# ReefCast for Coral Resilience: A Research-based Interdisciplinary Project for Developing a Machine Learning Model for Predicting Coral Bleaching

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**Abstract:** Coral reefs, which support nearly 25% of all marine species, are facing a global crisis due to climate change-induced mass bleaching events. These ecosystems protect coastlines from storms and erosion and support fisheries and tourism, making their preservation a global imperative. Traditional forecasting models rely largely on Sea Surface Temperature (ST) and Degree Heating Weeks (DHW, but these statistical methods often fail to capture the complex, non-linear interplay of multiple stressors such as ocean acidification, turbidity, and salinity that trigger bleaching. Current approaches in engineering education are increasingly tackling such multifaceted problems through interdisciplinary frameworks. Many programs utilise project-based learning (PBL) and senior capstone projects that require students to build solutions by integrating principles from engineering, data science, and environmental biology, while also emphasising research-based methodologies that promote scientific inquiry and data-driven problem solving. However, even with these pedagogical advancements, environmental challenges like coral bleaching are often overlooked in undergraduate research. This paper presents ReefCast, a research-driven interdisciplinary project focused on building a solution to this global problem. The project was born out of an integration of two courses: Integrated Communication for Engineering [ICE for Engineering [ICE for Research] Engineering (ICE) and Machine Learning and Pattern Recognition (MLPR)]. This research-guided approach to machine learning proved effective for developing an AI/ML model that could predict coral bleaching. Our approach began with intensive research into the problem of coral bleaching, which consisted of exploring traditional solutions, studying the evolution of machine learning models used within the domain, and developing our solution. The research principles taught in the ICE course helped us find often-neglected oceanic and coral features and incorporate them as features of our model while exploring novel approaches for its development. This initial phase served as the project's proof of concept, requiring the intensive integration of a 25-year, multi-source dataset and the implementation of methods to handle the severe class imbalance typical of rare event data. This provided a rich, end-to-end engineering challenge, pushing us to move beyond simple accuracy, which is often misleading in imbalanced datasets, evaluating performance using a comprehensive suite of metrics where recall was prioritized, as the ecological cost of a false negative (a missed bleaching event) is far more damaging than a false positive. This rigorous evaluation demonstrates that our machine learning models can significantly outperform traditional approaches, as our models were engineered to process the complex, non-linear interactions between multiple stressors, allowing them to identify bleaching events that simpler methods might miss. Beyond technical innovation, this project serves as a case study in engineering education for marine and coastal ecosystem health, demonstrating how research-based and project-oriented pedagogy can bridge theory and practice. Students learned to balance accuracy with ecological responsibility, selecting evaluation strategies that prioritise the prevention of missed bleaching events. ReefCast thus represents both a scientific contribution to coral reef conservation and is evidence of the importance of using research-based interdisciplinary projects for training future engineers to design solutions to global environmental challenges.

**Keywords:** Coastal Resilience, Coral Bleaching, Marine Health, Research-based Interdisciplinary Project

## 1. Introduction

The field of oceanography is currently navigating a "data deluge," transitioning from a data-scarce discipline to one characterized by continuous, high-resolution monitoring. However, a significant "skills gap" persists in the workforce.[1] Wilson et al. (2018) also note that while the observational capacity of the global oceanographic community has expanded, there is a shortage of professionals capable of navigating the entire data lifecycle, from acquisition and harmonization to analysis and visualization of ocean imagery.

Simultaneously, the ecological stakes are higher than ever. Coral reefs, which support nearly 25% of marine biodiversity [13], are facing existential threats from climate change-induced thermal stress. Traditional forecasting models for assessing coral bleaching, such as those used by NOAA Coral Reef Watch, largely rely on sea surface temperature (SST) thresholds and Degree Heating Weeks (DHW). However, recent literature indicates these single-variable models often fail to capture the complex, non-linear interplay of stressors like ocean acidification and salinity.

Traditional undergraduate engineering curricula often fail to address this intersection of big data and complex ecology of the coral reefs. Most of the coral reefs' datasets require a lot of preprocessing to cleanse noise and bring consistency across images before they can be fed to a machine learning (ML) algorithm. However, ML is typically taught in academia using pre-cleaned datasets. Furthermore, domain sciences are often siloed from computational training when teaching ML. This leaves undergraduates taking ML courses ill-equipped to address planetary challenges such as assessing the severity of coral bleaching. This paper presents ReefCast as a pedagogical case study. It demonstrates how a "Dual-Track" course integration, combining technical implementation with rigorous research communication training, can train generalist engineers to function as Ocean Data Scientists capable of building advanced predictive models (such as long-short term memory networks or LSTMs) for marine conservation.

## 2. Evolution of the Oceanographic Discipline

The pedagogical history of oceanography reveals a discipline that has historically struggled to transition from a specialized research trade to a broad undergraduate curriculum. The 1929 National Academy of Sciences report, known as the Lillie Report, noted that oceanography suffered from a severe lack of educational opportunities, forcing practitioners to be "largely self-taught" or recruited from other basic sciences like chemistry and zoology.[14] For much of the 20th century, the discipline operated on an apprenticeship model, focusing almost exclusively on producing doctoral graduates to replenish the ranks of academic researchers rather than training a diversified workforce.[15]

This "research silo" persisted even through the rapid expansion of the field following the establishment of the Office of Naval Research (1946) and the National Science Foundation (1950). While research infrastructure grew, educational strategy remained stagnant; the 1969 Stratton Report continued to overlook the necessity of standardized undergraduate education [15], viewing students primarily as manpower for federal research needs rather than as learners. Consequently, oceanography historically "missed out on the chance to lead the burgeoning interest in interdisciplinary education," isolating itself from the undergraduate population and failing to integrate with broader earth science applications.

The legacy of this educational model is evident in contemporary employment statistics that highlight a disconnect between training and professional versatility. Historical data indicates that oceanography Ph.D. recipients are approximately 50% more likely to remain in academic research than their counterparts in physics, whereas physicists are three times more likely to enter the industrial workforce. This suggests that traditional oceanographic pedagogy has been uniquely successful at replicating academic researchers but less effective at equipping students for the diverse "Ocean Data Scientist" roles required by the modern blue economy. The skills gap identified by Wilson et al. (2018) is not merely a recent phenomenon but a structural inheritance from a history that prioritized specialized apprenticeship over interdisciplinary breadth.

## 3. The Global Landscape: Current Paradigms in Ocean Data Education

To understand the significance of the ReefCast intervention, one must situate it within the broader computational turn occurring in marine science. Scientists from disciplines other than Computer Science are now actively applying ML methodologies and Marine Sciences are no exception.[16] ML is promising in Oceanography and allied disciplines for several reasons (i) Modern Instruments produce large volumes of data which require scaling up tools that can facilitate data processing and adaptability of ML methods position them as best choice for such automation. (ii) This automation helps reduce biases introduced by manual processing, improving reproducibility (iii) Finally, ML is adept at handling high degrees of uncertainty associated with unknown mechanisms.[19] As the discipline evolves, universities globally attempt to close the skills gap created due to “data deluge” through two primary models: Structural Integration and Module Integration.

### 3.1. Structural Integration

Top-tier research institutions have largely responded by creating entirely new degree structures. The University of Washington (UW) has a "Data Science Option," a specialized track that overlays the oceanography major. This curriculum mandates courses like “OCEAN 215: Methods of Oceanographic Data Analysis”, anchoring Python instruction directly in the analysis of oceanographic data.[20] Similarly, the University of Miami offers a double major in Marine Science and Computer Science, designed to guide students through the fields of both, Computer Science and Machine Science.[21] While highly effective, these structural interventions are resource-intensive, requiring new degree codes and extensive faculty coordination.

### 3.2. Module Integration

A more common approach is the embedding of "Big Data" modules within traditional science degrees. For instance, the University of Plymouth (UK) offers “OS317: Big Data for Marine Science”, a final-year module focused on sourcing and manipulating open-access data to address societal challenges such as climate change.[17] Meanwhile, institutions like the University of Queensland utilize R-based Data Science course (“SCIE3360”) to equip biologists with the statistical rigor needed for Great Barrier Reef management.[18]

### 3.3. The ReefCast Gap: Pedagogy over Institutionalised Structure

While these paradigms are successful, they often exist in silos: the structural integration model requires a specialized major, and the module integration model effectively runs independent of other courses. We propose a third alternative: Pedagogical Linkage. Rather than creating a new major or a solitary module, we linked two existing generalist courses through a shared problem. This suggests that engineering schools do not necessarily need new degrees to contribute to the discipline of Oceanography and marine conservation; they simply need to restructure how existing technical and research courses interact.

## 4. Pedagogical Framework: Integrating ICE and MLPR

To address the need for interdisciplinary competency, the coral reef project was executed through a "Dual-Track" framework integrating two core courses: *Machine Learning and Pattern Recognition (MLPR)* and *Integrated Communication for Engineering (ICE)*. This approach aligns with recent findings by Liu et al. (2022), who demonstrated that applying AI to tangible marine challenges significantly improves student engagement and domain retention compared to abstract coursework. This interplay was accomplished by conducting both courses simultaneously, with the initial weeks (1-9) in MLPR focusing on the fundamentals of preprocessing real-world datasets and applying pattern recognition methods such as feature extraction, dimensionality reduction, and classification, while the parallel ICE literature review identified the limitations of these static approaches for coral bleaching. This research insight directly informed the transition to MLPR's second module (Weeks 10-15), where the curriculum shifted to Deep Neural Networks. Leveraging this training, students implemented and optimized LSTMs rather than standard classifiers to capture temporal dependencies. The final output synthesized these optimized neural network results into a persuasive ICE research script, ensuring that the engineering solution was not just a codebase, but a socially relevant intervention for a real-world problem.

### 4.1 The Technical Track: Machine Learning and Pattern Recognition (MLPR)

The MLPR course provided the technical scaffolding, moving beyond theoretical algorithms to end-to-end application building. The specific Course Learning Outcomes (CLOs) applied to this project included: 1) **Handling Real-World Data:** Malde et al. (2020) emphasize that data accessibility and compatibility are primary barriers in marine science. Consequently, students were required to aggregate disparate, noisy sources, harmonizing monthly biological data with daily satellite indices through the help of open-source datasets, and 2) **Prototype Evaluation:** A key requirement was to "evaluate the efficacy of developed solutions". This forced students to benchmark advanced Deep Learning models (LSTMs) against simpler baselines (Random Forest) to justify their architectural choices technically.

### 4.2 The Research Track: Integrated Communication for Engineering (ICE)

Simultaneously, the ICE course provided a framework for a structured enquiry. While engineering curricula often treat the problematic-domain-sensitivities as an afterthought, ICE integrated it as a core driver of the research process leading to address the pitfalls of poor interpretability.[22] The research training included: 1) **Research Design & Gap Analysis:** Through instructor led workshops and weekly check-ins with tutors, students received critical feedback on their literature reviews. Students identified that existing models, such as Random Forest approaches used by Udomchaipitak et al. (2022), were largely static (snapshots in time), ignoring the cumulative nature of thermal stress. This "Research Track" insight directly informed the decision to use LSTM networks, and 2) **Technical Communication** where students were taught and assessed on their ability to pitch technical concepts to a mixed jury. They had to translate algorithmic metrics (like recall) into stakeholder value (coral conservation), bridging the gap between engineering and ecology.

## 5. Methodology: Student-Led Discovery

The methodology of ReefCast reflects a student-led journey of discovery, where engineering decisions and tool creation were driven by the research-based learning pedagogy.

### 5.1 Data Harmonization

A primary educational objective was to expose students to the complexity of oceanographic data. The initial problem that emerged was the lack of a dataset encompassing all the required features as identified by students through preliminary research, especially for the geographical region focused in this study. Students constructed a 25-year dataset (1995-2020) covering four Indian reef zones: Andaman & Nicobar, Lakshadweep, Gulf of Mannar, and Gulf of Kachchh. This required the integration of:

1. **Physico-chemical data:** pH, fCO2, and Salinity from OceanSODA-ETHZ.
2. **Climatic Indices:** ENSO and IOD from NASA, which are critical macro-climatic drivers for the Indian Ocean.
3. **Biological Data:** Coral genera distribution and bleaching records, validated against historical reviews by Thangadurai et al. (2024).

### 5.2 Addressing Data Imbalance

A critical learning moment occurred when students encountered severe group imbalance: bleaching events were rare compared to healthy instances across the data collected over many months. Initial models yielded high accuracy simply by predicting "No Bleaching" every time. Through the ICE research track, students identified that in conservation biology, a False Negative (missing a bleaching event) is far more damaging than a False Positive. This insight drove the technical implementation of SMOTE (Synthetic Minority Over-sampling Technique), as proposed by Chawla et al. (2002). This technique generates synthetic examples of the minority group (bleaching events), ensuring the model remains more sensitive to actual bleaching risks. This oversampling technique was only applied on the training dataset i.e. the dataset used to train the ML model while the Test Set was not manipulated with so that artificial samples are not injected while testing the model. This approach was complemented by emphasis on Recall as a metric, which measures the ratio of true positive (bleaching) events to the sum of the events that are actual bleaching events (true positive) and those that were missed by the model despite being bleaching events (false negative). In this way, the model encodes the idea of false negatives being crucial for ecological prediction since missing any actual bleaching would be catastrophic for the marine environment.

### 5.3 Model Selection: From Interpretable to Temporal

Students trained and evaluated four distinct architectures. While Random Forest models have shown promise in previous global studies, students hypothesized that bleaching is a cumulative process that happens over a long period of time. Drawing on the hydrology literature of Kratzert et al. (2019), which utilizes LSTMs for modelling complex environmental time series, students implemented LSTM networks to capture the "memory" of thermal stress over time.

## 6. Assessment of Student Learning & Case Study Findings

The project results served as direct evidence of student learning across technical and interdisciplinary dimensions.

## 6.1 Technical Mastery

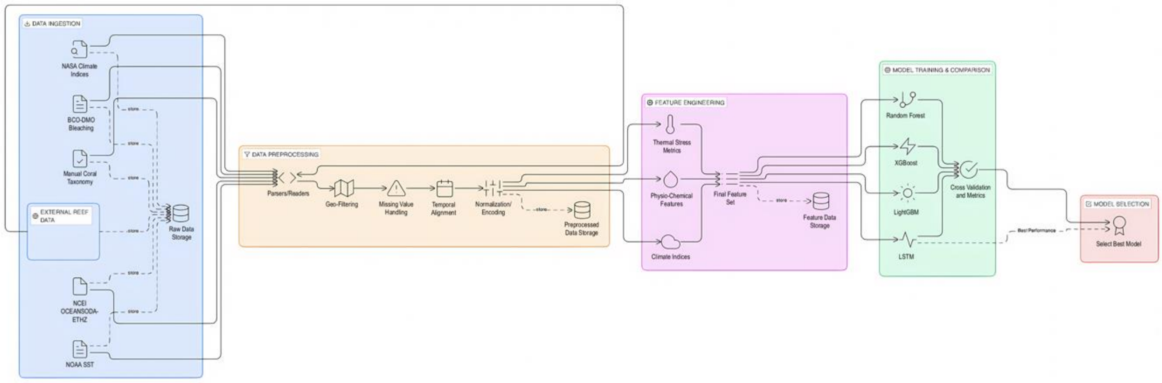


Figure 1. Research Methodology Flowchart: An end-to-end pipeline ingests and preprocesses multi-source environmental, climatic, and biological data (1995–2020), engineers thermal-stress, physico-chemical, and climate features, and then trains and compares Random Forest, XGBoost, LightGBM, and LSTM models using SMOTE-balanced, chronologically split time series to select the best predictor of site-specific coral bleaching in India.

The students' ability to apply ML concepts to a novel domain was validated by the model's performance. The **LSTM model** developed in this case study achieved a **Recall of 0.91** for bleaching events.
As shown in **Table 1**, the LSTM significantly outperformed the static Random Forest model (Recall 0.64) in identifying bleaching events. This validated the students' hypothesis that temporal modelling is superior for capturing slow-burn environmental stress.

| Model | Recall (Bleaching Class) | F1-Score (Bleaching Class) | Accuracy (Test Set) |
|---|---|---|---|
| LSTM | 0.91 | 0.47 | 0.90 |
| LightBGM | 0.60 | 0.60 | 0.97 |
| XGBoost | 0.70 | 0.58 | 0.96 |
| Random Forest | 0.64 | 0.45 | 0.93 |

*Table 1: Evaluation Metrics for Student-Developed Models on the Test Set*

### 6.2 Interdisciplinary Synthesis

Student synthesis was assessed through three explicit graded deliverables mapped to the Dual-Track framework:
1. Research Manuscript (ICE): Students submitted a structured research script with literature review, gap articulation, methodology justification, and claims supported by evidence.
2. Technical Prototype (MLPR): Students developed and evaluated an end-to-end ML pipeline, including baseline comparison, model selection, and performance reporting.
3. Stakeholder Pitch (ICE): Students presented technical findings to mixed technical and non-technical audiences, translating metrics into decision-relevant implications.

A key mechanism enabling these outcomes was the check-in cadence across both courses. In ICE, tutorial submissions and timely research check-ins provided iterative feedback on question framing, literature quality, and argument coherence before final manuscript submission. In MLPR, bi-weekly project progress discussions, midterm project evaluation, and final project evaluation created milestone-based technical accountability around preprocessing, methodology choice, metrics, and deployability. Together, these parallel check-ins reduced late-stage drift and ensured that research reasoning and technical implementation co-evolved through the semester.

### 6.3 Ethical Ecological Reasoning

A significant indicator of student learning was the shift in evaluation metrics. Students moved beyond accuracy (which was misleadingly high at >90% for all models due to class imbalance in the Test Set) to prioritize recall and F1-score. This decision proved that students understood the data justice dimension of the project, recognizing that an algorithm is not just a math problem, but a tool with ecological consequences where missing a bleaching event creates a deficit in conservation planning.

### 6.4 Learning Outcomes and Student Learning Impact: Pre-Integration (Spring 2024) vs Post-Integration (Spring 2025)

To quantify student learning impact, we compared project-portfolio evidence from Spring 2024 (pre-integration) and Spring 2025 (post-integration). We evaluated each project using observable indicators aligned to Dual-Track outcomes, including architecture strategy and real-world framing.

Each student project PDF is treated as one observation, and all percentages are normalized by the total number of projects in that cohort. For every project, each indicator is coded as present/absent using keyword-based rules, then aggregated to cohort-level shares.

Indicators are non-exclusive tags, so one project can be counted in multiple categories when it shows evidence for each. Because overlap is preserved, percentages across rows are not expected to add to 100%. For derived indicators (e.g., “any Kaggle”), union logic is used: a project is counted once if it matches at least one constituent tag, avoiding double counting within that derived row.

| Observation | Spring 2024 | Spring 2025 |
|---|---|---|
| Classical baseline benchmarking (e.g., RF/XGBoost/SVM families) | 40.6% | 65.9% |
| Hybrid deep + classical pipelines | 28.1% | 40.9% |
| Deployment/real-world framing language | 28.1% | 75.0% |

*Table 2: Shifts Across Batches*

First, the increase in baseline benchmarking indicates stronger experimental reasoning. Students more frequently justified model choice against alternatives instead of presenting single-model claims. Second, growth in hybrid pipelines suggests improved technical judgment, with teams combining models to match problem structure rather than defaulting to one algorithm family. Third, the sharp increase in deployment-oriented framing indicates higher transfer of classroom work to stakeholder and implementation contexts, which is a core intended outcome of the ICE track.

The integrated design appears to have improved three dimensions of learning simultaneously: (i) methodological discipline (how students validate choices), (ii) interdisciplinary synthesis (how research logic informs technical execution), and (iii) applied communication (how results are translated into practical value). The evidence therefore supports the claim that the Dual-Track framework improves not only what students build, but how they reason about, justify, and communicate what they build.

## 6.5 Facilitating Adoption at Other Institutions

The Dual-Track model is intentionally transferable and does not require a new degree program or major structural reform. It can be implemented by synchronizing two existing courses, one communication/research-focused and one technical ML-focused, around a shared semester project. A practical adoption template is: (i) align assignment timelines so literature review and gap analysis occur before advanced model selection, (ii) define three common outputs across both courses (research manuscript, technical prototype, stakeholder pitch), (iii) run parallel check-ins with shared rubrics for methodological justification and evidence quality, and (iv) use a joint midterm and final review process with mixed-discipline evaluators. This lowers institutional barriers because departments retain course ownership while coordinating milestones and assessment criteria. In this form, the framework can scale across institutions by adapting project domains to local priorities (for example, climate, health, mobility, or agriculture) while preserving the same pedagogical structure.

## 7. Conclusion

This work contributes a Dual-Track pedagogical framework that integrates ICE and MLPR to produce research-grounded, technically defensible, and stakeholder-communicable student outputs. ReefCast is the case study through which this framework is demonstrated; the primary contribution is curricular and assessment design, not only model development.

The framework operationalizes a clear chain: literature review and gap identification (ICE) to model selection and benchmarking (MLPR) to manuscript, prototype, and stakeholder communication (ICE + MLPR). In the ReefCast case, this chain explains why temporal architectures were selected and how metric interpretation was tied to ecological risk.

Pre/post cohort comparison further indicates improved methodological maturity after integration, including stronger baseline benchmarking, more hybrid modeling strategies, and substantially stronger deployment-oriented framing. These findings suggest that integrated research-and-technical instruction can accelerate interdisciplinary engineering readiness for complex domains such as ocean and climate applications.

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