Bull Mar Sci. 99(3):379–394. 2023
https://doi.org/10.5343/bms.2022.0012

coral reef paper

Operational ecoforecasting for coral reefs using artificial intelligence and integrated near real-time environmental data

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Handling Editor: Laurent Chérubin

Date Submitted: 5 May, 2022.
Date Accepted: 15 May, 2023.
Available Online: 15 May, 2023.

ABSTRACT.—A synthesis of information products about environmental stressors provided in near real-time can serve environmental managers who seek to act decisively before stressors become unmanageable. We have created ecological forecasts, i.e., ecoforecasts, based on input from a variety of environmental sensors that report in near real-time, and we subsequently send those ecoforecasts to environmental managers. The application behind these ecoforecasts is Python-based software that uses an artificial intelligence (AI) inference engine called an expert system. This National Oceanic and Atmospheric Administration (NOAA) Environmental Information Synthesizer (NEIS), formerly the Environmental Information Synthesizer for Expert Systems (EISES), has been developed over two decades to meet the needs of environmental managers and scientists. NEIS integrates environmental data from multiple sources, including in situ and satellite sensors. The application produces ecoforecasts designed to identify environmental conditions conducive to mass coral bleaching and bleaching of specific coral species, as well as other marine environmental events such as algal blooms. This study evaluates the efficacy of coral bleaching ecoforecasts generated by NEIS for the Florida Reef Tract covering the years 2005–2017.

The ecological response to multispecies coral bleaching is the result of complex interactions between biological, chemical, and physical processes, some of which are not currently well understood (van Oppen and Lough 2018). The coral holobiont (i.e., coral organism, zooxanthellae, and microbiome) experiences stress as a result of a variety of environmental extremes and fluctuations. The ecological forecasting or "ecoforecasting" of multispecies coral bleaching (Brandt et al. 2006) over wide geographic areas presents at least three major challenges: (1) near real-time (day-of or day-after) integration of multiple environmental variables; (2) timely assessment of those integrated variables to determine the likely impacts on coral reefs; and (3) accounting for the distinct bleaching antecedents, the environmental conditions most likely to result in bleaching, of different coral species across different reef communities. If we are able to meet these challenges and collect, interpret, and package data accurately and efficiently enough to make these assessments in near real-time, this benefits researchers and ecosystem managers enormously. An alert issued at the beginning of a destructive ecological event gives researchers and stakeholders the opportunity to both observe and study these events, as well as a chance to mitigate environmental damage and potential human impacts through management actions.

Previous efforts to remotely monitor coral reefs and alert managers about the potential incidence of coral bleaching have been based on evaluations of satellite-observed sea surface temperatures (SSTs; Liu et al. 2014). These alerts are somewhat broad in spatial character and based solely on temperatures at the surface of the ocean. Such an approach is not always optimized for effective, near real-time feedback for stakeholders, dockmasters, researchers, and other users in the field. The tool described in the present study is designed to provide quick, usable feedback to enable users to adapt to generalized, potentially deleterious biological conditions on a specific spatial and temporal scale. Coral Reef Watch (Liu et al. 2014) is the most similar ecoforecasting system operating on the Florida Reef Tract; it is an early warning system based on current satellite SST and climatological conditions. Recent updates to Coral Reef Watch (CoralTemp; Skirving et al. 2020) have improved the core products to daily temporal resolution. These are robust and helpful tools but the majority of their actual ecoforecasting products are created and reviewed on a weekly time scale and at 5 km resolution, which is not effective for the type of environmental damage mitigation and responsiveness that we are seeking to enable/motivate. Another study which approached the problem of reef monitoring using satellite data at higher (1 km) resolution was that of Hu et al. (2009): this study represented an advance in relating SST with ecosystem impacts; however, it still relies on data solely at the surface, and makes use of only one predictor variable (SST). The present study seeks to address these limitations by demonstrating a system that makes full use of hourly physical environmental data, including wind and other variables as well as in situ sea temperature, gathered at the location of individual sensitive coral reef sites in the Florida Keys.

Use of in situ observations can be important because physical environmental extremes that affect marine ecosystems are directly impacted by the dominant scales of atmospheric and radiative forcing and ocean response. The extremely fine-scale, high-relief bathymetry found on barrier and fringing coral reef ecosystems results in very high-frequency physical environmental variability (Gramer 2013, Rosales et al. 2019, Dobbelaere et al. 2020, 2022, Hendee et al. 2020); hour-by-hour observations of both sea temperature and wind speed provide valuable context for forecasting the extremes of heating and flow that individual reefs may encounter, and therefore for improving the accuracy and extensibility of bleaching ecoforecasts.

Photosynthetically active radiation (PAR) has been shown to play a role in the enzymatic activities in coral bleaching (Lesser et al. 1990, Lesser 1997, Lesser and Farrell 2004). Although in situ observations of PAR at these monitoring stations in the Florida Keys were far too sparse relative to either wind or temperature to be used in the present study, the authors acknowledge that the addition of hourly observations of in situ PAR would help to further elucidate any synergistic or cumulative effects of environmental stressors on bleaching. While Skirving et al. (2017) is the first attempt we are aware of to use satellite derived measures to include the role of light in bleaching forecasts, Lachs et al. (2021) mentioned the possibility of including Coral Reef Watch's Light Stress Damage (LSD) satellite-based product model into their heat accumulation metric.

Environmental variables that are measured in situ and reported remotely in near real-time are limited; however, technologies are well established for measuring sea and air temperatures, wind speed and direction, barometric pressure, tide heights, and surface irradiance in reef environments (Ogden et al. 1994, Pitts 1994, Hendee et al. 2001). Instrumentation for salinity, underwater irradiance, turbidity, and ocean currents are also available, but often more costly to deploy and maintain. Measuring and reporting these data in near real-time provides modelers with more accurate information and environmental managers with more detailed ecological forecasts.

Measurements with the most immediate consequences for benthic ecosystems—those made throughout the water column—are particularly challenging to report in near real time. Such measurements can vary over small spatial scales in the coastal ocean (Obura et al. 2019, Hendee et al. 2020). Therefore, it is ideal to have a dense sensor network and the technical ability to process, synthesize, and interpret data from that network (Hendee et al. 2020). Ecoforecasting benefits from having access to near real-time data, a variety of sensors, and occasionally, in situ observations suitable for ecoforecast validation.

We demonstrate a partial solution to these challenges for assessing multispecies coral bleaching through the assessment of in situ measurements and the application of proven artificial intelligence (AI) methods. Regional operational ocean, atmospheric, and surface-wave models and satellite remote-sensing products were also evaluated for this purpose, but issues of horizontal and temporal resolution as well as data availability for the earlier periods of the study (prior to 2005) made use of model and satellite data problematic. Using the National Oceanic and Atmospheric Administration (NOAA) Environmental Information Synthesizer (NEIS), we operationalized the forecasting of coral bleaching by integrating observations from in situ sources whenever available. To make sense of these streams of disparate data, potentially gathered over fairly wide geographic regions, we used AI techniques to apply observed bleaching criteria and "triggers," i.e., thresholds beyond which the environmental event of concern has historically occurred. The primary technique applied was heuristic programming, an expert system methodology that does not rely on single environmental triggers, but instead assigns semantics using fuzzy logic to complex data streams using an approximation of intuitive reasoning (Dias et al. 2020).

The choice to use expert systems was based on pragmatism—at the time of this study, there was not a high enough temporal or spatial resolution of validation data (coral bleaching monitoring) to accurately train a neural network or other more complex machine learning (ML) models. In future research, we would like to see experiments using other ML techniques (e.g., self-organizing maps; Gramer 2013) to further our particular goal of developing flexible, extensible tools for use in near real-time monitoring situations. However, at present, the fuzzy logic assessment can be site specific based on sparse validation observations, and this tool can simultaneously be readily adapted for use in monitoring both large regions and areas with a large number of monitoring locations.

Heuristic programming as employed here is a practical method, not guaranteed to be optimal, but instead sufficient for reaching an immediate goal. Heuristics are strategies derived from previous experiences with similar problems—in this case, coral bleaching response to environmental stressors. Although heuristic programming based on fuzzy logic is a relatively old AI technique it is well suited to diagnosis, i.e., the monitoring of environmental health. Heuristic programming in general is well-suited to problems with open and imprecise data representation and logical rules. It succeeds in making accurate, if broad, conclusions where other AI or ML techniques might misfire due to the low precision of validation data. This technique also prioritizes efficiency and utility at the cost of precision to create near real-time monitoring alerts that can facilitate management actions and/or timely chronicling of an event utilizing one of the coral monitoring protocols (e.g., AGRRA 2022).

The result is a computer system based on open-source components similar, for example, to those presented in Zhang et al. (2018). This system automatically integrates measurements and estimates from different models, such as the Berkelmans bleaching curve (Berkelmans 2002), that consist of data with different units and spatial-temporal resolutions. The system then automatically assesses the possible meaning of these data for marine ecosystems, alerting managers and other stakeholders about potential impacts. We report here on the results of applying this technology to mass coral bleaching ecoforecasts for the Florida Keys by using in situ hourly measurements of wind and sea temperature for the period of 1991–2017.

Methods

Near Real-Time Environmental Data.—SEAKEYS (Sustained Ecological Research Related to Management of the Florida Keys Seascape) stations were a network of lighthouses and daymarkers along the Florida Reef Tract that were instrumented with meteorological and oceanographic sensors, solar power, and satellite-broadcasting technology since 1987 (Ogden et al. 1994). These observing platforms are part of the Coastal-Marine Automated Network (C-MAN) maintained by NOAA's National Data Buoy Center (NDBC). C-MAN stations have historically transmitted hourly observations that are quality-controlled and archived by both the NDBC (Gilhousen 1998, NDBC 2009) and NOAA's Coral Health and Monitoring Program (CHAMP; Hendee 1996, Manzello 2004).

For the present study, NDBC quality-controlled historical data from four C-MAN stations served as calibration and validation data for a mass coral bleaching ecoforecasting model (Hendee et al. 2007). The Lower Keys C-MAN station at Sand Key, SANF1, ceased transmitting late in 2005, while the Middle Keys lighthouse at Sombrero Key Reef, SMKF1, ceased transmitting in early 2008. The lighthouses offshore of the Upper Keys (Molasses Reef, MLRF1) and Biscayne Bay (Fowey Rocks, FWYF1) continued transmitting sea temperature and wind data throughout the study period, with brief interruptions at FWYF1 during the summers of 2005, 2011, and 2015.

Ecoforecast Alert System.—The first implementation of NEIS was developed in the late 1990s using the C Language Integrated Production System (CLIPS; Donnell 1994) to summarize the large amount of hourly data produced by SEAKEYS for the benefit of environmental managers, divers, and fishermen in the Florida Keys (Hendee 1998). Coral bleaching ecoforecasts were the original goal, but NEIS was also designed to produce ecoforecasts for all types of marine environmental events

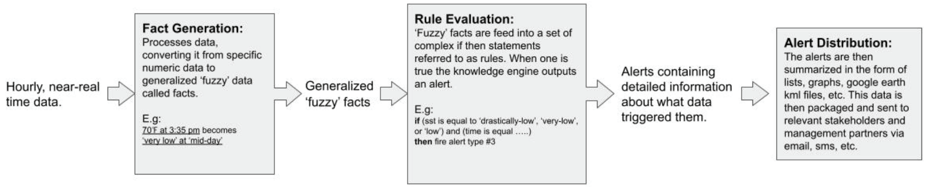

Figure 1. Schematic flow chart showing NEIS data flow. The data flow/processing occurs in three main procedural steps: (1) fact generation, (2) rule evaluation, and (3) alert distribution.

for which the contributing factors were known or guessed, and for which there was a sensor or sensors to measure those variables. Figure 1 is a schematic flow chart outlining the major components and data flows of the NEIS system. One strength of NEIS lies in its consideration of synergistic contributing factors, including sea temperature, wind speed, and other environmental variables (Gramer 2013). The system has been adjusted to calibrate ecoforecasts using in situ observations. NEIS has also been used for coral spawning (Hendee et al. 2007) and onshore surface transport or "drift" applications (Gramer et al. 2009).

Currently, NEIS has been reimplemented as a Python package that converts in situ data into multispecies bleaching alerts based on three procedural steps: fact generation (Hendee 2000), knowledge engine analysis (Hendee 1998, Gramer et al. 2009), and output/distribution of ecoforecast alerts (Fig. 1). However, the application as documented here is also meant for use by marine environmental agencies to monitor other types of events such as harmful algal blooms or turbidity plumes affecting coral reefs.

The initial procedural step involves Python code created to read and parse various in situ, satellite, and model data sources. These data streams are parsed into time-series objects called data-frames using the Python package pandas. Data frames are then checked for missing or repeated times and used to calculate 3-hr averages for each variable, regardless of the original sampling frequency. These quality-controlled data-frames are then separated by date and saved as self-annotating text files in JavaScript Object Notation (JSON) format.

The fact-generating code loads one or more JSON files for the data being analyzed and applies "fuzzy logic" to the data-frame to generate fact objects for each 3-hr average. Fact objects contain a fuzzy-time-of-day value, interpolated according to the local solar time at each observing location, as well as a fuzzy-intensity value, interpolated from each average according to a data lookup table of site- and season-specific ranges called a fact-factory. Afterwards facts are then saved to JSON files, and their location is passed to the knowledge engine code.

The data ranges for fact factories are generated, first, by calculating the corresponding percentile brackets for each variable/station combination according to number of standard deviations calculated in observational data distributions, as follows: 00.62%, 02.27%, 06.68%, 15.87%, 30.85%, 69.15%, 84.13%, 93.32%, 97.72%, 99.38%. Secondly, the fact-factory tables are further refined manually using bleaching observations, as well as the false negatives/false positives alerted to over the training period. The goal of these fact range adjustments, which was achieved, was to reach zero false positives and false negatives in the training set; we achieved this by having three degrees of freedom in the manual adjustment: three-hourly temperature ranges, monthly mean temperature ranges, and wind speed. For example, say that after reviewing the alerts generated by the training data, multiple false positive high temperature alerts are generated for station SANF1. After reviewing the station-specific criteria and averaged temperature values in the context of bleaching observations from the training period, it may be found that a 95.32%–97.72% range is better suited than a 93.32%–97.72% range for generating the corresponding "very-high" heuristic value.

The knowledge engine is encoded with production rules (basically, if/then constructs) to analyze facts and determine alerts. These production rules are calibrated using multispecies bleaching reports, making the multispecies coral bleaching alert expert system distinct from a species-specific alert system. Knowledge engines are implemented using the Python package experta (Pérez 2019). Alerts are stored as JSON files, then passed to the final stage of analysis where they are packaged by day and location and sent via email or text message to subscribers.

Stimulus/Response Index.—Each alert includes a numeric measure of the likelihood and severity of the ecological response that is being forecast, based on the physical data and fact-factory ranges that resulted in the alert. This numeric measure, the Stimulus/Response Index (S/RI), is calculated for each day as a count of the number of hours for each contributing variable that matches the corresponding ecological forecast criteria for that variable (Hendee et al. 2009). For example, if an ecological forecasting production rule was based on the combined effect of high sea surface temperature and low wind speed, the S/RI from the sea surface temperature would be added to the S/RI from the low wind speed to calculate the total S/RI for the corresponding alert. During periods when particular physical variables have extreme enough values (stress, or stimulus) to suggest a qualitatively greater ecosystem response, the S/RI associated with those variables is multiplied by a factor of 2 before being added to the daily total; where data suggest a particularly severe response, the S/RI is multiplied by a factor of 2.5 to reflect the rather rare but significant contributing environmental factor. For a more thorough explanation of the reasoning behind the S/RI concept, the appointing of points per production rule fired, and the multipliers, please *see* Hendee et al. (2009).

For example, on a day when wind speed is low and sea temperatures are high for only 3 hrs each, the S/RI would be calculated as 3 + 3 = 6; if high sea temperatures persisted all day (i.e., 24 hrs), the total S/RI would be 24 + 3 = 27. A day with 24 hrs of high sea temperatures, low wind speed for 21 hrs, and "very low" wind for 3 hrs would have an S/RI of 24 + 21 + (3 × 2) = 51. Finally, a 24-hr period with "drastically high" sea temperatures and "drastically low" wind speed would be assigned an S/RI value of (24 × 2.5) + (24 × 2.5) = 120. Drastically high or low values were considered to be extremely rare instances of the variable in question. For instance, a high sea temperature of 32 °C would be considered drastically high in an oceanic environment and was labeled as such at most of the stations analyzed for this study. Due to the nature of heuristic programming, the S/RI is subjective and used to indicate the cumulative severity of the time and intensity of multiple variables that contribute to a rule firing. The context under which we assign different levels of severity to environmental values in constructing fuzzy intensities, rules, and our S/RI are also discussed in an earlier work (Hendee et al. 2009). That earlier methodological work also provides a set of tables and a figure to clarify this approach.

Historical Bleaching Observations.—We calibrated the criteria for the ecoforecasting model by comparing its outputs for the training period of 1991–2004 with historical reports of coral bleaching in peer-reviewed literature (Manzello et al. 2007, van Hooidonk and Huber 2009, van Oppen and Lough 2018).

All sources for bleaching observations were based on diver reports collected from a community of professional scientists and dive operators, utilizing Reef Check, SECREMP (2020), and AGRRA (2022) monitoring protocols. The granularity of these data was site- and species-specific and reports were gathered monthly (e.g., van Hooidonk and Huber 2009).

The record of physical measurements across multiple subregions of the Keys began in 1991. The years 1997 and 1998 were years with severe bleaching at many sites. These thus represented important "positive signals" to include in the training period. Bleaching was again observed to be relatively severe in 2005 and later years in the in situ record; for this reason, and to demonstrate the broader applicability of the method, we choose 2005–2017 as our validation period (*see* below).

During the training period, when widespread bleaching was observed in each subregion of the Florida Keys, the criteria were loosened as necessary to produce an S/RI; where this resulted in false alarms for the training period, the criteria were tightened again as needed. This process depended critically on having more than one criterion to adjust. For example, where 3-hr temperature values from other years would have suggested a positive S/RI in a given year but no bleaching was observed, a criterion based on low winds could be made more stringent. Similarly, where 3-hr temperature values might not suggest bleaching based on observations in the training period, but bleaching occurred, a criterion based on wind or on the monthly mean temperature could be tightened. Our approach was to manually adjust these criteria, demonstrating that a multivariate ecoforecasting system provides the degrees of freedom needed to perfectly match observations of coral bleaching. Further research could refine this approach to make use of machine learning for generating optimal fact ranges from observations (e.g., Ul Islam et al. 2020, Jamei et al. 2022); however, such an approach would have to be site specific based not only on regional differences in organism adaptation but also available environmental data.

We validated the model based on observations of bleaching by year and subregion (i.e., Upper, Middle, and Lower Florida Keys) from BleachWatch (Maynard et al. 2009, Walter and Bartels 2018) and The Nature Conservancy's Florida Reef Resilience Program (FRRP; Lirman et al. 2014, Gintert et al. 2018). These observations covered the validation period of 2005–2017, with an emphasis on BleachWatch observations in the fore-reef zone where the four C-MAN stations reside. This zone is generally the farthest area from shore where larger-scale reef structures are found and where lighthouses have been historically placed.

The spatial granularity of these historical bleaching reports, i.e., subregions of the Florida Reef Tract, was similar to or coarser than the available physical data in this study. The time granularity of reports, generally monthly, was coarser than the hourly time resolution of the physical data. Historically, due to the limited availability of bleaching observations, we have had to rely primarily on monthly BleachWatch reports, summarized seasonally in this analysis, as the basis of our validation data. Finally, in the analysis of results we summarized our model outputs as the annual sum of the S/RI at each lighthouse and took these annual S/RIs to be representative of the entire fore-reef zone of the subregion in which the respective lighthouse resided. This approach has been gradually improved over years of development since its first implementation in the Florida Keys National Marine Sanctuary (Hendee 1998).

Validation-Forecast Skill.—Following van Hooidonk and Huber (2009), we estimated a Peirce Skill Score (PSS; e.g., Stephenson 2000) for ecoforecasts during the validation period as follows. Within a given subregion, BleachWatch data that showed bleaching within a given year would cause that year to be marked as a positive observation. Where the S/RI of the ecoforecast was nonzero during that year, the year was marked as a positive forecast. Years with both a positive observation and a positive forecast were marked as *hits*, while years with a positive observation and a negative forecast were marked as *misses*. Where neither observations nor forecasts indicated bleaching in a given year, the year was marked as a *correct negative,* and where a forecast suggested bleaching but none was observed, the year was denoted as a *false alarm*. The PSS was then calculated as follows:

$$PSS = \frac{hits}{hits + misses} - \frac{false\ alarms}{false\ alarms + correct\ negatives} \qquad \text{(Eq. 1)}$$

Results

Stimulus/Response Index.—The concept of a Stimulus/Response Index was first implemented and discussed in Hendee et al. (2009) and has been implemented in NEIS. We examined the averages of hourly environmental data for the entire physical record from each of four Florida C-MAN stations, including the 3-hr rolling average sea temperature and wind speed, 3-day average wind speed, and 30-day average sea temperature. During certain summers, we found extreme values in the averaged sea temperature (highs), wind speed (lows), or both at each lighthouse that were outliers within the multiyear record for that site (Fig. 2). From these outliers, we calculated a total S/RI for each day of the evaluation period during which the outliers occurred, and then summed the S/RI values over each year for final analysis (Fig. 3).

We implemented email and text alerts to be generated in real-time when conditions that resulted in a nonzero S/RI for a given day were satisfied; similarly, for historical reasons the system was made to generate emails summarizing seasonal total S/RIs. Email and text alerts could be generated for a subscriber on a site-by-site, subregional, or regional basis that incorporated links to automatically generated visual reports (e.g., Fig. 4).

During validation, the Florida Keys-wide coral bleaching event reported by divers in 2005, for example, was reproduced at three of the four lighthouses: SANF1, MLRF1, and FWYF1. The sole site that failed to produce ecoforecast alerts for 2005 was the Middle Keys lighthouse at Sombrero Reef, SMKF1. Interestingly, this corresponded with observations from both the FRRP and BleachWatch that offshore bleaching in the Middle Keys was less prevalent than it was elsewhere during that year. Outlier events in 2007 at the Middle Keys (SMKF1) and Upper Keys (MLRF1) lighthouses, and in 2009 at the Biscayne Bay lighthouse (FWYF1), corresponded with FRRP and BleachWatch observations from those years that confirmed coral bleaching had occurred there. For the years 2006, 2008, 2010, 2012, 2013, and 2017

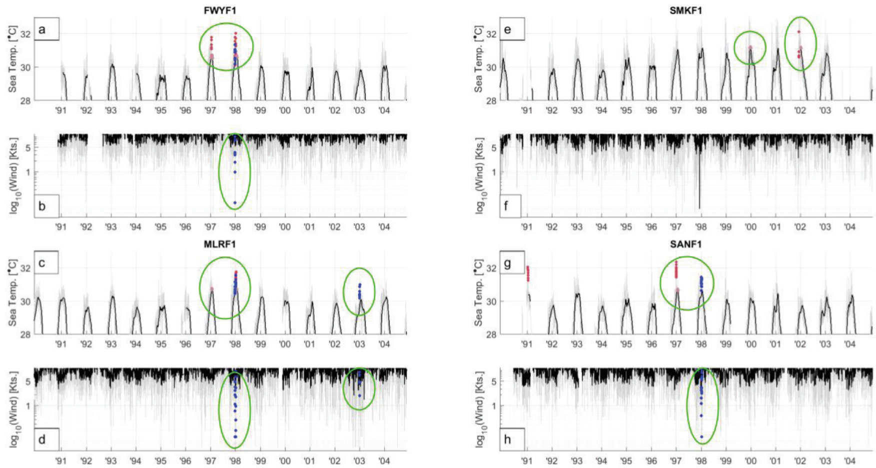

Figure 2. Physical data and alerts for each site in this study for the calibration period 1991–2004: (A) Fowey Rocks (FWYF1) sea temperature and (B) wind, (C) Molasses Reef (MLRF1) sea temperature and (D) wind, (E) Sombrero Key (SMKF1) sea temperature and (F) wind, and (G) Sand Key (SANF1) sea temperature and (H) wind. Gray denotes 3-hr averages, while black represents longer averages (3 d wind, 30 d temperature). Alert days are highlighted by dots whose colors correspond with the criteria triggering each alert: dark red for 3 hr temperature only, light red for 30 d temperature only; dark blue for 3 hr temperature together with 3 hr wind; and light blue for 3 hr temperature together with 3 d wind. Regions of the record where the physical data produced a trigger are highlighted by green ellipses.

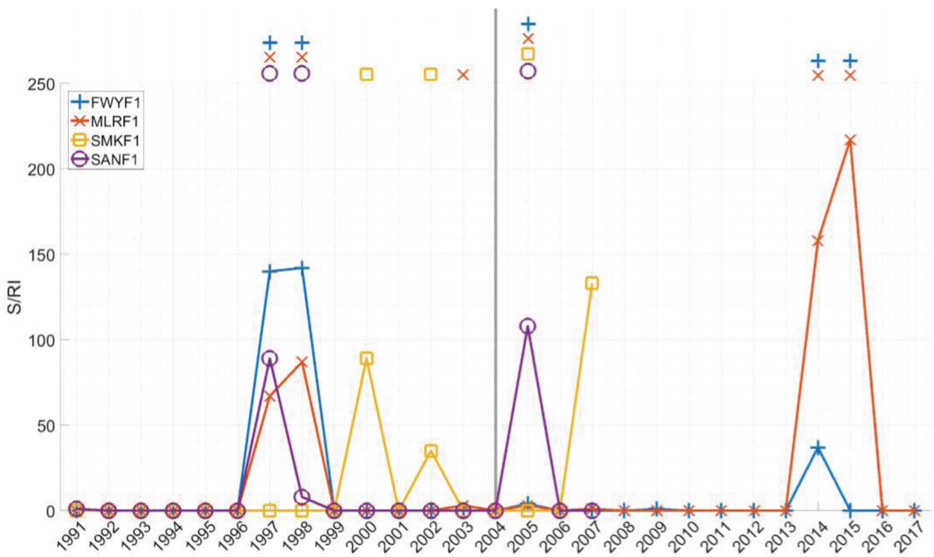

Figure 3. Stimulus/Response Index (S/RI) estimated by the multispecies coral bleaching ecoforecasting model for all four monitoring sites for the period 1991–2017. The validation period for the model (2005–2017) is discussed in more detail in the text. Color-coded markers at the top of the figure show the years when bleaching was observed at each site. The vertical grey line separates the training period of 1991–2004 from the validation period of 2005–2017.

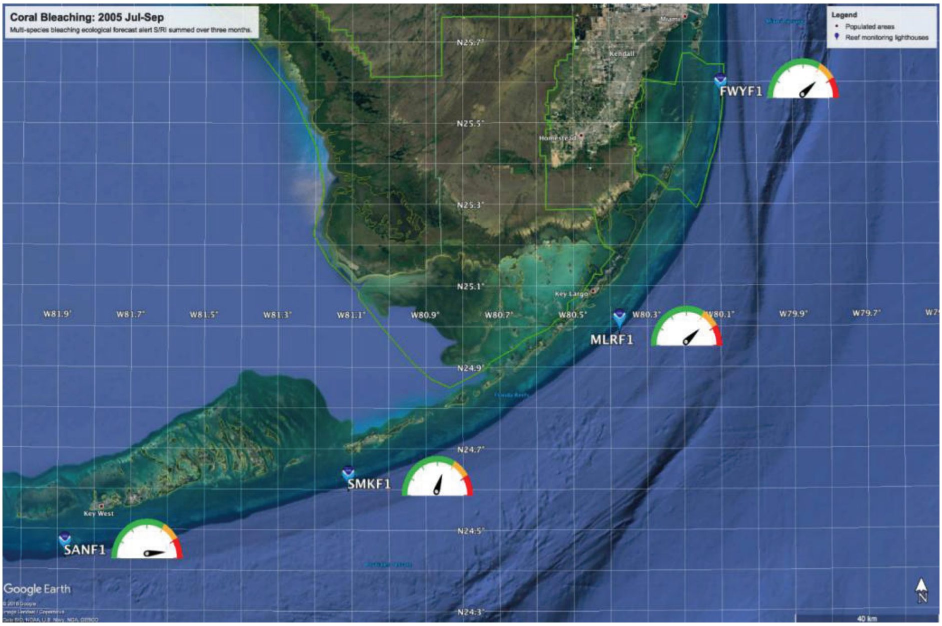

Figure 4. Automated visual report for alert subscribers from the ecoforecasting system that shows multispecies coral bleaching "gas gauge" indicators in geographic context, based on the summed S/RI for the period July–September 2005.

when few or no outlier alerts were produced, we also found few or no historical observations of bleaching. These results are summarized for the validation period in the contingency table (Table 1) and ecoforecast skill score section that follows.

Ecoforecast Skill Score.—The overall PSS for the 13-year record of bleaching observations and S/RIs for 2005–2017 was calculated from the contingency table (Table 1) using Equation 1. The PSS was found to be 7/8–1/22 = 0.83. This score compares with the published PSS for satellite-derived coral bleaching products (van Hooidonk and Huber 2009) of 0.83, indicating that NEIS had a degree of accuracy in identifying coral bleaching conditions on a yearly scale at subregional resolution during the validation period comparable with satellite methods, while also being able to incorporate other environmental triggers like in situ wind measurement.

Wind Speed and Coral Bleaching.—A consideration of wind speed in combination with sea temperature averages over various lengths of time was important in this study, as noted in the Methods section. One limitation of simple, single-variable numerical criteria (such as sea temperature cutoffs) is that extremes can occur when no event is observed and vice versa, confounding the calibration of models with historical data. Adding additional criteria associated with demonstrable ecological impacts allows the model designer, or in this case the "knowledge engineer," to better distinguish the years when sea temperatures may have been high but other factors potentially reduced the ecosystem response. For example, ocean currents, vertical mixing, and waves are all associated with higher winds (e.g., Nakamura and van Woesik 2001, Gramer et al. 2008, Gentemann et al. 2009). Based on the importance

Table 1. Contingency table that shows the years used to calculate the Peirce Skill Score (PSS). Event counts (hits, misses, etc.) are summed across the two subregions for which continuous data were available during the validation period (Biscayne Bay = Fowey Rocks and Upper Keys = Molasses Reef).

	Station-years with bleaching	Station-years with no bleaching	Total forecast station-years
Station-years with forecast	Hits = 7	False alarms = 1	8 station-years
Station-years with no forecast	Misses = 1	Correct negatives = 21	22 station-years
Total observation station-years	8 station-years	22 station-years	30 station-years

of the wind criteria, one or more of these processes appeared to alleviate the effects of thermal stress on corals at some of these sites, e.g., at SMKF1 in 1997, and at three of the lighthouses (FWYF1, MLRF1, SMKF1) in 2005 (Fig. 3).

Of interest, the criteria we found for “alert” outliers—those extremes that corresponded with observed bleaching events—differed significantly between the lighthouses (Figs. 2 and 3). The average distance between neighboring lighthouses in this study was approximately 80 km (Fig. 4). Different studies (Maynard et al. 2009, Lirman et al. 2014, Manzello et al. 2019) have suggested that reef communities in Florida vary in their exposure and response to stress across similar alongshore spatial scales, consistent with this finding.

Summary and Discussion

We calibrated an ecoforecasting model for coral bleaching within the Florida Reef Tract using historical data and observations for the period 1991–2004. Calibration was necessary to match observed conditions with historical bleaching records. The outputs of this calibrated model were daily reports and monthly and yearly summaries of expected coral bleaching by station, i.e., subregion. These outputs were designed with two target stakeholder groups in mind: for Marine Protected Area (MPA) managers, we wished to provide information on bleaching “the sooner the better” in order to allow managers to marshal resources or issue MPA enforcement guidance. However, for the second group of stakeholders, field researchers, we wished to provide information on environment and bleaching response which could be used to validate the ecoforecasts and provide data for the literature on environmental effects on bleaching. “Proactive responses” can only occur when the responding parties are awake, so during the day, usually. For this reason, ecoforecast rules and alerts were designed to be near real-time, i.e., per day. It should also be noted that the near real-time nature of the alerts is intended to be valuable for field-based observations when the precise onset of bleaching (or spawning, etc.) must be known to validate a model.

We then successfully validated this model using environmental and site-specific bleaching observations from the years 2005 to 2017. We evaluated forecasts relative to bleaching observations by subregion, and then calculated a PSS following the approach of van Hooidonk and Huber (2009). The PSS for our evaluation period of 2005–2017 was 0.83, similar to that of the method of van Hooidonk and Huber which was based on satellite data alone. However, our region-wide PSS accounts directly for individual multivariate variations within subregions, rather than calculating single-variable results individually within subregions and averaging them globally as in van Hooidonk and Huber (2009). The long record of direct in situ measurements for multiple environmental variables makes this more general approach feasible.

This multivariable approach also opens the possibility of using the NEIS system, with further research, to provide stakeholders and researchers with information to evaluate potential alternatives among mitigating factors. With the ability to incorporate new variables into the rule-based system as needed, future research could apply more complex, neural network-based analysis during both the data abstraction and trigger design processes, to produce more sophisticated expert-system based ecoforecasts.

As with any historical analysis, we estimated the statistical distributions and extremes in our environmental data from a fixed historical subset. We found these historical distributions from 1991–2004 to be useful as predictors for bleaching during the years 2005 to 2017. However, the usefulness of model outputs for upcoming bleaching seasons may depend on whether these environmental variables still remain within the historical bounds that prevailed during our training period.

Going forward into future years, the validity of our forecasting model may further depend on factors we could not consider here. These factors include coral holobiont population changes and adaptation, as well as reef ecosystem dynamics such as changing fish populations or the succession of more resilient coral genotypes. Other influences on ecosystem health not considered here, but also likely to affect future forecasts, include changes in ambient turbidity, nutrient availability, and land-based sources of pollution. However, this automated system is flexible and can be adapted to monitor and assess these conditions. This adaptation would need to include appropriate historical and near real-time data sources for these variables to be used in calibrating a future ecoforecast model. We feel it is important to emphasize that NEIS is not just a coral bleaching ecoforecasting tool, but a construct for modeling any marine environmental event to which the environmental stimuli are known or suspected, and where precision instruments are available (and routinely maintained) to measure those stimuli.

Our system is readily adaptable to changes in the ecosystem, in addition to changes in conditions, as long as feedback from the field that characterizes those ecosystem changes is timely and available. For example, a useful feature incorporated into earlier versions of NEIS was a blog for site maintainers and scientific/biological monitoring divers at monitored sites. The blog allowed for site-specific records to be kept of changes in instrumentation, station infrastructure, benthic and pelagic biological community, and other conditions. These records were then cross-referenced with in situ, electronically-monitored data and the resulting ecoforecasts. Although testing of this Python-based newer version of the original CLIPS-based system (Hendee 1998) precluded the use of such maintenance blogs, we feel timely use of feedback from the field—whether via blogs or other chronicling of the changes to the instrumentation and/or environment—is absolutely essential to a successful deployment of instrumental arrays with NEIS as the ecological forecasting component (e.g., *see* Fletcher et al. 2022).

Such a system will be integrated into future adaptations of NEIS, for example, in monitoring turbidity and sedimentation at reef sites impacted by ongoing human activities in Florida. What must be kept in mind is that correct ecoforecasts are only as good as (1) the precision of the instruments, which means regular cleaning, maintenance, and, if necessary, replacement of them, and (2) timely feedback from the field as to whether or not (or to what degree) the ecoforecasts were correct, thus permitting the necessary fine-tuning of the thresholds within the rule-based system.

Furthermore, regarding the optimal timescale of environmental measurements, each species is going to react differently, but for research stakeholders, it is important to know how long after the threshold of temperature (and potentially, synergistic effects of light and wind) is met for a specific coral species to exhibit bleaching. The answer to that may not be known by the research stakeholder a priori, but having access to ecoforecast alerts based on hourly and daily measurements of the environmental stressor(s) can provide a valuable context for answering such research questions. Higher-frequency environmental stressors can result in important ecosystem responses on coral reefs within periods of 24 hrs or less.

Based on our successes with open-source components and the methods presented in this study, we are collaborating with partners in NOAA operational (non-research) line offices and other agencies to expand this system to daily operations that cover coral reefs and other sensitive marine ecosystems in disparate locations. We expect the system to ultimately find applications in nowcasting harmful algal blooms, upwelling, and enhanced turbidity related to human activities. However, so long as (1) the basic environmental influences of a particular phenomenon are known, (2) the instruments are available to measure those environmental variables, and, (3) there is in place a reliable feedback system of maintenance recording and field observations of the phenomenon in question, the system described herein should find applicability in a multitude of ecological forecasting events.

NEIS is currently being enhanced for use in an adaptive management plan for a Port Everglades (Fort Lauderdale, Florida USA) dredging project (USACE 2021). NEIS will be used to monitor turbidity levels, total suspended solids, sediment deposition, and PAR, among other environmental variables, to deliver alerts that warn stakeholders when compound ecological stressors exceed predefined thresholds. This will enable ecosystem managers to adapt the dredging schedule to mitigate potential environmental damage.

Code and supporting files for the NEIS are archived at https://github.com/NOAA-CHAMP/EISES.

Acknowledgments

Funding from NOAA's Office of Oceanic and Atmospheric Research and NOAA's Coral Reef Conservation Program allowed for the development of this system and preparation of this manuscript. Funding and support from NOAA's National Marine Fisheries Service-Southeast Regional Office (J Karazsia) and the US Army Corps of Engineers enabled the current adaptation and development of NEIS operations at Port Everglades. The insightful comments of two anonymous reviewers also led to substantial improvements in the manuscript, for which we are grateful. Comments from University of Miami writing consultants J Schneider and L Albritton were helpful in the completion of the manuscript.

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