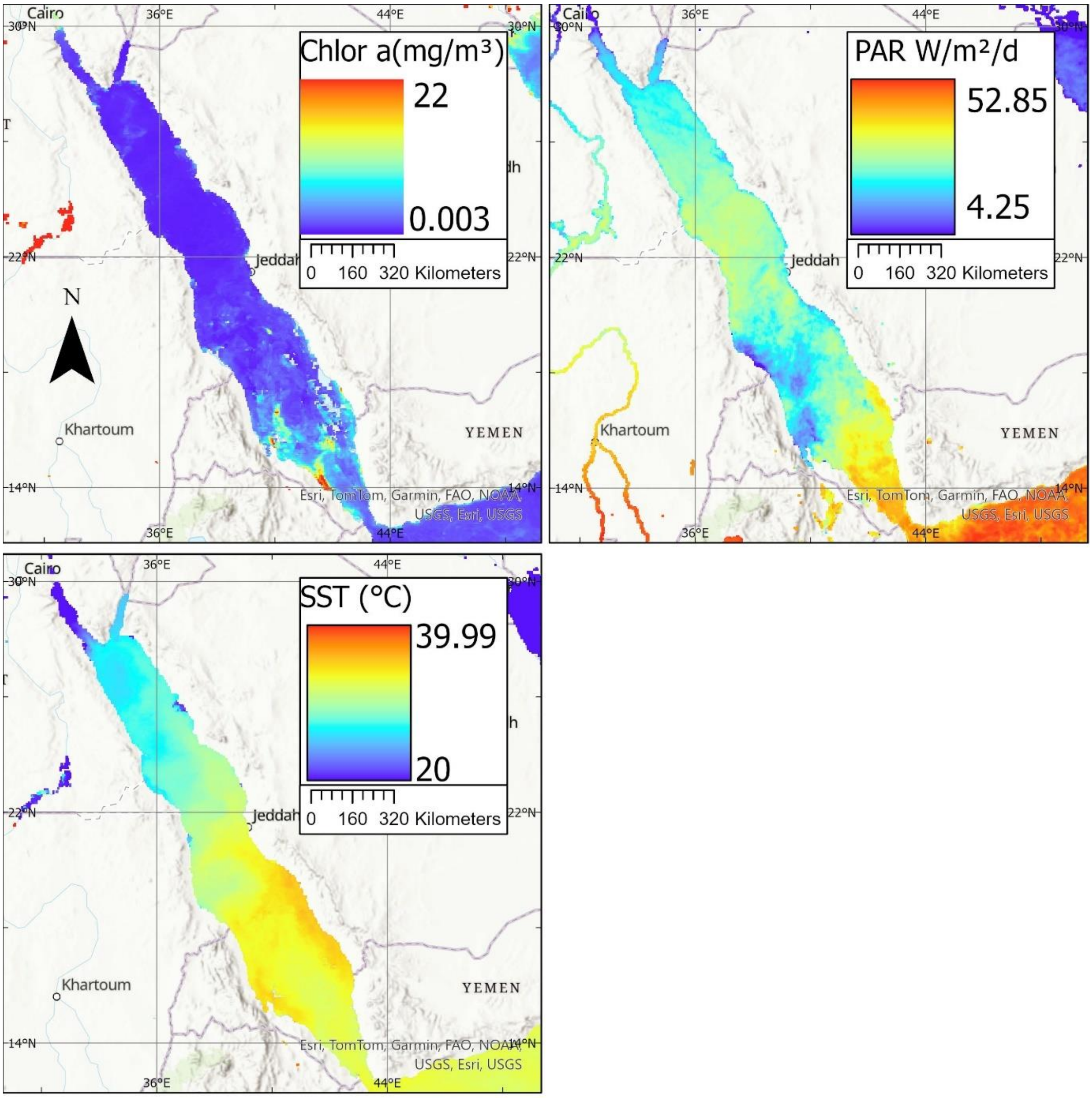

Figure 2: Data from MODIS showing the extent and resolution, January 2007. Where, SST= Sea Surface Temperatures, chlor a= chlorophyll a, & Ein=Einstein.

3.3.2 Salinity, pH, wind speed & surface currents

Data for salinity, pH, wind speed, and surface currents were obtained from various products of *Copernicus,* which the ESA (European Space Agency) contributes to, and downloaded from .

Sea surface current data was obtained from the *GLORYS12V1* product from the Copernicus Marine Service (CMS). It's made by combining data from satellite measurements, such as sea level or temperature with models. It gives daily and monthly

averages of various environmental factors such as sea level and sea water potential temperature. It also gives the eastward and northward sea velocity, both of which were used to compute the sea surface current velocity.
Wind speed was obtained from the *Global Ocean Hourly Reprocessed Sea Surface Wind and Stress from Scatterometer and Model Product*. It contains surface wind parameters and stress fields at varying resolutions. It is bias corrected by scatterometer observations from several satellites, such as Metop-A and QuikSCAT SeaWinds. Similarly, to currents, it has many variables such as air density and surface downward stress. However, to get data for wind speed, both the Eastward wind and Northward wind datasets were used.

Data for pH was obtained from the *Global Ocean Biogeochemistry Hindcast* product. It has numerous variables concerning biogeochemistry from phosphate concentration to dissolved oxygen concentrations. A numerical model, it uses the NEMO modelling platform, more specifically the PISCES biogeochemical model to obtain the variables. Salinity data was obtained from the *Global Ocean- Delayed Mode gridded CORA- In-situ Observations objective analysis in Delayed Mode Product*. It is an objective analysis estimation method based upon in-situ global observations using the ISAS (In Situ Analysis System) software.

It was possible to choose the spatial range of all the data thus a rectangle with the following extent was chosen from 9.3 °N to 33.1 N, and 28.5W to 53.3W. This was done to cover the entire study area and to reduce the file sizes. Wind speed and pH both had a resolution of 25km while sea surface currents had a resolution of 9km. The only option for salinity was in rectangular raster format, which had a resolution of 10km*50km resolution.

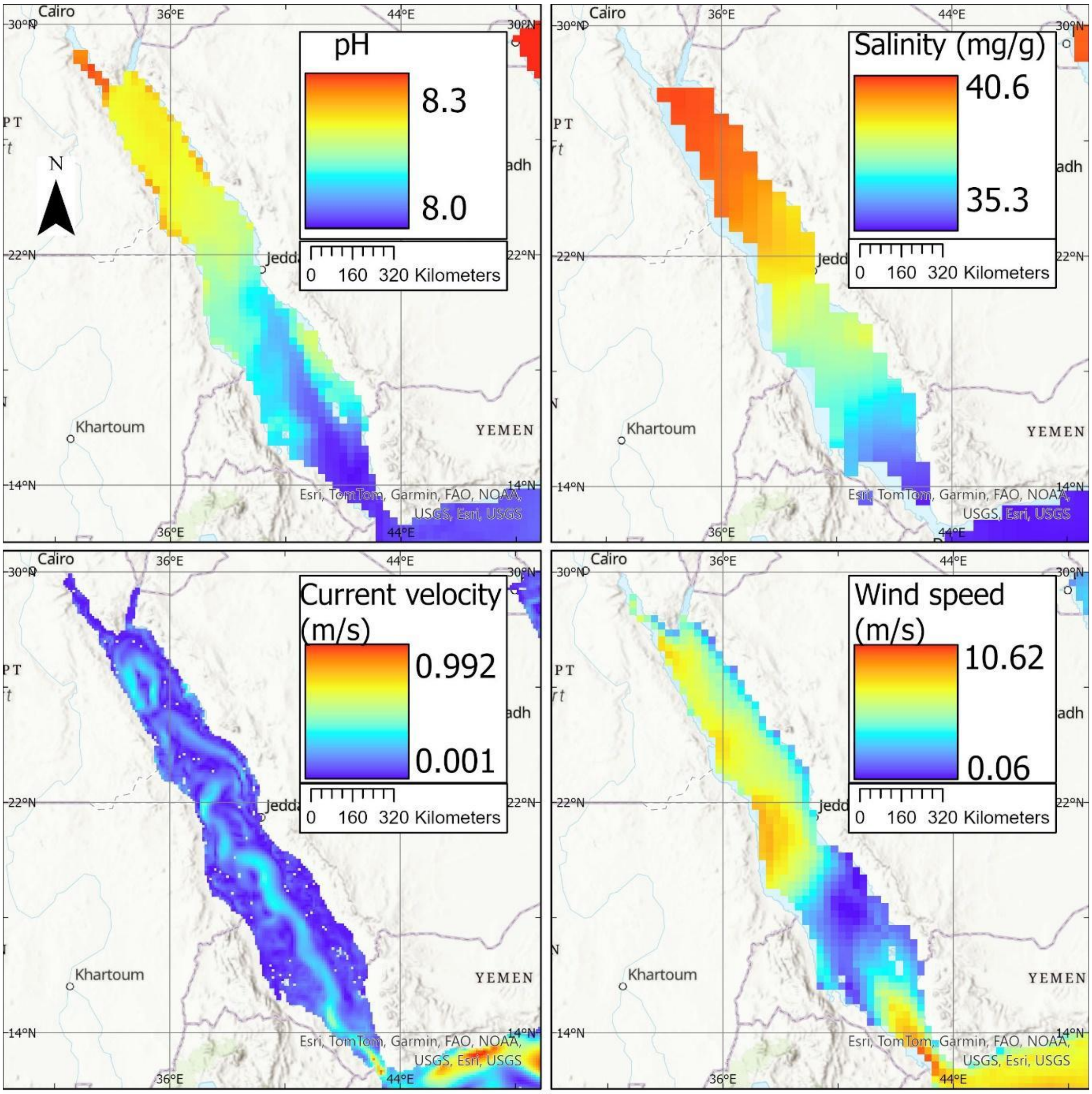

Figure 3: Maps showing different environmental parameters extent and resolution from January 2007.

3.4 Data harmony and GIS processing

All the data were downloaded as *NetCDF* files so could not be directly imported into ArcGIS Pro. Therefore, the tool *Make NETCDF raster file* had to be used.

For surface currents and wind speed, the NETCDF files contained vectors in the u and v directions. For surface currents these values were *uo* and vo, while for wind speed they were *eastward_wind* and *westward_wind*. In order to calculate wind speed and sea surface current velocity, the Pythagorean theorem was implemented to calculate speed. As some of the reef sites were quite close to the coast and due to the resolution and spatial extent of the pH, salinity, surface currents and PAR layers, many of the sites were not covered by these raster layers. Thus, IDW, Inverse Distance Weighting, interpolation was carried out on each of these layers after converting the raster layers into point data.

IDW, a multivariate spatial interpolation method is commonly used as it is an easy technique to implement. It assumes that nearby values are similar and uses this along with weights to estimate the value at a given point based on its proximity to other points- (Panigrahi, 2021) The power function for distance was set to 2 and the search radius was variable with 12 points chosen for the interpolation. The extent was chosen to match the PAR layer and the cell size was chosen to remain constant.

In order to overlay these layers with the point data they needed to be converted into polygons. However, in ArcGIS Pro it is impossible to convert a floating-point raster file directly into a polygon. Thus, raster calculator was used to multiply all the layers by either 1000 or 10000 depending on the decimal precision of the data. After this the *INT* tool was used to convert the rasters into integer format. Then *Raster to polygon* was used to transform them into polygons. Next, the *Union* tool was used to combine all these polygon layers.

Finally, using *Select,* sites with matching months and years were chosen and this was overlain using *Overlay Layers* with the union of all the polygon layers, which outputted the sites with the data for any specified month and saved into a separate geodatabase with the naming convention “Month_Year” i.e. June_2007

As this needed to be done for each month that had a record of coral bleaching, the processes were automated into a tool using *Model Builder* and a simplified workflow for the entire process can be seen in Figure 4. The entire workflow used in the model builder can be seen in appendix 5.

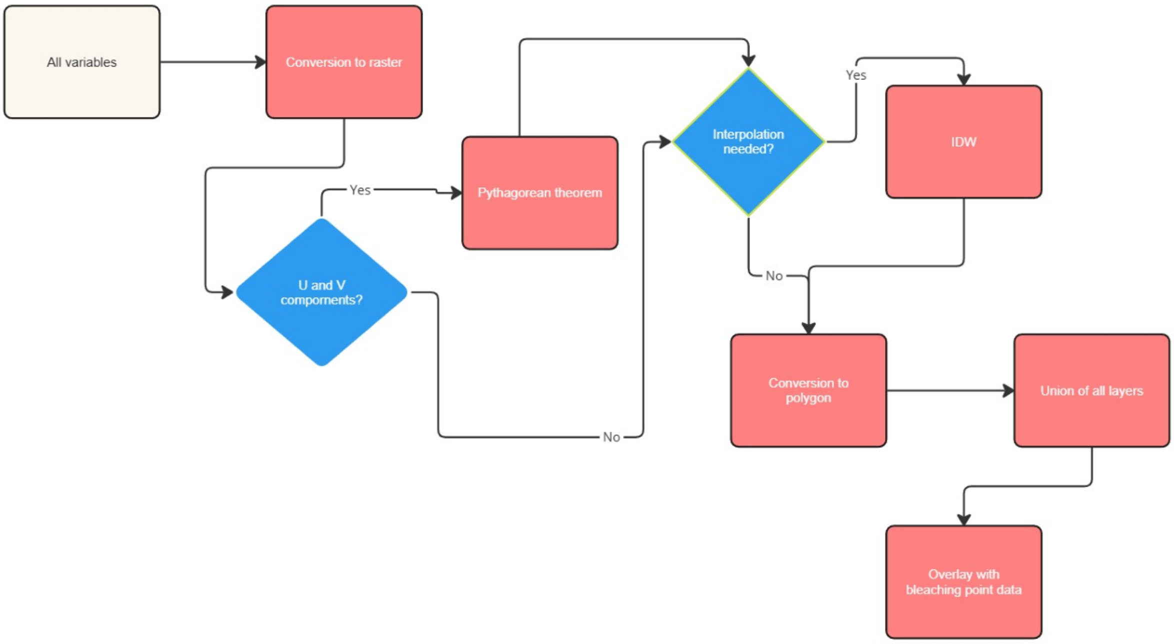

Figure 4: Simplified workflow diagram.

Finally, these resulting monthly layers were merged using the tool *Merge*. This was then exported into excel and corrected by dividing by either 1000 or 10000 depending on the multiplication carried out earlier in the process. This layer was then saved as a CSV file to be used in the next stage of the analysis.

3.5 Correlation coefficients & Regression methods

A correlation is a measure of the strength of association between two variables consisting of a dependent and an independent variable. It ranges from -1 to +1, with -1 indicating a perfect negative correlation, while +1 indicates a perfect positive correlation. A perfect negative correlation means that as one variable increases the other decreases proportionally. Conversely, a perfect positive correlation is as one increases so too does the other variable. There are many different methods to compute a correlation and three such methods, and the methods chosen for this study, are the correlation coefficients Pearson, Spearman, and Kendell Tau (Stewart, 2024).

Pearson's correlation coefficient was developed by Karl Pearson,1896 from previous studies done by Francis Galton, and Auguste Bravais, a eugenicist and physicist respectively. The formula for the Pearson correlation coefficient is:

$$r = \frac{[n(\Sigma xy) - \Sigma x \Sigma y]}{\sqrt{[n(\Sigma x^2) - (\Sigma x)^2][n(\Sigma y^2) - (\Sigma y)^2]}} \quad (1)$$

Equation (1), where: r= Pearson's correlation coefficient, x= independent variable, y= dependent variable, n= sample size and Σ= sum of all values.

While this is a measure of the strength of a, usually, linear relationship between two variables, it does not measure whether or not that relationship is significant. In order to do this, a t-test is used to measure the difference between the observed r and what may be expected under one's null hypothesis (Stewart, 2024).

Spearman's rank correlation coefficient is a nonparametric measurement of correlation. Developed in 1904 by Charles Spearman, a psychologist, it is considered to be one of the oldest rank statistics. If there are two sample sizes of (*X*1, *X*2,...,*Xn*) and (*Y*1,*Y*2,...,*Yn*) then Spearman's correlation coefficient is calculated as follows:

$$\rho = 1 - \frac{6\Sigma_{i=1}^{n} d_i^2}{n(n^2-1)} \quad \textit{(2)}$$

Equation (2), where: Spearman's correlation coefficient. Where ρ= Spearman's correlation coefficient, n=sample size, di= Rx i - Ryi, where Rxi and Ryi are the ranks of Xi and Yi in both of their respective samples.

If the datasets consist of identical values, then corrections can be applied. Like Pearson's correlation coefficient it shows only the correlation strength and direction. In order to test for significance, 3 different tests are carried out depending on the null hypothesis. The null hypothesis consists of one bilateral relationship, that is either positively or negatively correlated, Case A, or two unilateral relationships, positive correlation, Case B, and Case C, a negative correlation. Then the null hypothesis is assessed with a different formula depending on which case it is, (A, B, or C) and either accepted or rejected depending on the results and significance level chosen. (Dodge, 2008)

Similar to Spearman's, The Kendall rank correlation coefficient is also a non-parametric correlation measurement. It was discussed as far back as 1897 with MG Kendall rediscovering it and studying its applications using a non-parametric approach. It is computed using the following formula:

$$\tau = 1 - \frac{4Q}{n(n-1)} \quad (3)$$

Equation (3), where τ= Kendall's correlation coefficient, Q= the degree of agreement, or disagreement among the ranked variables, and n= sample size.

Q measures the number of pairs (Xi, Yi) that are not in order when Yi is arranged in order based on Xi. Thus, Q ranges from 0, when all the pairs are ordered perfectly, to n(n-1)/2, when they are completely mismatched. Two different formulae for Tau are used depending on whether the pairs are in increasing or decreasing order. And a third is used for cases when they are neither concordant nor discording. Significance levels are chosen and tests run either two sided or one sided and the null hypothesis is rejected or accepted depending on the result and the significance threshold chosen. (Dodge, 2008)

Regression is used to measure and study the relationship between two or more variables. Roger Joseph Boscovich discovered a way to determine regression line coefficients. Regression aims to estimate the value of one variable as a function of the other variable(s). In regression there is a dependent and independent variable, usually denoted as x and y, respectively.

Three regression models were chosen for the analysis, based on their performance, Random Forest, Decision Tree, and K-Nearest Neighbour. Though Linear, Ridge, Lasso. Support Vector and Gradient Boosting were also evaluated but due to their high MSE (Mean Squared Error) and low R^2 value they were omitted from the next stage of analysis.

A decision tree is a machine learning regression technique used for predictions in a plethora of fields. It derives the outcome of an event using a series of classifications and regressions. Using inductive classification, it extracts relevant information from unknown data by splitting the data repeatedly. It has advantages over standard regression due to its effectiveness when modelling nonlinearity. Its instabilities can be reduced by bagging and boosting. The inclusion of bagging techniques in a decision tree model changes it to random forest. Bagging essentially generates multiple datasets for training the model using randomization techniques and repetitive combinations. This in turn decreases the variance in the prediction. Boosting, similarly, creates various sets of training data and through seeing which classifications are incorrect, it adjusts the weights, based upon the best iterative class of an observation. (Panda & Sagar, 2022)

Random Forest is a learning algorithm that is supervised i.e. the data it operates on contains outcomes or levels. It creates many decision trees that are randomly chosen from subsets of the data. This aggregation of all outputs allows it to make predictions for unseen data points. Thus, it is more robust than a simple decision tree model as it is the amalgamation of numerous decision trees. It is important to identify which of your variables are the most important for the random forest regression model. This was done by performing a PCA based upon random forest regression. This weighs each parameter assigning it a value between 0-1 depending on its importance to the model (Sahai, 2023).

The k-nearest neighbour algorithm was designed by Hodges and Fix in 1951. It was designed to provide a non-parametric solution to the problem of discrimination i.e. whether a random variable with an observed value is distributed across a p-dimensional space according to one of two parametric distributions. With several applications in the field of geoscience such as improving pixel based remote sensing classification, it is also used in estimations in regressions (Sreevalsan-Nair, 2021).

3.6 Implementation of PCA, correlation and regressions

Three correlations were carried out using the open-source python software: *SPYDER*. The scripts used in the analysis can be found in the appendix. The correlation script in appendix 1, the PCA script in appendix 2 &3, and the Regression scripts in appendix 4.

The correlation script used the python library *pandas* and *numpy*. *numpy* is a numerical library in python which is a useful package when dealing with scientific computing. *pandas* is an open source, python library built upon the *numpy*. It provides various functions which are used in data analysis and manipulation. The PCA and regression scripts used *scikit-learn*, an open-source, python library that deals with machine learning. It contains various regressions, classifications, and cluster algorithms such as random forest, gradient boosting and more. All these libraries were installed before the scripts were run using the *Command Prompt* terminal on Windows.

Pearson, Spearman, and Kendell Tau correlations were chosen as it was decided that more than one correlation would lead to a more rigorous output. The output was saved as a text file and imported into excel. A significance level of P=0.05 was chosen for all three scenarios with significant correlations marked in bold and italics.

To carry out a regression analysis to predict coral bleaching under RCP 8.5 data for projected SST were required. The IPCC estimates that, under RCP 8.5 between 2005-2100, SSTs are predicted to rise by 0.44°C decade^{-1} in the Red Sea (Fox Kemper et al., 2021). At 0.044 °C year^{-1}, SST values were updated for each bleaching site based on the year the measurement was taken and updated to reflect predicted SST in 2050, 2070 and 2100. For example, if a measurement taken in 2010 had 25 °C as its value for SST than it's predicted temperature for 2050 would be 25°C + (0.044 °C year^{-1} * 40 year) = 26.76°C

SPYDER was once again used to run a series of regressions based on the data. The data was split into training and evaluation subsets. Then the following regressions were run and their MSE and R^2 values taken. Linear Regression, Ridge, Lasso, Decision Tree, Support Vector, Gradient Boosting Regression, Random Forest, and K-Nearest Neighbors Regression. The three best performing models, those with lowest MSE and highest R^2 were taken and used in the analysis.

A PCA was then carried out on two of the three regressions, it was not possible to do this on K-nearest neighbour due to the nature of the regression itself, unlike Random Forest and Decision Tree it doesn't assign weights or importance coefficients to each variable thus it returns nothing if a PCA is run. The PCA analysis was performed to see which variables are the most important for the predictions within the regression. The four variables with the lowest importance for each were dropped from the dataset and the regression was run once again including only 3 of the 7 variables. This was done as the assumption was that all other variables remain the same while SSTs increase is extremely unlikely. Thus, in order to reduce uncertainties in the regression models, only the three most important variables at predicting coral bleaching were used.

3.7 Sources of uncertainty/error

Regarding uncertainties with the data, as the data layers were obtained from either Copernicus or MODIS, they are subject to well documented errors and biases. However, bias correction obtained from in-situ measurements is often used to reduce these errors and biases. While the implementation is purely technical, the following sources of uncertainty must be discussed and considered in order to be able to correctly interpret the obtained results.

3.7.1 Wind Speed

The data is biased corrected by scatterometer observations from the *Metop-A* satellite, which reduces bias from -0.12 to 0.03. However, local biases can be many orders of magnitude larger. Furthermore, the bias correction tends to overcompensate positive bias and enhance negative bias in the tropics. Regarding the northward wind, biases are again largest in the tropics where it can exceed +-1 m/s. However, with bias correction it is reduced on a large scale but there can still be local bias with a smaller magnitude. While both have low error margins once corrected, they still tend to underestimate wind speed in both directions, European Union-Copernicus Marine Service, (2019).

3.7.2 Sea Surface Currents.

There are some uncertainties regarding the currents layer. There is an overestimation of current strength in the Western Pacific. Meanwhile an underestimation is present in the Equatorial undercurrent. However, there is good agreement between the model and mooring observations, especially in the tropics, European Union-Copernicus Marine Service, (2019).

3.7.3 Salinity

It is interpolated based upon in-situ data and validated against other in-situ data. Between 1960-2007 the bias was -0.024 mg g^{-1}, this improved to -0.009 for the period 1960-2022. However, even with the improvement it underestimates salinity in both scenarios and thus in reality the ocean is more saline than the data shows (Szekely et al., 2024).

3.7.4 pH

The data for pH is also subject to some bias. It has a positive bias of 0.02 which means it is slightly more acidic than in-situ observations. It has generally good agreement with a more acidic *tropical tongue*, which is designated the equatorial region between the west coast of the Americas across the pacific. A correlation analysis was done between the modelled data and in-situ observations and a correlation coefficient of 0.95 was recorded, with a positive bias of 0.02 and a RMSE (Root Mean Squared Error) of 0.04m European Union-Copernicus Marine Service, (2018).

3.7.5 SST

One of the greatest sources of error regarding SST from MODIS is due to cloud obstructions. Reflected sunlight also affects the measurement of mid-IR SST. Also, the presence of aerosols and atmospheric gases and emissions can hamper the accuracy. Finally, surface water characteristics can also affect the accuracy of measurements (MODIS Aqua Level 3 SST Thermal IR Monthly 4km Daytime V2019.0).

In the MODIS SST algorithm empirical coefficients are derived from the regression of MODIS brightness temperatures with in-situ observations obtained from stationary and moving buoys. The regressed SST is converted to a skin SST measurement by taking in-situ measurements from the *M-AERI* radiometer (Marine-Atmospheric Emitted Radiance Interferometer), leading to an adjustment of -0.2°C. Data is said to be accurate to +-0.4°C, however, no confidence intervals are given. (MODIS Aqua Level 3 SST Thermal IR Monthly 4km Daytime V2019.0)

3.7.6 Chlorophyll a

The MODIS sensor is also responsible for estimating chlorophyll a concentration. It measures ocean colour, and it is from this that chlorophyll a concentration can be derived. It is calculated by using an empirical relationship combing remote sensing reflectance in the blue-green wavelength with in-situ measurements of chlorophyll. (NASA Earth Observations (NEO), n.d.)

Regarding errors concerning chlorophyll a concentration. There is no documentation concerning error margins or confidence intervals. However, the atmospheric corrections that are utilised, and the potential errors associated with them, concerning atmospheric absorption, aerosol properties and surface water reflectance can propagate into the measurements themselves (NASA Earth Observations (NEO), n.d.).

3.7.7 PAR

The algorithm employed in estimating PAR was assessed for accuracy by Frouin et al. (2001). They state that the algorithm assumes that cloud/surface system is stable throughout the day. In reality, this is very rarely the case, thus in areas with strong diurnal variability in cloud cover, the estimates are degraded. Additionally, they say that the factor needed to convert units of mW cm^{-2} μm^{-1} to Einstein m^{-2} day^{-1} has an inaccuracy of a few percent regardless of weather conditions.

When comparing the algorithm with the ISCCP (International Satellite Cloud Climatology Project) PAR products measurements the agreement is good with and RMS difference of 3.6 Einstein m^{-2} day^{-1} on a monthly timescale. When comparing the algorithm with in-situ measurements there is good agreement. An R^2 value of 0.994 was obtained when compared with a dataset obtained from buoys off the west coast of Canada. Overall, the accuracy tends to increase when looking at monthly rather than daily data. This is likely due to the cloud errors being averaged across many days and, as a result, the uncertainties associated with clouds are reduced.

3.8 Additional errors

Furthermore, many layers, which did not cover the entire spatial extent of the Red Sea had to be interpolated. After deliberations IDW was decided as the best method. IDW assumes autocorrelation between nearby points and calculates the value for the point based upon a search radius and weighting the nearby points based on how close they lie to the point being interpolated. Due to the nature of IDW, however, it is unable to estimate above or below the local maxima and minima. And given the nature of ocean data it is probable that some of the interpolated areas could have had values greater than the local maxima and minima.

Also, on salinity, there are several desalination plants along the coast of Saudi Arabia, 25 of which can be found by the Red Sea. After desalination is carried out, the excess brine is expelled back into the sea. However, the spatial extent of the data did not cover the coastal regions and thus it is likely that salinity was underestimated after the interpolations were carried out, especially in areas close to the coastline.

Something that is true for all the data layers is due to the nature of the raster data. Raster data assumes homogeneity within the entire resolution of each pixel. It therefore doesn’t take into account any spatial variability within each pixel and given how environmental variables can deviate even across a small spatial range, there are some uncertainties here.

It is important to note about the subjectivity of measuring coral reef bleaching. Many of the surveys were conducted by Reef Check. Their main method of measuring bleaching is using the belt transect method. This method randomly lays out a belt after which quadrants are placed over the belt and the percentage of bleaching is estimated for each quadrant before being averaged across the entire belt transect. While this is a method that requires little equipment aside from scuba diving apparatus, it is not categorical, and some subjectivity is inherent. There are newer methods to measure coral bleaching, such as using photographs alongside machine learning algorithms that classify bleaching based on spectral information. It is certain that as these methods improve and become more widespread, that documenting and quantifying bleaching will become more accurate.

3.9 Different resolutions

Many of the datasets had different resolutions. However, it was chosen to keep the datasets with their current resolution. If the datasets were to be harmonized it would have required some interpolations which would propagate the existing errors. Thus, it was decided to keep the resolutions consistent with their availability. While IDW (Inverse Distance Weighted) interpolations were carried out to fill in data gaps, the resolution of the interpolations were made to match that of the input data. Furthermore, given that no calculations were carried out within ArcGIS Pro, it was deemed sufficient to keep the data at different resolutions.

4. Results

4.1 Correlation results

Table 1: Pearson correlation matrix. L= Latitude, PB = Percent bleached, SST = Sea Surface Temperature, Ca= chlorophyll a concentration, WS = Wind Speed, S = Salinity, SC = Sea Surface Currents, and PAR = Photosynthetically Active Radiation. A heat map is used to display low values in red and high values in green.

Pearson's	L	PB	SST	Ca	WS	S	pH	SC	PAR
L		***-0.41***	***-0.4***	***-0.4***	***-0.09***	***0.76***	***0.42***	***-0.4***	-0.09
PB	***-0.41***		***0.33***	***0.44***	***-0.24***	***-0.36***	***-0.48***	0.09	-0.01
SST	***-0.4***	***0.33***		***0.1***	***0.16***	***-0.11***	***-0.51***	***0.14***	***0.23***
Ca	***-0.4***	***0.44***	***0.1***		***-0.15***	***-0.33***	***-0.14***	-0.05	***-0.17***
WS	-0.09	***-0.24***	***0.16***	***-0.15***		0.09	0.01	***0.31***	***0.31***
S	***0.76***	***-0.36***	***-0.11***	***-0.33***	0.09		***0.54***	***-0.27***	***-0.16***
pH	***0.42***	***-0.48***	***-0.51***	***-0.14***	0.01	***0.54***		***-0.14***	***-0.33***
SC	***-0.4***	0.09	***0.14***	-0.05	***0.31***	***-0.27***	***-0.14***		***0.31***
PAR	***-0.09***	-0.01	***0.23***	***-0.17***	***0.31***	***-0.16***	***-0.33***	***0.31***	

All the environmental factors are significantly correlated with bleaching with the exception of PAR and Sea Surface Currents. The strongest correlation of any factor with bleaching was found to be pH. With a value of -0.48, it shows that as pH decreases, bleaching increases. Chlorophyll a had the strongest positive correlation with 0.44. Bleaching decreased as latitude increased (-0.41), this is likely due to SST also decreasing with increasing latitude. SST was expected to have the strongest correlation with bleaching but had a value of 0.33. As hypothesised wind speeds were negatively correlated with bleaching, as too was salinity, however the opposite was hypothesised with salinity. Sea surface currents and PAR yielded insignificant and weak correlations.

Table 2: Correlation matrix using Kendall Tau correlation.

Kendall's	L	PB	SST	Ca	WS	S	pH	SC	PAR
L		-0.38	-0.37	-0.16	-0.12	0.59	0.25	-0.34	-0.05
PB	-0.38		0.39	0.21	-0.13	-0.37	-0.39	0.07	-0.05
SST	-0.37	0.39		-0.27	0.11	-0.33	-0.74	0.17	0.18
Ca	-0.16	0.21	-0.27		-0.23	-0.11	0.25	-0.09	-0.32
WS	-0.12	-0.13	0.11	-0.23		-0.06	-0.02	0.23	0.25
S	0.59	-0.37	-0.33	-0.11	-0.06		0.29	-0.21	-0.11
pH	0.25	-0.39	-0.74	0.25	-0.02	0.29		-0.1	-0.16
SC	-0.34	0.07	0.17	-0.09	0.23	-0.21	-0.1		0.23
PAR	-0.05	-0.05	0.18	-0.32	0.25	-0.11	-0.16	0.23	

In the Kendall Tau correlation pH and SST were equal with their correlation though the direction of the relationship was opposite, -0.39 and 0.39, respectively. Salinity was again negatively correlated (-0.37) as was wind speed (-0.13). Chlorophyll a had a positive significant correlation of 0.21 with wind speed negatively correlated at -0.13. Again, both surface currents had weak and insignificant correlations.

Table 3: Correlation matrix using Spearman's correlation.

Spearman's	L	PB	SST	Ca	WS	S	pH	SC	PAR
L		-0.47	-0.53	-0.23	-0.19	0.75	0.34	-0.49	-0.06
PB	-0.47		0.49	0.27	-0.16	-0.47	-0.5	0.09	-0.07
SST	-0.53	0.49		-0.29	0.18	-0.45	-0.89	0.25	0.32
Ca	-0.23	0.27	-0.29		-0.33	-0.21	0.28	-0.13	-0.52
WS	-0.19	-0.16	0.18	-0.33		-0.09	-0.06	0.32	0.35
S	0.75	-0.47	-0.45	-0.21	-0.09		0.37	-0.32	-0.2
pH	0.34	-0.5	-0.89	0.28	-0.06	0.37		-0.15	-0.32
SC	-0.49	0.09	0.25	-0.13	0.32	-0.32	-0.15		0.34
PAR	-0.06	-0.07	0.32	-0.52	0.35	-0.2	-0.32	0.34	

SSTs correlation was highest in Spearman's correlation, (0.49). pH was again the highest with -0.50 salinity was more negatively correlated here than in any other correlation method (-0.47). Chlorophyll a was more correlated in this method than any other (0.27). Wind speed was again negatively correlated with a value of -0.19.

Regarding the initial hypotheses, it was predicted that SSTs and bleaching were positively correlated with each other, and all three correlations confirmed this with 0.33, 0.39 & 0.49, values for Pearson's, Kendall's, & Spearman's respectively. Chlorophyll a concentration was also hypothesized to be correlated positively which was also confirmed by the correlation analysis, with significant correlations of 0.33, 0.21, & 0.27.

It was hypothesized that salinity would be positively correlated with bleaching, but the correlation analysis showed that the inverse was true with negative correlations of -0.36, -0.37, & -0.47.

SSCs was hypothesized to be negatively correlated to bleaching but the correlation analysis showed small insignificant correlations, 0.09, 0.07, & 0.09. The same was predicted for PAR and while all were negative correlations, they were weak and insignificant -0.01, -0.05, and -0.07. Wind speed was also predicted to be negatively correlated with bleaching, while this was true and the correlations were significant, they were quite weak, -0.24, -0.13, & -0.16. Finally, pH was expected to be negatively correlated with bleaching and the analysis proved this to be true with correlation coefficients of -0.48, -0.39 & -0.5.

Regarding the covariance of the parameters with one another, SSTs and pH were strongly and significantly correlated with negative correlations of -0.51, -0-74, & -0.89. Similarly, salinity had a strong correlation with Latitude, showing that as latitude increases so too does salinity. This is likely due to the high evaporation rates and low precipitation in the surrounding terrain. Regarding, parameters that had little or no significant correlation with one another, wind speed had low correlations with both salinity and pH, average values of -0.02 and -0.0233, respectively. This means that salinity and pH levels are not affected by increases or decreases in wind speed.

4.2 Regression analysis and PCA

Several regressions were assessed using MSE and R^2 and can be seen in table 4. The best performing regressions were chosen based on the lowest MSE and highest R^2 value (table 4). While the gradient boosting regression had good values for both, it was omitted as it gave negative values for bleaching. Thus, the three regressions that were used were *Decision Tree, Random Forest*, and *K-Nearest Neighbours*.

Table 4: Regression performance with Means Squared Error and R squared.

Regression	MSE	R^2
Linear	175.00	0.21
Ridge	181.37	0.18
Lasso Regression	186.85	0.16
Decision Tree	42.70	0.81
Support Vector	228.05	-0.03
Gradient Boosting	31.92	0.86
Random Forest	28.66	0.87
K-Nearest Neighbours	21.55	0.90

After finding the best performing regressions, a Primary Component Analysis was run to find which variables are most important to the regression model for predicting coral bleaching and the results can be seen in table 5. PCA isn't possible on k-nearest neighbours as it does not weigh variables in the same manner as decision forest and k nearest neighbours, thus it was excluded from the PCA.

Table 5: Results of the PCA for random forest and decision tree regressions.

Variables	Importance Random Forest	Importance Decision Tree
SST	0.810	0.806
Wind speed	0.074	0.090
pH	0.043	0.050
Surface currents	0.025	0.009
PAR	0.019	0.008
Salinity	0.017	0.021
Chlorophyll a concentration	0.012	0.016

The PCA on both random forest and decision tree showed that SST, wind speed and pH were the three most important variables, while disagreeing on the order of the 4 least important factors. As both agreed on the 3 principal components it was decided to use these three in the following regression analysis. After removing the least important variables from the dataset, the model was run once again. And the updated performance, MSE and R^2 were documented and shown in table 6.

Table 6: Regression performance after PCA removed unimportant variables.

Regression	MSE	R^2
Decision Tree Regression	21.75	0.90
Random Forest Regression	22.81	0.90
K-Nearest Neighbours Regression	33.64	0.85

The trained models were used to predict future bleaching. All three regression methods predicted increases in bleaching in each of the future scenarios. Decision Tree and Random Forest were similar in their outputs while K nearest neighbour had lower values for bleaching, figure 6. In both decision tree and random forest there is a sharp increase in bleaching between 2070 and 2100, resembling almost exponential curve. With K nearest neighbour, it is a more linear increase in bleaching.

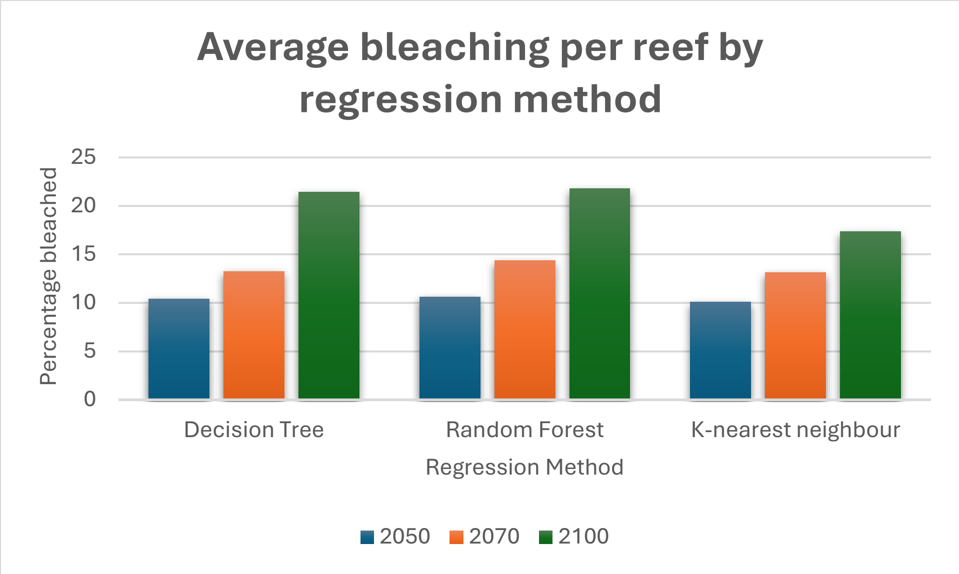

Figure 6: Average predicted bleaching at different points in the future using different regression methods.

5 Discussion

Regarding the first research question, the variables most strongly correlated with bleaching were pH and SST. pH had a moderate negative correlation with bleaching. The values obtained for any study area ranged between 7.90 to 8.14. The study done by Antony et al. (2008) showed that in low pH scenarios bleaching was observed. However, their range for low pH was 7.6-7.7, and as no values were observed in this range perhaps this is why the correlation wasn't stronger. However, on the 10 occasions when pH dropped below 8.0 average bleaching values of 32% were seen. With average bleaching recorded across the 474 points at 6% this reinforces the notion that ocean acidification can cause bleaching. Regarding SSTs, while there was a moderate positive correlation with bleaching, it was not as high as anticipated. However, on the 19 occasions that SSTs exceeded 32°C average bleaching stood at 69.8% showing that elevated SSTs can cause bleaching. Furthermore, DHWs are often used instead of simply SSTs as a metric to predict bleaching. This measures not only temperature anomalies, but the duration of the heat anomaly is also factored in. While this would have been possible to calculate for each site, it was beyond the time scope of this study.

The study done by Moberg et al. (2009) claimed that in hyposaline, 10-20 mg g^{-1}, environments there could be bleaching. However, no such hyposaline events were observed in the study period with salinity levels steady and ranging from 35-41 mg g^{-1}. This could explain why there was little correlation with bleaching. Furthermore, the salinity data had the coarsest resolution. Because of this, interpolations were required so that the data would cover the entire study area. This doesn't account for the desalination plants along the west coast of Saudi Arabia. Here salinity levels are potentially higher, but this data was essentially missing from the study because of the resolution.

In terms of windspeed, the study done by Paparellea et al. (2019), said that wind speed value of greater than 4 m s^{-1} led to reduced bleaching. On the 74 occasions where wind speed was greater than this threshold value, bleaching averaged just 0.67% which is in line with findings from the aforementioned study. While Keighan et al. (2023) found a negative correlation between chlorophyll a concentrations and bleaching, the inverse was found in this study with positive correlations ranging from 0.21 - 0.44. Exactly why this is the case is unclear, however when chlorophyll a concentration exceeded 1 mg m^{-3} average bleaching stood at 41%.

All variables excluding PAR and surface currents were significantly correlated with bleaching though the strength of the correlations varied. PAR didn't show any strong or significant correlation with bleaching. However, the study done by Sridhat et al. (2012), showed that PAR values of greater than 118.05 W $m^{-2}day^{-1}$ alongside temperatures of 30 °C can cause bleaching. Out of the 474 records of bleaching between 2007-2023, these conditions were only observed in 28 of the surveys done. And bleaching was recorded on

25/28 records, with an average bleaching of 27.6% when these conditions were present. This is considerably higher than the total average bleaching of 6.2%. This implies that while SSTs may be important in causing bleaching, often it is the combination of it and other stresses that can cause bleaching.

With SSC, it was hypothesised that increases in current speed would act to reduce bleaching, however this was a weak and insignificant correlation of between 0.07-0.09. The average SSC across all areas was 0.08, taking all occurrences when SSC were greater than this value, average bleaching was 10% showing that SSC didn't act, as hypothesised, to reduce bleaching. This could be due to the counteractive effects of currents. As currents increase so too does upwelling from deep waters. It is likely that nutrient upwelling may have acted to eutrophy the ocean water increasing bleaching likelihood.

There was some correlation seen between the environmental parameters themselves, especially SST and pH. With an average correlation coefficient of -0.71. This shows the two factors are linked, as SST rise, pH decreases. This could be due to higher evaporation rates in hotter water leaving more hydroxide ions in the solution making it more acidic.

Regarding the second research question, investigating how increases in SST under RCP 8.5 will affect bleaching, all the regression models predicted increases in bleaching, with RMSE and R^2 values of 4.66 and 0.9, 4.78 and 0.90, and 5.8 and 0.85 for decision tree, random forest and k -nearest neighbours respectively. It shows good accuracy, with a maximum bleaching value of 100, the average error stands at 4.6%, 4.78% and 5.8% respectively. However, this model assumes that all the other environmental factors stay static, in reality this would likely not be the case. This is why the PCA was used to find just the most important parameters. Given that PCA uses only the most important factors when predicting future bleaching and as future projections for the other parameters were unavailable only projections in SSTs were used. It would have been of greater interest to add projected changes in both pH and wind speed too and rerun the regressions, however this was beyond the time scope of the project. It is worth noting too that the regression output is sensitive to potential increases in thermal and acidic tolerance of corals and their endosymbionts. It assumes that this stays static from the present into the future which is likely not the case. However, it is possible that reefs here are already living close to their thermal threshold, especially in the south and increases in temperature of a few degrees may be enough to cause mass coral bleaching and potentially even mass mortality.

Additionally, it is possible that the lack of people living alongside the Red Sea acts to reduce harmful additional stresses to reefs. Due to the harsh surroundings of the Sahara Desert, population density is low and restricted to a narrow belt alongside the coast. Due to this, there is likely less pressure from anthropogenic sources, for example, coastal pollution, than in other more densely populated coral regions such as Indonesia.

Regarding future studies, it is well established that coral reefs are threatened mainly due to increasing SSTs. While in the Red Sea this doesn't seem to be as prominent, due to the higher thermal thresholds that corals here display, they are still not immune to bleaching and other factors, as this study points out may also contribute to coral bleaching. Ocean acidification can also stress corals leading to bleaching, and with CO_2 emissions rising steadily the pH of the oceans is set to decrease.

Likewise hyper-saline environments may also act to bleach corals. With more desalination plants necessary to provide clean drinking water to growing populations along the Red Sea, salinity levels may increase in the locality of these desalination plants. An interesting study would be to measure seawater salinity and coral health which are close to such desalination plants. A continuation of that study could be to evaluate the salinity thresholds of corals here to see if they have developed some type of tolerance to a more saline environment, though perhaps not enough time has elapsed to see changes in tolerance to any environmental factors.

Coral bleaching happens due to stresses on corals, these stresses come from environmental factors as outlined in this report. While some are out of our control, many can be reduced if carbon budgets are met. With a focus on reducing carbon emissions this may act to reduce the speed at which oceans warm and acidify. This more gradual rise in temperature and acidity may allow for the selection of heat and acid resistant corals.

Furthermore, the divide between the North and Southern Red Sea in terms of temperature means that if temperatures become too extreme in the southern regions, there is space for them to migrate northwards. Thus, the north acts as a thermal refuge for corals. Corals between 11 - 21° N had average bleaching values of 42% while those between 21 - 29.5° N had just 2.8%. While there is greater coverage with more surveys conducted in the north than the south, there is still a clear divide seen between the two halves of the Red Sea. With bleaching negatively correlated with Latitude it is further evidence of the divide between the two. It would have been better to divide the data into north and south to analyse different patterns in bleaching and perhaps even identify different drivers of bleaching. This could have shown differential bleaching response of corals of the same species within one body of water.

Regarding potential future studies, it would be interesting to include many different coral regions in a similar study. Comparing the primary components of bleaching in other areas may shed light on the exact mechanisms causing bleaching. However, despite the lack of bleaching in the Red Sea as opposed to other areas, the PCA showed that SSTs was still the principal component regarding bleaching.

Coral bleaching happens due to stresses on corals, these stresses come from environmental factors as outlined in this report. The report also showed the susceptibility of corals to increases in SSTs, as seen in the regression analysis. While some changes in environmental factors are natural and cyclical, many can be reduced if carbon budgets are met. With a focus on reducing carbon emissions this may act to reduce the speed at which oceans warm and acidify. This slower rise in temperature and acidity may allow for natural selection of thermal and acid resistant corals.

6 Conclusion

In conclusion, coral reefs are increasingly under threat from climate change, particularly due to rising SSTs and ocean acidity, as highlighted in the report. Both increased SSTs and acidity were significantly correlated with coral bleaching, with SSTs identified as the primary driver. However, it is often the combination of various environmental stresses that leads to bleaching.

With corals worldwide already living near their thermal, acidic, and other environmental thresholds, the prevalence of bleaching and subsequent mortality is likely to increase, even in regions that have so far experienced relatively little bleaching. This underscores the importance of continued research into the exact mechanisms of coral bleaching. Investigating the thermal thresholds of specific species, along with selectively breeding and transplanting those with higher thermal tolerance, could provide valuable insights and help to preserve these ecosystems.

Moreover, further studies on hyper-saline environments and their effects on corals are crucial, especially as the need for desalination plants grows with increasing populations and the demand for clean drinking water. Given the significant variations in environmental factors correlated with latitude, dividing the data by region and analysing the drivers of coral bleaching at different spatial scales could uncover more bleaching patterns. This approach might reveal how these drivers vary by location and identify different principal components beyond SSTs that influence coral bleaching.

The report also demonstrated the susceptibility of corals to SST increases through regression analysis. While some environmental changes are natural and cyclical, many can be mitigated by meeting carbon budgets. Focusing on reducing carbon emissions could slow the warming and acidification of oceans, allowing for the natural selection of thermally and acid-resistant corals.

Conserving these rich and biodiverse ecosystems is not only beneficial for us but also crucial for future generations. By addressing the immediate threats and understanding the complex drivers of coral bleaching, we can work towards preserving these vital ecosystems.

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8 Appendix

Correlation word.txt

Appendix 1: Script used in the correlation analysis.

PCA random forest word.txt

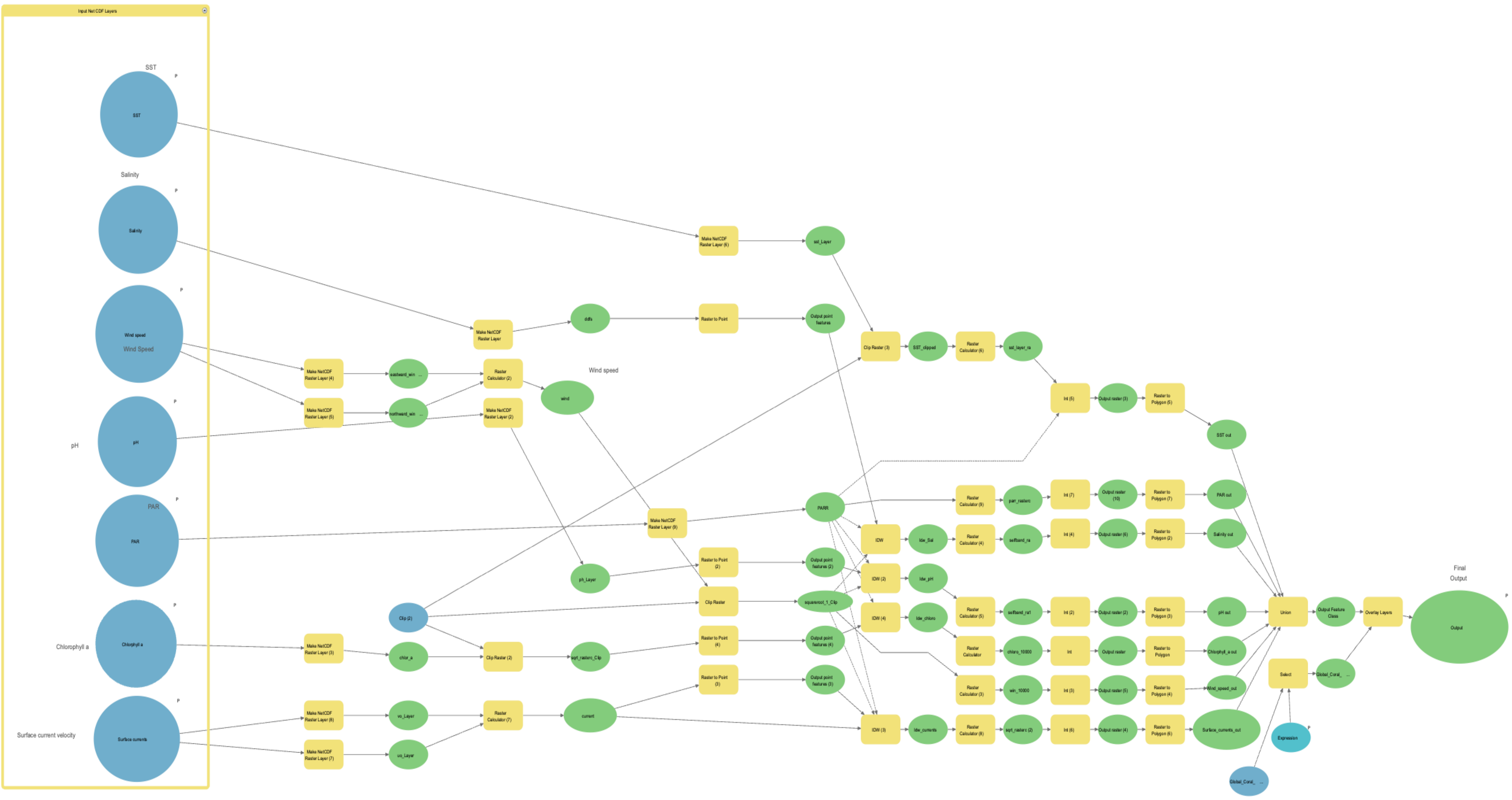
Appendix 2: Script used for the Random Forest PCA.

PCA Decision Tree word.txt

Appendix 3: Script used for the PCA for the Decision Tree.

Regression word.txt

Appendix 4: Script used in the regression analysis.



Appendix 5: Entire model builder used in the GIS processing step