Universal Remote Observation of Coral Health (UROCH): Studying the Efficacy of Extending Existing NASA Instruments to Detect and Monitor Coral Reefs

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***Abstract*— Coral reefs, one of the most biodiverse ecosystems on the planet, are facing the threat of extinction. This is projected to cause severe environmental damage, especially on the fronts of climate change and marine life. Although multiple efforts are being made to evaluate coral reef health and revitalize those witnessing severe bleaching, these efforts remain expensive and unsustainable. In this project, we study the capability of using satellite data from NASA's Landsat-8 and MODIS-Aqua to detect coral reef presence and evaluate coral bleaching severity. We adopt a multi-faceted approach by merging data from Allen Coral Atlas and Global Coral Bleaching Dataset with satellite data in the Caribbean and Great Barrier Reef regions. Using a gradient-boosted tree-based classification model, we achieve 96.5% accuracy in identifying coral/algae, implement a temporal voting-based classifier to distinguish coral from algae, and achieve 96.94% weighted precision in evaluating bleaching severity in the Great Barrier Reef. Using this machine learning pipeline and the dashboard developed from it, coral reef experts can identify regions where the reefs are at risk and act to revitalize them, all while viewing metrics showing trends in sea surface temperature in those areas.**

I. INTRODUCTION

Coral reefs, which are constituted of thousands of small marine animals called corals and exist in over 2000 species, have been witnessing large-scale and global degeneration as a result of different natural and man-made conditions. This poses a grave danger on the environment as a whole and contributes to the exacerbation of climate conditions around the world because coral reefs play a critical role in biodiversity preservation and marine life sustainability. In addition to that, they play a major role in shoreline protection [1]–[4]. Although reef degradation has been occurring since the 1900s, the recent widespread reef mortality has been associated with the bleaching phenomenon [5].

Given the urgency of the threats facing coral reef health, there have been many initiatives centered around coral reef monitoring and in-situ assessments worldwide such as Reef Check, CoralWatch, Coral Vita and many others. Data from these programs support different efforts such as the Global Coral Reef Monitoring Network that publish reports on coral reef health globally. Although the efforts put by these initiatives are crucial in understanding the roots of the problem, it has been proven that such on-site surveys - which require funding, labor, and other resources - are difficult to sustain. In addition to that, they lack an element of consistency between the different groups and organizations that are working on them despite current global efforts towards reaching standardized mechanisms to monitor and record data on coral reefs [5]. These concerns about the reliability of survey data on coral reef health in addition to the issue of scalability of such projects worldwide have instigated research on alternative methods to determine coral reef health. A significant aspect of that research focuses on utilizing remote sensing data that is available through different sources as an alternative to field surveys. Remote sensing, and satellites in specific, offer a significantly more cost-effective mechanism to assess coral reef health than traditional surveying. Despite certain limitations that satellite data could pose (such as layers of detail and accuracy in the backscatter or image data), it does provide significant coverage of the areas of interest with both temporal and spatial components [7].

With the availability of survey on-site data on coral reef health and the open source satellite data provided by multiple NASA projects, this project approaches determining the health of coral reefs from a machine learning perspective. It is important to note that the health of coral reefs is determined by the bleaching phenomenon, which is the corals' reaction to stress factors. This entails collecting data about coral reef health in the Caribbean and Great Barrier Reef regions from credible sources such as Allen Coral Atlas and the Global Coral Bleaching Database and setting those as ground truths used to calibrate predictive machine learning models. The said models are trained using open-source NASA satellite data (MODIS and Landsat-8) to provide two layers of prediction. The first identifies coral presence and uses a temporal voting-based method to distinguish between coral and algae. The second layer then evaluates the bleaching status of points identified as coral. This is a multi-phase project that first collects the data from the selected sources, then aggregates the satellite and ground truth data through temporal and spatial alignment, and finally trains and tests machine learning models to predict coral presence and evaluate their vitality. The project also provides a dashboard that serves as a user interface for the models, by which the users can input certain longitudes and latitudes and retrieve model outputs indicating coral presence and bleaching level.

II. Literature Review & Background

The urgency in the need to monitor the location and health of coral reefs has pushed researchers to search for scalable methods that often combine satellite imagery with machine learning techniques to identify and classify coral presence and health [8]. NASA's Landsat program holds multispectral satellite imagery and provides open access to data, thus has been popular in research. However, identifying coral bleaching using satellite imagery continues to be a difficult problem, as bleached corals have similar spectral values as sand and similar reflectance properties to algae [9]. Additionally, coral bleaching and recovery typically occur over a span of weeks or months, thus cannot be captured in a singular satellite image. Past studies have used Sentinel-2 for detecting coral bleaching but results have been largely unsatisfactory, as sand and rubble are often misclassified as bleached coral [10].

Due to unsuccessful attempts at using satellite imagery alone, researchers have turned to adding other indicators to their models to identify bleaching. In excessively warm water, zooxanthellae will leave the tissue of the coral, resulting in bleaching. Other causes of bleaching are runoff and pollution, overexposure to sunlight, and extreme low tides that leave coral exposed to air [11]. The National Oceanic and Atmospheric Administration (NOAA) has used sea surface temperature to predict bleaching, and relies on marine heatwaves as an indicator for potential bleaching events. They establish a temperature baseline and compare daily temperatures to it. Furthermore, the bleaching phenomenon has also been associated with fluctuations in chlorophyll A. In fact, studying SST without considering the physiological state of chlorophyll A from zooxanthellae is rather limiting [13]. Jones (1997) suggests that chlorophyll A concentration decreases during bleaching events, only to increase again in the months following the event. This zooxanthellar chlorophyll A has also been observed to change in different water temperatures. Though the presence of chlorophyll A had been previously associated to algal cells, it has been shown that in certain bleaching events, algal cells remain constant despite a change in chlorophyll A concentration. Therefore, this led to speculation about a relationship between corals themselves and chlorophyll A concentration [14].

Previously used models for remote coral reef mapping include maximum likelihood classifiers, support vector machines (SVM), random forests (RF) with the latter yielding the highest accuracy scores [9]. A study conducted on Landsat-7 and Landsat-8 images to predict coral reef health in locations on the Pacific Ocean known to house coral reefs collected survey data and used it as ground truth. After spatial and temporal matching between satellite and ground truth data, a support vector machine was trained and validated, per-pixel classification was performed. This method is well-founded and its framework will be used as a starting point in this project [5].

III. Data Sources, Collection & Fusion

Data collection and fusion was a crucial component to this research project and the four data sources used in this study were the Allen Coral Atlas, the Global Coral Bleaching Database, and the MODIS and Landsat-8 satellites.

A. Allen Coral Atlas

The Allen Coral Atlas is the result of a project that is maintained by the Arizona State University Center for Global Discovery and Conservation Science, in collaboration with Planet, the Coral Reef Alliance, and the University of Queensland. It contains a global map of coral reefs, identified using analytical techniques on satellite imagery from PlanetScope's Dove and SkySat satellites. This map is in near real time, with 4-10m resolution satellite imagery that updates biweekly.

The Atlas contains mapped areas that are preloaded for ease of download for the user. Our team downloaded data from the following two mapped areas in the Atlas- (1) Great Barrier Reef and Torres Strait, (2) Northern Caribbean, Florida, & Bahamas. The download contained a benthic mapping in GeoPackage format, which was loaded into a pandas dataframe. The benthic map is composed of six classifications categories, which are coral/algae, seagrass, microalgal mats, rock, rubble, and sand. The benthic map class description document explains that the satellites used by the Atlas are not able to identify key reef health assessment measures such as living and dead coral cover, coral bleaching, and functional forms of algae, thus the coral information on benthic map is constrained to the broad category of coral/algae.

The Allen Coral Atlas also partners with the National Oceanic and Atmospheric Administration (NOAA) and displays data from NOAA's Coral Reef Watch program. The information on display in the Atlas is pulled from the most recently published NOAA data on sea surface temperature (SST), SST Anomaly, Coral Bleaching HotSpot, Degree Heating Week (DHW), a 7-day maximum Bleaching Alert Area, and 7-day SST Trend, and results in a mapping of coral bleaching into the categories of low, moderate, and severe. Although this data is not yet available for download, the methods for bleaching inference using SST are documented and were used as inspiration for our attempts to identify bleaching.

B. Global Coral Bleaching Database (GCBD)

The global coral bleaching database is composed of seven previous coral bleaching studies consolidating research from 1980 to 2020 into one database structure. [18] The included "Query 1 Summary Bleaching Cover" connects much of their relational database to a table containing latitude & longitude coordinates, the date the study was conducted, and one of three output variables. Those variables being Percent Bleached, a zero to one continuous output representing the percent of coral bleached within the area, as well as Bleaching Prevalence Score and Severity Code, both categorical variables articulated as integers from negative one to four. These integers are codes which represent various ranges of bleaching levels which we then converted to the continuous Percent Bleached output as outlined in table I to create a consistent target variable to train on. Records with Bleaching Prevalence Scores were directly converted to the median value of the range that they represent. For the Severity Code, in around half of the cases the records also had a continuous value for the percent of coral bleached in that area. Because of this, we took the median value from the known percent bleached records of each bucket and entered that as the percent bleached score where one was not already present. Then any unknown values from either variable were dropped from our final dataset.

TABLE I: Conversion of Categorical GCBD Values to Continuous Bleaching Percentages

Original Code	Bleaching Prevalence	Continuous Value	Severity Score	Continuous Value
-1	N/A	N/A	Unknown	Dropped
0	0%	0%	0%	0%
1	1% - 10%	5%	1% - 10%	4%
2	10% - 25%	17.5%	11% - 50%	32.85%
3	25% - 50%	37.5%	50% - 100%	75%
4	50% - 100%	75%	N/A	N/A

Lastly, records from the ReefCheck study were often split between two bleaching categories – population and colony. The population category was chosen so that one value was present for each time and location. This study also often collected multiple bleaching percentages for different depths. These values were averaged for all depths at a given location to avoid confusion in our model training that would arise from two identical inputs having different outputs.

C. Satellite Data: Landsat-8 & MODIS

Two satellite sources were used to build the dataset: Landsat-8 and MODIS. Landsat-8 launched in February 2013 whereas MODIS was first launched December 1999 aboard the Terra satellite. A second satellite, Aqua, was launched in May 2002 which also included a MODIS instrument. The time it takes for orbits to repeat is 16 days for Landsat and every 1-2 days for MODIS. In this study, we utilized surface reflectance data provided by each of the instruments. In total, six surface reflectance bands as well as the pixel quality from Landsat and nine surface reflectance bands from MODIS were used. The scale at which data for Landsat and MODIS was gathered is at 10x10m and 1000x1000m, respectively. Collection of this data was possible by taking advantage of the Google Earth Engine API.

D. Data Fusion

The process of aligning our coral and satellite data sources together was straightforward due to the fact we collected our satellite data from Google Earth Engine. We were able to create queries for a specific location and time using the longitude, latitude, and date from the respective coral dataset. Since Landsat did not repeat orbits daily, we had to create monthly queries. In the case that multiple data points were returned, only the data point that occurred closest to the time of the coral record was kept. Once data for both satellite sources was collected, they were able to be merged together by longitude and latitude. Both Allen Coral Atlas and the Global Coral Bleaching Database were used to create their own combined datasets.

IV. Data Analysis & Feature Engineering

This section describes the findings from exploratory analysis performed on both the Global Coral Bleaching Dataset and the MODIS data. It also delineates the process of feature engineering that was performed using MODIS data based on research in the field of coral bleaching.

A. GCBD Exploratory Data Analysis

Following our steps described in the Global Coral Bleaching Database setup, we were left with 22,955 rows. This was further condensed upon being joined with Landsat 8 which began collecting data in 2013 causing us to lose over 30 years of bleaching history. As we focus down to our specific regions, we are left with our final training data of 1162 rows. As seen in 1, these rows are skewed to lower bleaching values with far less data at higher bleaching levels.

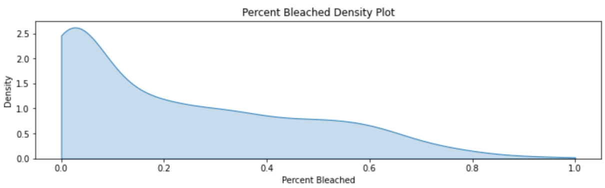

Fig. 1: Density Plot of Percent Bleached Data in GCBD

B. MODIS Data Analysis & Feature Engineering

Data from MODIS was collected and contained reflectance bands in addition to information on sea surface temperature, chlorophyll A, particulate organic carbon, and normalized fluorescence line height.

Given the literature on the existence of a relationship between coral bleaching and chlorophyll A concentration, chlorophyll A data was pulled from MODIS-Aqua to be studied and different features were engineered from it. Similar to the methodology used in studying sea surface temperature data, chlorophyll A data was collected from MODIS for each of the locations (longitude/latitude) present in the Global Coral Bleaching Database. For each location and date, the chlorophyll A data from the past 90 days was retrieved and the following metrics were calculated:

- *Average chlorophyll*: the average chlorophyll A concentration at the given point over the 90-day period
- *Minimum chlorophyll*: the minimum chlorophyll A concentration at the given point over the 90-day period
- *Maximum chlorophyll*: the maximum chlorophyll A concentration at the given point over the 90-day period
- *Chlorophyll change*: the difference between the last and first record of chlorophyll A at the given point over the 90-day period

These features were calculated in order to provide insight into the fluctuation of chlorophyll A that the point being studied has witnessed in the 90-day window. This allows the detection of sudden changes and aids in understanding the magnitude at which these changes occurred. These same features are also created for POC (particulate organic carbon) and NFLH (normalized fluorescence line height) data as these are collected for every instance of chlorophyll A and will potentially serve as useful features for the model. Research on the relationship between POC and NFLH was not performed as part of this project but could be studied should this project be further developed in the future.

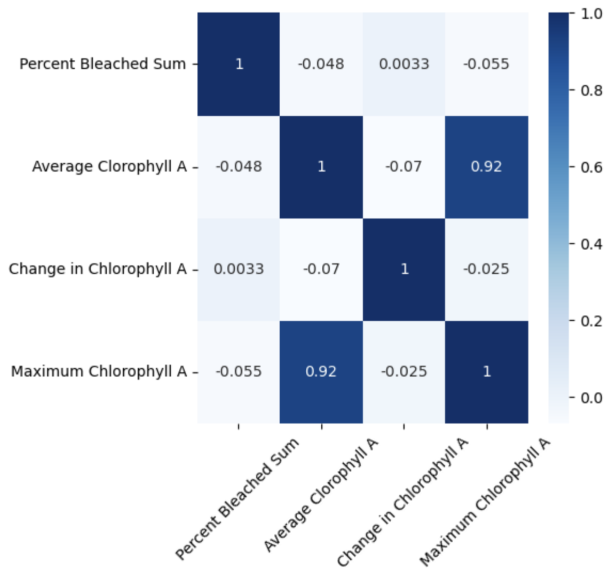

Fig. 2: Correlation between Percent Bleaching & Chlorophyll A Features

Figure 2 shows the correlation matrix between the features generated for chlorophyll A and the percent bleaching reported by GCBD. As observed, we can see that no strong correlation exists between any of the features and bleaching. However, this does not necessarily mean they would not be helpful in our model. It is also critical to note that according to previous studies, it is difficult to determine the cause of changes in chlorophyll A concentration, as contributing factors include changes in coral health, fluctuation in algal cell presence, or existence of phytoplankton in the area.

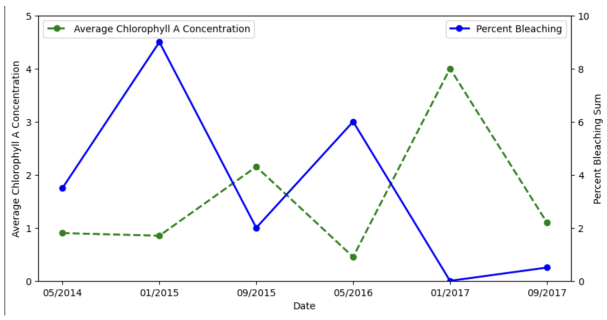

Fig. 3: Coral Bleaching Sum vs. Average Chlorophyll A Concentration

At the point (lat=-26.645 and lon=153.160806), figure 3 shows an increase in the average chlorophyll A concentration and chlorophyll A change during bleaching events (2014/10 - 2015/05) while bleaching decreases, and an increase in those averages before that (bleaching period). However, we also observe a decrease in both bleaching and chlorophyll between 2016/09 and 2017/01. This indicates that changes in chlorophyll A concentration may correspond to bleaching events, although many other factors are also at play. Most notably, this example suggests that changes in chlorophyll A concentration could be a lagging indicator of bleaching levels at a given location. After performing this analysis, we decided to incorporate chlorophyll A features in our models.

Following previous research showing the impact of rising sea surface temperatures (SST) on coral bleaching, we also extended the SST data for a 90 day history before each prediction in order to capture the environmental stress on the coral. Previous work showed that sustained temperatures beyond the monthly maximum mean (MMM) increases the risk of bleaching events [19]–[21]. More specifically, the Monthly Maximum Mean is the warmest average temperature of any month at a particular location. This work is further documented in Liu Et al. (2017) outlining the benefits of sea surface temperature to MMM based metrics HotSpot and Degree Heating Weeks (DHW) succeed as predictors for bleaching events. HotSpot functions as the direct SST – MMM comparison while DHW is defined by the following function:

$$DHW_i = \sum_{j=i-83}^{i} (\frac{HS_j}{7}); \ where \ HS_j >= 1$$

Using MODIS, we were able to access sea surface temperatures at any location and time through the scope of the data. However, to create the MMM, pulling multiple years of history to create monthly averages for the entire globe was infeasible. This was instead created with data from NOAA, accessed through the Columbia IRI Data Library [23]. This data source contained the monthly mean sea surface temperatures for each degree around the globe from 1980 - 2020. From there the monthly maximum mean was calculated at each available point. There is some error created by calculating this with a one degree difference per data point. At the furthest possible extent, a coral point could be 68km away from the closest MMM location to the GCBD point. Also, the work cited earlier by NOAA works within a half degree resolution. Because of this and initial comparisons to GCBD showing extensive bleaching with 0 DWH, we decided to average a variety of top months to lower the threshold for data collection. Ultimately, we landed on using the top three months as this best captured the variability of GCBD's bleaching values.

Using this dataset, we pulled a 90 day history of sea surface temperatures at each record in the GCBD dataset to compare with its location's closest MMM. From this we pulled out a variety of features including, the maximum temperature, the maximum temperature beyond the MMM, the cumulative degrees above MMM, and the number of days above MMM, NOAA's HotSpot and DHW. DHW is the current standard for predicting bleaching events. However, we found that the high floor required for DHW to start capturing data resulted in it mostly producing zeros. Curious

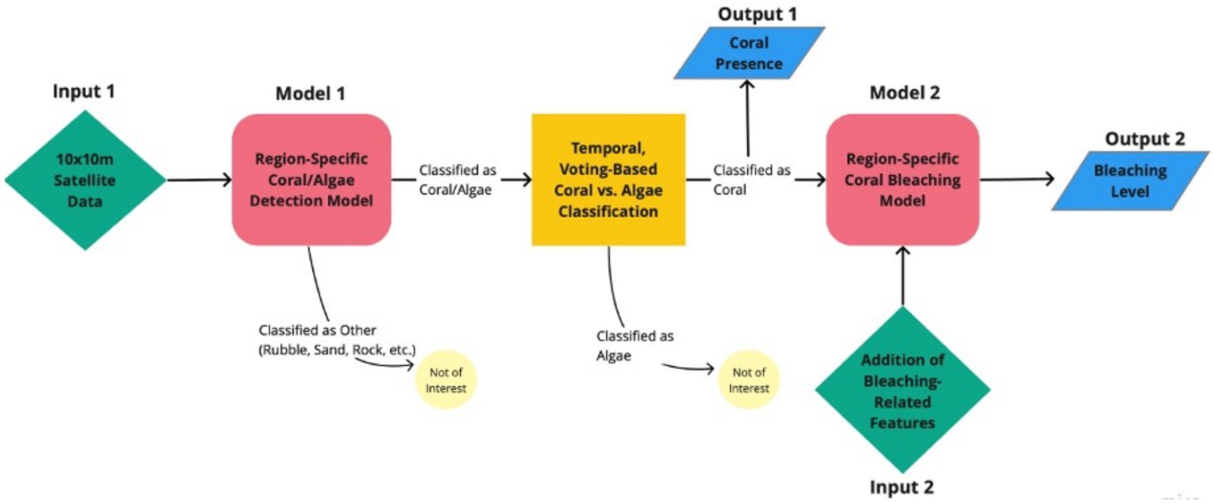

Fig. 4: Flow Chart of Modeling System Architecture

if GCBD's data collection was performed beyond 90 days from a bleaching event, we decided to capture the metric over a longer history. Following the work indicating that healing from severe bleaching events can take three years or longer, [24] we then extended the DHW's data collection to go back three years. To capture this difference in data collection, the date when the maximum Degree Heating Week value occurred was captured as a separate column.

Beyond high sea surface temperatures, we also built a set of features inspired by work which found that rapidly rising temperatures can cause bleaching at an overall lower threshold than the MMM [25]. They found this relationship was best captured when the coefficient of variation (CV) over a rolling fourteen day period increased beyond 1.9. This finding was replicated within our features as the maximum CV over the past 90 days, the cumulative CV when above 1.9, and the total number of days above 1.9. These were also duplicated as "summer corrected" features which only counted CV values when the temperature was increasing. The result of this work created eleven individual features capturing both the extremes and the extent of sustained high temperatures, as well as how rapidly those temperatures changed prior to the GCBD record collection. These features, along with the nine features related to POC, NFLH, and chlorophyll A encompass an expanded view characterizing the reef's environment over the past three months and how detectors for organic matter have adjusted.

V. Overview of System Architecture

Figure 4 depicts the system adopted by this study to remotely identify coral presence and monitor the health of coral reefs using satellite data from NASA instruments. The system consists of the multiple steps outlined below:

1) Collection and fusion of surface reflectance features and spectral indices from the Landsat-8 and MODIS satellites for a given 10x10-meter area
2) Use of the features gathered in step 1 to infer coral/algal presence using an XGBoost classification model trained on a large volume of Allen Coral Atlas data from the same region of the ocean as the given 10x10-meter area
3) A temporal, voting-based method for distinguishing between coral and algae to determine coral presence at the given location
4) Incorporation of features inferred from the MODIS satellite that are known to be associated with coral bleaching including sea surface temperature and chlorophyll A concentration
5) Use of a mixture of features gathered in step 1 and step 4 to infer coral bleaching level using a model trained on available Global Coral Bleaching Data

The subsequent sections will describe each component of the proposed system in detail, discuss the motivation for various design choices, and highlight current results and suggestions for future expansion.

VI. Model Development, Results & Discussion

This section explains the development of each of the models created, the data used for each of them, and the results/output generated in addition to a discussion on their capacities and limitations.

A. *Coral/Algae Detection*

The first model within the system architecture is detecting coral/algae from other benthic classes using an XGBoost model. Two regional models were created, one for the Northern Caribbean and another for the Great Barrier Reef. The features used in these models are the surface reflectance bands from both satellites and spectral indices calculated from Landsat. The Northern Caribbean model yielded an accuracy of 84.6% and the Great Barrier Reef model produced an accuracy of 96.5%. We believe the discrepancy between the two accuracies is caused by the Great Barrier Reef having larger contiguous areas of coral compared to other regions. This makes it easier to determine coral/algae from non-coral, hence the higher accuracy. In order to produce reliable results, models need to be made for each specific region. This is because not all regions contain the same species of coral, so the models have a hard time generalizing to regions that are not included in the training data.

B. Coral/Algae Differentiation: Temporal, Voting Based Classification

As noted in the previous section, the first model in the proposed system architecture serves to distinguish coral/algal presence from other benthic classes like rubble, rock, and sand for a given location. This grouping of coral and algae into a single class arises from the challenge of discerning between coral and algae by their spectral properties alone as our system does using Landsat and MODIS surface reflectance and spectral indices. Figure 5 illustrates the

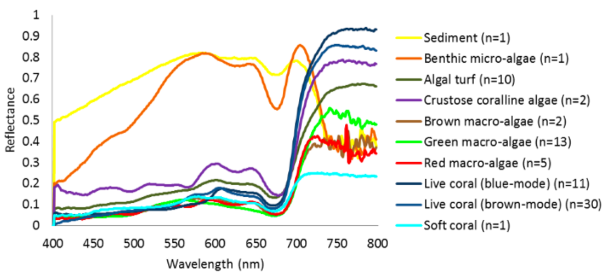

Fig. 5: Spectral Signatures of Various Coral & Algae Species (Leiper 2014)

similarity in the mean spectral reflectance signatures between certain classes of benthic algae and coral species at Heron Reef from a 2014 study from Leiper et al [15]. Note the similarity in the spectral signature of live coral, algal turf, and crustose coralline algae. Crucially, the values shown in the figure are spectral measurements done in-situ, or in the ocean, using a spectrometer from only 5 centimeters away. In this work, we look for ways to distinguish between coral and algal species from NASA instruments in orbit, having to also contend with factors like ocean turbidity, varying cloud aerosol opacity, and ocean surface roughness that further obscure the measured spectral properties of a given location [16]. However, an effective method for distinguishing between coral and algae is essential to the success of a system to identify the presence of coral reefs and monitor their health. While coral and algae display very similar spectral properties, they differ in that algal presence is seasonal. Both benthic algae and floating algal mats have been found to exhibit seasonal changes in abundance and composition, mainly attributable to water temperature and salinity changes across different seasons [17]. Considering these findings, we propose a temporal, voting-based method for distinguishing between coral and algae.

Given the capability of the coral/algae identification model outlined in section VI-A (coral presence section) and the seasonal changes in algal presence, using the model inference at different time points over the course of a year could be used to determine if a given location contained coral or algae. This results from the fact that we would expect coral presence to be consistent in every season, while algae presence would change season-to-season, which should be revealed in the coral/algae model predictions. To implement this idea, we propose using satellite data for the given location at six time intervals throughout the year and predicting coral/algae presence throughout the year to exploit the seasonal differences between coral and algae. This concept is illustrated in the figure below. In the first plot, we can see that there is a clear change in MODIS surface reflectance features at the given location during the summer months and that those changes correspond to model prediction of coral/algal presence in that period. Given that the model only predicted coral/algal presence in the summer period (southern hemisphere), this follows the expected behavior of an area of algae that experiences seasonal changes in composition or abundance. Conversely, in an area containing coral, we would expect consistent model predictions of coral/algae over regardless of the season.

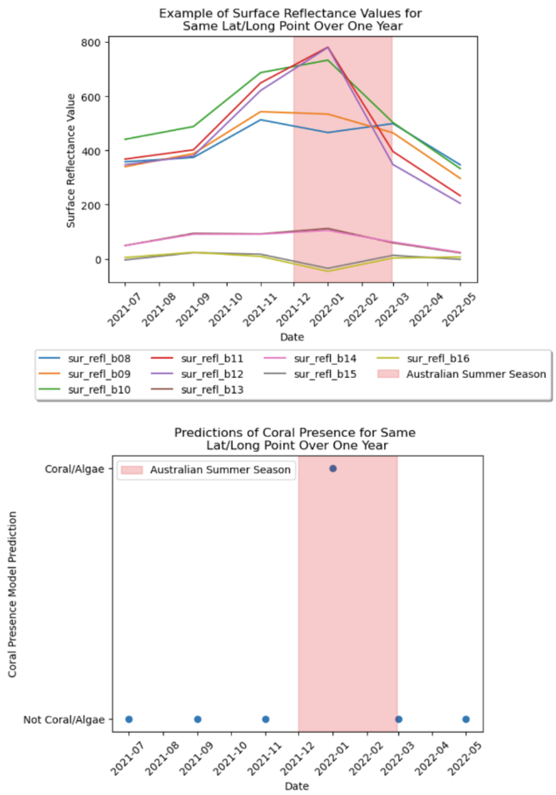

Fig. 6: Changes in MODIS surface reflectance features at the given location during the summer months and corresponding changes in model prediction of coral/algal presence in that period

Drawing from this intuition, a quantitative method was developed to capture this idea and distinguish between coral and algae based on seasonal variation in model predictions. Our method takes the predicted probabilities generated by the coral/algae identification model at the six time points throughout the year and computes a weighted average. Weights for each time period are allocated based on the ability to differentiate between coral and algae in that season. In general, less weight is given in the warmer, summer months as that is the period when algal abundance is expected to be the highest. The figure below illustrates our quantitative approach. We can see the model's predicted probabilities at the six time points throughout the year and the resulting weighted average. Since the weighted average predicted probability is less than 0.5, this point would be classified as algae.

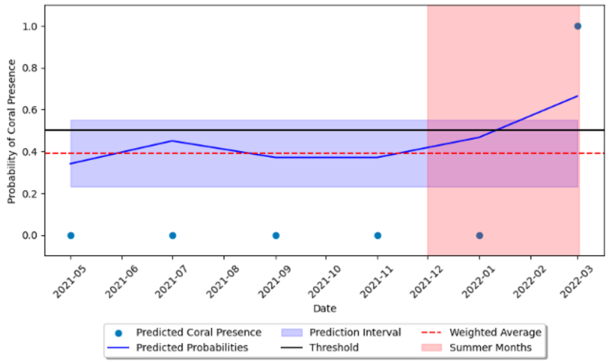

Fig. 7: Predicted Probabilities, Prediction Interval, and Decision

Additionally, generating multiple model predictions for a single point allows us to generate a 95% prediction interval associated with the probability of coral presence in that location using the mean and standard deviation of the six predicted probabilities (blue shaded region in above figure). The ability to quantify uncertainty is especially important for this problem as it allows us to provide guidance to researchers with limited time and resources on where their efforts are best spent.

C. Bleaching Model

With the features captured from Landsat-8 and MODIS, we tested a variety of models to predict the extent of bleaching. We began by splitting the data into temporal train, validation, and test sets to account for locations that were documented more than once. This resulted in us testing on 628 rows, validating on 128 and testing on 151 records. First, we trained a gradient-boosted decision tree regression (XGBRegression) model to predict bleaching percent directly along a 0 to 1 continuous output. This resulted in an overall mean absolute error of 13.95%. However, that value represents comparatively high accuracy in the more frequent low bleaching records with error rates increasing dramatically (30%-70%) when exclusively looking at higher bleaching values. This appears to be a result of the data's imbalance at the upper limits leading it to almost never predict values over 30% bleached. Given these results, we tried using the model not as a predictor of absolute value but instead to rank the locations observed. This potentially allows for increased usability even if the absolute values contained higher than desired inaccuracies. By ranking the records along the predicted output and comparing it back to their true ranking we began to see hints of positive results. Figure 8 shows a matrix comparing the actual to predicted rankings among our test set. These bins represent each 25th percentile rankings and show that the model has some success in identifying the most extreme percentiles. However, it struggles much more with identifying how to rank those in the center.

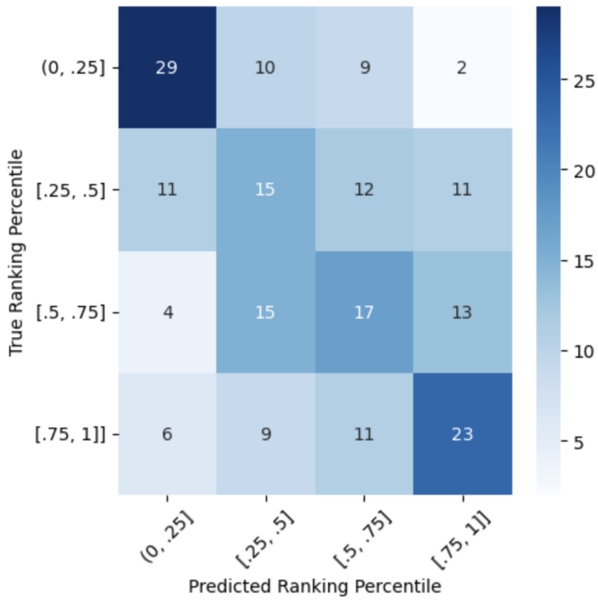

Fig. 8: Evaluating the Ranking Performance of a Coral Bleaching Regression Model

Lastly, we trained a series of gradient-boosted decision tree classification models (XGBClassifier) to predict one of several bins. This allowed us to resample our data using synthetic minority over sampling technique (SMOTE) to rebalance our testing bins [26]. With this technique, new artificial records are created by interpolating features within the underrepresented classes to match the dominant class. Using this technique, we trained a three binned model which classified regions below 20% as low, 20%-50% as moderately bleached and above 50% as severely bleached. The resulting model showed promising results classifying the low bleaching cases. However, it struggled differentiating between moderately and severely bleached corals. Overall, it had a weighted F1 score of 76.13% and recall of 68.14%. However, that was mostly supported by the low bleaching scores. Comparatively, recall in the moderate and severe buckets averaged close to random chance. Consequently, we then trained a model to predict a dual classification system splitting the data at 30% bleached. The resulting model showed more promise, accurately identifying 80% of moderate/severe records as seen in figure 9 with an overall weighted F1 score of 81.59%, a recall of 72%, and a weighted precision of 96.94%.

To better understand how this model is making decisions, three of our top features are analyzed through SHAP values below. SHAP values calculate the marginal impact a particular feature played into a model's decision. To better

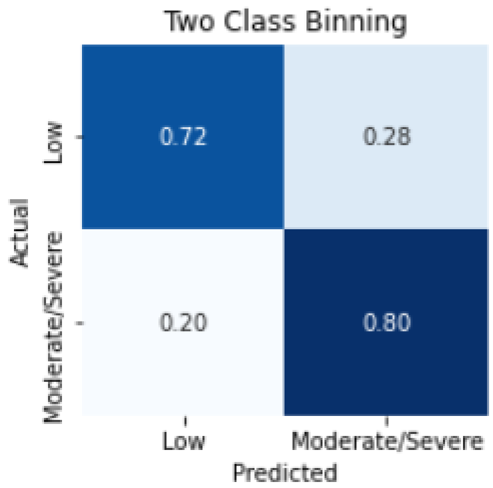

Fig. 9: Confusion Matrix of the Final Model Selected for the Dashboard

understand these values, they were then converted to a [0,1] function representing the probability that the model will predict either class through the length of the feature space.

Figure 10 displays the resulting charts for several of our most important features. The red line shows the average marginal impact that our model will predict moderate to severe bleaching based on changes in the dependent variable. The blue area represents one standard deviation caused by the covariance that multiple variables play in the model's decision. All of these show a generally positive relationship between increases in the dependent variable to increases in the probability of predicting moderate to severe bleaching. Maximum POC shows a generally positive relationship where as long as the value is not very low or null, the model is more likely to predict some level of bleaching. The second chart shows the relative impact of a feature representing the cumulative stress from rapidly rising sea surface temperatures. This accumulates the total coefficient of variation when the value is over 1.9 and the temperatures are rising. High values indicate either repeated upswings in sea surface temperatures or intense periods of continuously increasing temperatures over the previous 90 days which expectedly leads the model to often predict moderate to severe bleaching. The final chart shows the cumulative degrees above the maximum monthly mean representing stress from high sea surface temperatures. This feature most closely represents the thought process behind the global standard in predicting bleaching events- Degree Heating Weeks, while having a lower floor to when it starts to capture information. This result supports previous work showing that higher sea surface temperatures - even if below the threshold for a bleaching event – has a negative impact on coral health and impacts its ability to heal from previous damage. [27]

VII. Limitations & Future Considerations

Despite certain limitations encountered, our team uncovered potential considerations and suggestions that future

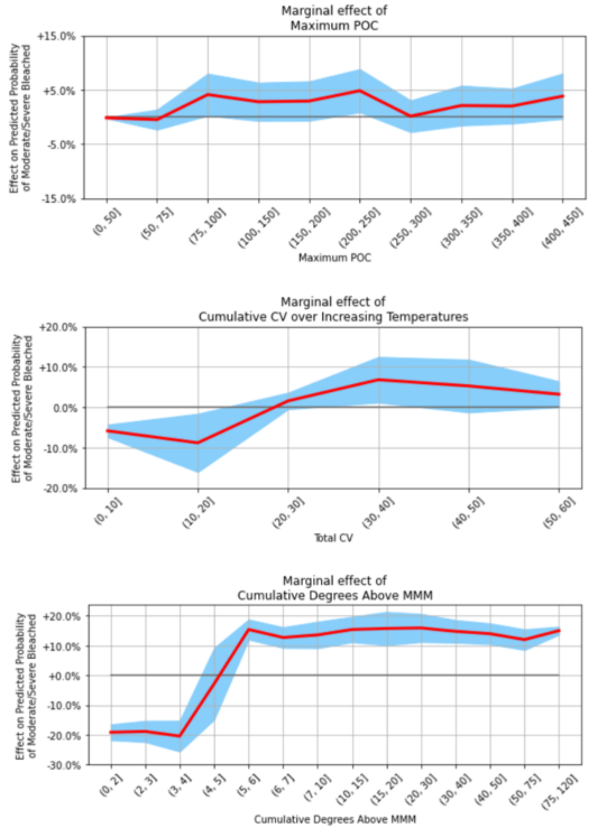

Fig. 10: Analyzing the marginal impact of three of the most important features on the model's decision

researchers could explore. The top constraint that our team faced was related to the data. The Allen Coral Atlas was the most robust coral data source that was found in our research, but rather than having separate classes for coral and algae, the Allen Coral Atlas classified the two together. The vision of this project was to identify coral, thus this grouped classification of coral and algae was initially an impediment to the achievement of our project goals. Our team worked around this issue by implementing the temporal voting-based classification to distinguish between coral and algae, but this comes with the caveat that we are unsure of the accuracy of this technique due to lack of ground truth data.

While we did receive six labeled ground truth points from the team at Coral Vita, more points would be needed to verify our temporal technique for differentiating between coral and algae. This type of data is lacking due to the aforementioned similarity in spectral signatures in coral and algae. This would require time-consuming, manual data collection, which is hard to do consistently at scale.

The coral bleaching model was also subject to limitations. While the Allen Coral Atlas did contain bleaching information, this data was not available for download at the time of the study, and was only available to view on the virtual atlas map. The Allen Coral Atlas specifies that the bleaching data is in Beta mode, thus further development could lead to this data becoming available for download in the future.

With the Allen Coral Atlas not being a viable resource for coral bleaching, our bleaching model relied on the Global Coral Bleaching Database. However, this source was limited in its size. While the GCBD contained 34,846 total rows, only 1,162 rows ended up being usable and within the spatial and temporal constraints of our study. Additionally, this database is the result of the combination of several different studies, all of which had slightly different methods for collecting and reporting the data. To improve the robustness of the data for the bleaching model and to improve the performance, our team engineered features related to sea surface temperature, particular organic carbon, normalized fluorescence line height and chlorophyll A presence. These features were generated as a result of conducting research on the environmental causes of coral bleaching, such as increased ocean temperature. The added features improved our model, and we see potential for the addition of more features. Storm-generated precipitation, overexposure to sunlight, and low tides are known causes of bleaching that were not included in the model features.

Additionally, we found that models trained on data from one region did not extend well to other regions. We believe that this could be attributed to the diversity of coral species and composition in different regions. This is another potential area to explore further in future research.

VIII. Ethical Considerations

A. Competing Interests

The authors declare no competing interests.

B. NASA's Ethical AI Principles

1) **Fair:** We consider and pay close attention to data bias and imbalance and use different measures to account for them such as SMOTE which tackles the lack of data in one region of study versus another. The project also utilizes open-source satellite and coral bleaching data that everyone could access.
2) **Explainable and Transparent:** Our project is both explainable and transparent. All of the data collection, data processing, and predictive modeling codes are explained in detail and justified in both the code notebooks and report provided, in addition to the presentation. Data sources are clearly cited and the machine learning models are well-documented.
3) **Accountable:** Our research respects intellectual property rules by citing all historical work that we used as reference or a starting point to ours. We also clearly state all our model accuracy, precision, and recall values to ensure that users and readers understand the capacities of said model.
4) **Secure and Safe:** Our team spent ample amounts of time evaluating the models developed and their results, including but not limited to training, testing, and validating their output. We also adhere to NASA's Software Management Plan that was developed during the initial phase of this project.
5) **Human-Centric and Societally Beneficial:** Human life and societal benefits sit at the core of this project. The entire goal of our work is to create a system that allows us to identify areas at which coral reefs are at risk and allow relevant organizations to take action to revitalize them. This supports the mission of maintaining the health of corals around the world, which preserves their function of supporting the environment and reducing the negative impacts of climate change. This all flows into the benefit of humans and maintaining a safe planet for them to survive on, with a safe and healthy environment and climate.
6) **Scientifically and Technically Robust:** Ensuring reliable data quality was a central aspect of this project. The data collection method and data fusion ensured that we only train models on relevant data that contributes to the robustness and reliability of our models. Our research is well-documented, thoroughly performed, and has been presented to subject matter experts in both coral reefs and data science which make it conforming to the scientific review process.

C. Potential Risks

There are several potential risks that could be associated with the output of this research project.

1) **Short-Term Gains:** It's possible that someone could take visibility of short-term positive outcomes of our model (showing that corals in a certain region are no longer at risk) to argue for a roll back on laws or regulations protecting the world's coral reefs before long term sustainability has been actually achieved.
2) **Impact of Model Errors:** Errors that fail to detect the presence of coral and/or degradation to coral health could result in reefs not receiving the care or attention that it would have received without this application. This could result in unnecessary harm to coral habitats as energy is incorrectly shifted away from these locations. Alternatively, false alarms for damage or bleaching to otherwise healthy areas or seabeds that have no coral at all will waste researchers' time and resources that could be better spent in other environments. To address these concerns, model errors of all kinds are thoroughly documented and published to help end users understand where these problems may occur.

IX. Conclusion

Bleaching of coral reefs, the main indicator of a decline in their health, evidently has negative implications on our environment. Although coral revitalization groups have been investing great efforts into detecting areas where coral bleaching is occurring, this effort remains constrained with financial and human resources. This project - sponsored by NASA and overseen by Coral Vita - focused on developing a scalable framework that allows for the detection of coral presence and the evaluation of coral health. After collecting data from NASA's Landsat-8 and MODIS-Aqua and aligning it both spatially and temporally with bleaching data the Global Coral Bleaching Database, a three-step modeling approach was implemented.

Our model first detects the presence of coral and algae as one unit, given their similar spectral indices and difficulty of distinguishing them from one another from orbiting satellites. A novel temporal voting-based classifier then separates coral from algae, an approach that had not previously been explored, therefore setting a starting point for further research on its functionality and replicability. Finally, gradient-boosted tree-based classifier was used to develop a 2-bin classifier that labels coral as either low-bleached or moderately/severely bleached.

This research has incorporated years of studies on coral health and the factors contributing to coral bleaching and opens the floor for scientists to further expand on the features we studied (such as sea surface temperature, chlorophyll A, particulate organic carbon) in the future. In addition to that, it also offers a practical solution for organizations concerned with coral health to use the dashboard we developed to identify regions with coral reefs and evaluate their vitality. In short, the project provides a solution that was validated by both data scientists and coral experts, follows NASA's Ethical AI framework, poses a set of questions that could be adopted as starting points for more extensive research, and offers a user-friendly tool that encapsulates the entirety of our modeling architecture.

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