Illegal, Unreported, and Unregulated Fishing: Empowering Effective and Efficient Interventions

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UNIVERSITY OF CALIFORNIA
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A report submitted in partial satisfaction of the requirements for the degree of Master of Environmental Science and Management for the Bren School of Environmental Science and Management

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The Bren School of Environmental Science & Management produces professionals with unrivaled training in environmental science and management who will devote their unique skills to the diagnosis, assessment, mitigation, prevention, and remedy of the environmental problems of today and the future. A guiding principle of the School is that the analysis of environmental problems requires quantitative training in more than one discipline and an awareness of the physical, biological, social, political, and economic consequences that arise from scientific or technological decisions.

The Group Project is required of all students in the Master of Environmental Science and Management (MESM) Program. The project is a year-long activity in which small groups of students conduct focused, interdisciplinary research on the scientific, management, and policy dimensions of a specific environmental issue. This Group Project Final Report is authored by MESM students and has been reviewed and approved by:

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I. Background and Significance

The world's oceans span an immense and unparalleled expanse, encompassing over 70% of the Earth's surface. This vast domain, characterized by its remote and challenging nature, poses a formidable monitoring and enforcement challenge for entities seeking to regulate maritime activities. This complexity has led to the ocean being aptly described by many as 'the world's largest crime scene.' Within this context, Illegal, Unreported, and Unregulated (IUU) fishing emerges as a global crisis, with the US Coast Guard declaring that "IUU fishing has replaced piracy as the leading global maritime security threat" (US Coast Guard, 2020). IUU fishing undermines ocean health by destroying marine ecosystems through destructive fishing practices, risks geopolitical stability as countries jostle over limited resources, and threatens global food security by jeopardizing a vital sea-based protein supply for millions of people.

The Food and Agriculture Organization of the United Nations (UNFAO) estimates that almost 90 percent of the world's fisheries are being exploited or have been depleted, while the global demand for seafood products continues to increase (UNFAO, 2022). IUU fishing has emerged as a result of this demand, with an annual illegal profit of $15.5 to $36.4 billion annually (Shaver and Yozell, 2018). IUU fishing encompasses many illicit activities such as fishing within marine protected areas, unauthorized fishing in sovereign waters of other nations, discarding catch unlawfully, engaging in illegal transshipment (i.e., illegally transferring catches between vessels), misreporting or underreporting catch, and perpetrating human rights abuses. Instances of sea slavery and organized crime have also been linked with IUU fishing activity (Mackay et. al., 2020). The challenges posed by IUU fishing is exacerbated by its disproportionate impact on under-resourced coastal nations, as many countries lack the capability for robust surveillance of their exclusive economic zones (EEZ). However, the integration of advanced technology offers promising avenues to address these resource deficiencies, potentially reducing the manpower and expenses required for comprehensive monitoring across vast marine territories.

The Allen Institute for AI (Ai2) is a nonprofit research institute with a mission to conduct artificial intelligence (AI) research for the common good. As a part of this mission, Ai2 has developed Skylight, an AI-powered data visualization software platform that leverages machine learning and satellite data to identify suspicious fishing activity. With a real-time alert system, Skylight provides actionable intelligence to maritime domain awareness (MDA) practitioners and other ocean health stakeholders and is free to the end-user. Skylight was identified in a recent study by international maritime agents as one of the most effective approaches to combat IUU fishing (Burroughs & Mazurek, 2019). However, there are limitations to satellite-based technology to monitor and enforce against IUU fishing alone.

Our team has identified three avenues to improve monitoring IUU fishing:

1) Increase awareness of the IUU fishing problem and investment in effective assets to monitor and enforce against IUU fishing.
2) Ensure that investments made in monitoring and enforcement result in quantifiable protection and restoration of marine resources.
3) Expand the number of countries engaged in IUU fishing monitoring and deterrence.

Our project will address each of these elements through a three-pronged approach. The goal is to support Ai2 and its partners by improving access to information on IUU fishing events and detection strategies and quantifying the impact of increased investment in those strategies. Additionally, we aim to provide insights on which countries to target IUU fishing reduction engagements.

II. Project Objectives

Objective 1: IUU Fishing Dashboard

Create an interactive web application for sustainable fisheries stakeholders to analyze possible monitoring strategies for various IUU fishing events based on specified parameters and preferences.
We accomplish this by:

- Conducting a literature review to determine the characteristics, capabilities, and costs of different monitoring technologies and strategies.
- Building a body of knowledge on different IUU fishing types and monitoring strategies.
- Developing a user-friendly Shiny Dashboard that allows IUU fishing events to be matched with monitoring strategies based on shared attributes and user constraints.

The overarching goal of this objective is to create an accessible resource to facilitate an understanding of different IUU fishing events and the monitoring strategies that could be used to monitor and enforce against such IUU fishing within user-specified constraints.

Objective 2: Bioeconomic Model

Develop a model to explore the relationship between improved IUU fishing monitoring and the health of the Indian Ocean yellowfin tuna (*Thunnus albacares*) stock in Indonesia. The following questions are assessed through this workflow:

- What is the optimal harvest level for yellowfin tuna?
- How does optimal harvest differ from fishers' actual decision on how much to harvest?
- How do improvements in enforcement affect illegal harvest?

The goal of this objective is to demonstrate the impact of increased enforcement on fish stock health.

Objective 3: Skylight Adoption Analysis

Analyze characteristics of active Skylight users to identify countries that are potential 'likely adopters' of Skylight technology. This will be accomplished by:

- Examining 51 country characteristic indicators from the World Bank and IUU Fishing Risk Index.
- Developing a binomial logistic regression model from key indicators to predict Skylight adoption.

The goal of this objective is to inform Skylight on shared characteristics of their active users and identify good candidates to target for future engagement.

III. Methods

The following sections are separated by project component, as each involves different workstreams, methods, and results.

IUU Fishing Dashboard

Goal

The goal for this component of the project is to create an accessible resource for sustainable fisheries stakeholders to expand their knowledge of different types of IUU fishing and possible monitoring strategies. To do so, we built an interactive R Shiny Dashboard that allows users to select an IUU fishing type, filter by jurisdiction of interest, and further refine results by specifying cost constraints and data type parameters (e.g. vessel location, video footage, imagery). The output provides suitable monitoring options, accompanied by short descriptions of their capabilities and limitations. Further information about IUU types and monitoring strategies can be found in additional tabs. The purpose of this tool is to provide useful information on monitoring strategies for various IUU fishing types for a range of use cases.

Data and Process

To begin, we performed a literature review to determine the features of monitoring strategies in three different categories: sensors, platforms, and satellites. Sensors were categorized as technology used to gather data, and platforms were the technology used to transport or carry the sensors. Satellites were treated as their own category since satellite technology payloads are predetermined. We recorded raw values representing their detection ranges, costs, resolutions, and other capabilities (e.g., speed, payload capacity, endurance). We also conducted a literature review to learn about various IUU events and determined the granularity of data required to detect each event (e.g., geographical location, individual species identification).

The literature review informed our sensor range values and the speed and endurance of the platforms. With the simplified assumption that a platform hosts one sensor, we calculated a sensor and platform combined range and approximate coverage area through the following process:

1. Multiply speed (km/hr) and endurance (hrs) of platforms to get total platform range (km).
2. Divide platform range in half to account for the need for a platform to return to deployment location after completing the monitoring mission.
3. Add each platform range to each sensor range, creating a combined platform and sensor range for every platform-sensor combination.
4. Calculate an approximate coverage area for each platform-sensor combination based on the area of a circle and assuming that the platform is deployed from its center. See illustration in **Figure I** for a visualization of this methodology.

Finally, we divided the calculated coverage areas into three groups of equal size to reflect local, regional, and international jurisdictions, with greater coverage areas associated with more remote jurisdictions. This was to address spatial considerations: monitoring strategies with smaller ranges are less suitable to monitoring large jurisdictions such as international waters.

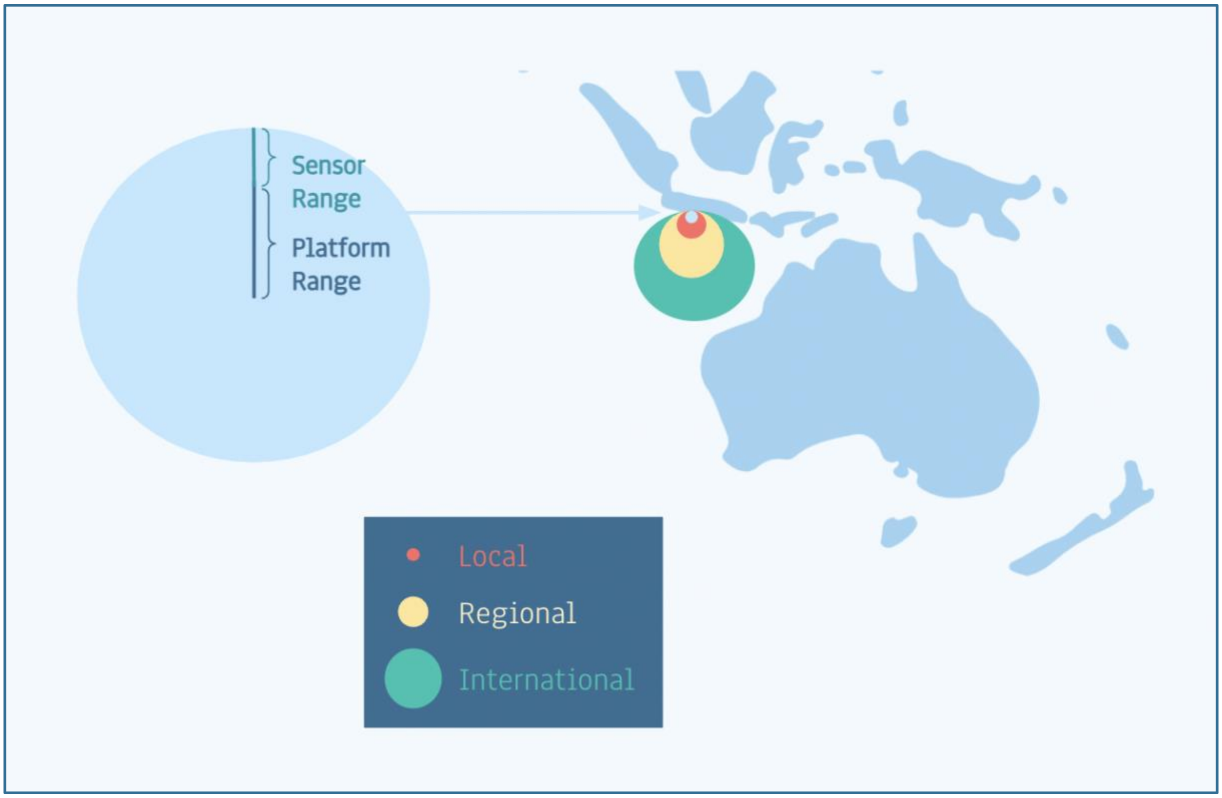


Figure I. Approximate coverage area of sensor and platform pairings. Area ranges are subsequently divided into local, regions, and international jurisdictions.

To recommend monitoring strategies for specific IUU fishing events, we developed a granularity index and matching logic. The granularity score represents the level of granularity of the information needed to detect a specific IUU fishing event. A granularity score of 1 represents the least granular data, while a score of 5 represents the most granular data requirements, as shown in **Table I**.

Table I. Granularity Index

Granularity Score	Definition
5	Identify a fish species and detailed onboard information
4	Identify the identity of a vessel and detailed fishing information
3	Identify vessel activity (e.g., fishing)
2	Identify vessel length and width
1	Identify the location of a vessel

Each IUU fishing type was assigned a granularity score based on the type of data needed to detect it. **Table II** depicts IUU types paired with granularity scores. For example, 'Underreporting of fishing effort' is assigned a score of '5' because detailed onboard information is needed to detect this event. 'Vessel in a prohibited zone' only requires the location of the vessel, which corresponds with a '1'. 'Illegal transshipment' is assigned a '2' since vessel size information is the minimum needed to detect two boats side-by-side for an extended duration.

Table II. IUU Type and Granularity Score

IUU Type	Granularity Score
Underreporting of fishing effort	5
Underreporting of fishing catch	5
Gear-related offense	4
Vessel in a prohibited zone	1
Illegal transshipment	2
Dark vessels (not broadcasting via VMS/AIS)	1
Fishing out of season	1
Fishing above quota	5
Vessel with false flag	4
Fishing without license	4

In addition to assigning index scores to IUU fishing events, we also developed an index matrix for sensor ranges to capture the change in detection capability based on distance from the target vessel. For example, a long-range camera can detect vessel presence at a distance of 20 kilometers, but that distance is much shorter if onboard species need to be detected. An example of the matrix is given in **Table III** and the complete matrix can be found in the GitHub repository**.**

Table III. Example Sensor Ranges for each Granularity Score

Granularity Score	Long-range camera (km)	Hydrophone (km)	Onboard Observer (km)
1	20	7	0
2	9	1	0
3	7	0	1
4	4	0	1
5	2	0	1

From the literature review, we also collected rough cost estimates for each monitoring technology. As the costs of different models range significantly based on manufacturer and technical specifications and are often not publicly available, we were not able to provide specific cost details. However, cost is an important constraint for fisheries MCS, so we developed an index to give a rough order of magnitude cost estimate, shown in **Table IV.**

Table IV. Cost Index

Cost Score	Order of Magnitude (USD)
1 ($)	10s of thousands
2 ($$)	100s of thousands
3 ($$$)	1 million +

The cost index allows the user to filter by cost constraint. Additionally, the data gathered by each sensor was categorized as ‘Location’, ‘Image’, ‘Video’, or ‘Eye-witness’ to allow another level of user specificity. Depending on a user’s needs and jurisdictional laws, certain data types will be more useful for ultimately prosecuting illegal fishing events.

With help from Skylight’s data sources, we compiled a final dataset for satellites and assigned granularity and cost scores. Based on a user’s IUU fishing type selection and cost selection, appropriate satellite options will also appear under sensor and platform solutions.

Ongoing Work

We intend for the IUU Fishing Dashboard web application to be updated as new information and better data becomes available. We anticipate that interviewing fisheries management stakeholders and discussing our app with potential users will provide valuable insights. These will be worth incorporating into the app to provide more accurate and useful outputs. Throughout the Spring 2024 quarter we intend to keep updating our repository and will discuss with our client how this should be handled in the future. We will also continue our work with incorporating scaled monitoring solutions (e.g., 100 smart buoys to cover desired area) to expand the application offerings.

Bioeconomic Model

Overview

The bioeconomic model allows Skylight to analyze the relationship between fish stock status, IUU fishing enforcement, and fishing harvest. It projects how improvements in enforcement translate to improvements in yellowfin tuna (*Thunnus albacares*) fish stock status, using Indonesia as a case study.

Yellowfin tuna management in Indonesia offers a compelling case study for numerous reasons. It is one of the most profitable fish stocks globally, with a recent Pew Charitable Trusts analysis valuing Indian Ocean yellowfin tuna at $4.19 billion USD annually (Pew, 2020). Despite – or perhaps due to – its economic value, yellowfin tuna is also overexploited. The graph below summarizes Indian Ocean yellowfin tuna biomass and catch data provided by the RAM Legacy Stock Assessment Database (RAM, n.d.). Catches (in blue) have increased steadily since the 1980s, while spawning stock biomass (in red) has plummeted.

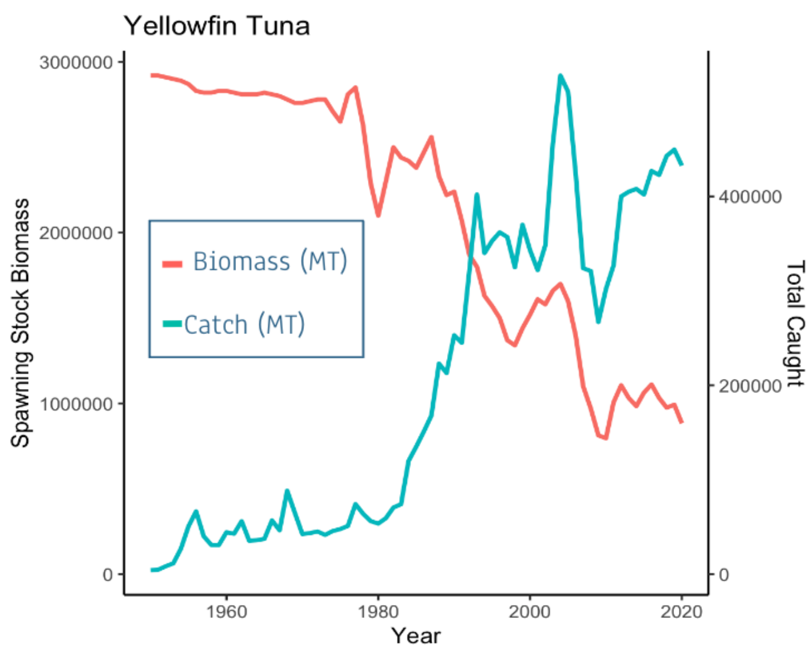


Figure II. *Yellowfin tuna (Thunnus albacares) spawning stock biomass vs. catch (1950 – 2020)*

Moreover, Indonesia is the only nation ranked within the IUU Fishing Risk Index's top ten countries at-risk from IUU fishing that also uses the Skylight tool (IUU Fishing Risk Index, 2023). Given the prevalence of IUU fishing risks, a demonstrated commitment to address IUU fishing with methods like Skylight, and Ai2's strong relationship with in-country officials and experts, Indonesia proves an ideal nation to test the bioeconomic model.

Drawing on data about both Indian Ocean yellowfin tuna stock status and Indonesian IUU fishing enforcement, the bioeconomic model seeks to answer the following questions:

1) **What is the optimal harvest level for any given level of yellowfin tuna biomass?**
2) **How does optimal harvest differ from actual harvest?**
3) **How do varying levels of enforcement (i.e., no enforcement (*e* = 0); partial enforcement (*e* = 0.5); full enforcement (*e* = 1)) affect illegal yellowfin tuna harvest?**

The model draws inspiration from McDonald et al., which evaluates optimal enforcement for a small-scale Caribbean lobster fishery (McDonald et al., 2016). Informed by both the article and primary research conducted at the Bren School, our analysis includes the following variables:

X: Yellowfin tuna stock biomass (metric tons (MT))
h: Legal fishing harvest, e.g., quota (MT)
ht: Total fishing harvest, e.g., the sum of legal and illegal fishing (MT)
int_stock: Initial stock biomass (MT)
δ**:** Discount rate
p: Price of landed tuna ($/MT)
c**:** Cost of fishing ($/MT)
et: Level of enforcement
γ: Enforcement effectiveness
K: Carrying capacity (MT)
r: Intrinsic population growth rate

Table V. Bioeconomic model parameters

Biological Parameters	Economic Parameters	Enforcement Parameters
Initial Stock (*int_stock*) = 883,400 MT	**Cost of fishing per unit (*c*)** = $1,678 per metric ton	**Level of enforcement (*et*):** ($0 < et \leq 1$)
Intrinsic growth rate (*r*) = 0.2	**Price of fish per unit (*p*)** = $2,397 per metric ton	**Detection probability at max enforcement** = 0.25
Carrying capacity (*K*) = 2,265,128 metric tons	**Discount rate (*δ*)** = 0.5	**Fine (per MT illegal harvest):** $8,398.50

Three-Step Process:

1) **Find the dynamic economically optimal harvest (e.g., the optimal quota) *assuming no illegal fishing occurs*.** Using value function iteration and backwards induction, the

model identifies the *optimal policy function* for Indian Ocean yellowfin tuna. This function quantifies the ideal quota, or harvest level (h), for any given biomass estimate (X). Note that instead of simply identifying Maximum Sustainable Yield (MSY) for a given level of biomass, the model relies on the Maximum Economic Yield (MEY). MEY evaluates both the revenue generated from a harvest and the cost of harvesting, which typically keeps harvest levels below MSY.

a) *Stock dynamics* are described according to a logistic growth model, where future stocks X_{t+1} are a function of stocks at current (X_t), intrinsic growth rate (r), carrying capacity (K), and optimal legal harvest (h_t).

$$X_{t+1} = X_t + r * X_t - \frac{r * (X_t)^2}{K} - (h_t)$$

b) *Public benefits, or profits*, are a function of fish stock (X_t), optimal harvest (h_t), the price of landed tuna (p), and the costs of fishing (c).

$$\pi_t = p * (h_t) - c * \frac{(h_t)^2}{X_t}$$

c) *Value* is a function of fish stock (X_t), optimal harvest (h_t), and the discounted value of future fish stocks (*Xnext*). By capturing the payoff value associated with future yellowfin tuna stocks, the model balances today's profits with tomorrow's healthy fishery.

2) **Introduce IUU fishing and find the *actual* total harvest.** The second step introduces a separate optimization evaluating a private profit function for fishers. The private profit function aims to capture how actors behave in the real world, where fishers behave myopically (e.g., they do not consider the discounted future value of stock) and seek to maximize profits here and now. Fishers' decision on how much to harvest is then based solely on the profits they can receive from their catch, the associated cost of fishing, and the likelihood of receiving a fine for fishing above the legal limit. Profits are calculated as a function of the current stock level (X_t), actual harvest (ht_t), and optimal harvest for that given stock level (h_t). Illegal fishing harvest is defined as the difference between actual harvest and optimal harvest. Illegal fishing is penalized according to enforcement effectiveness (γ) at a given enforcement level (*et*). Because illegal fishing occurs *in addition to* legal fishing, instead of independently, fishers have a greater likelihood of receiving a fine the more they harvest above quota. The private profit optimization captures thus the *decreased marginal productivity* of illegal harvest compared to legal harvest.

$$\pi_t = p * ht_t - c * \frac{ht_t^2}{X_t} - \gamma * e_t * (ht_t - h_t)$$

3) **Evaluate how changes in enforcement level (*et*) affect tuna harvest and overall stock.** We evaluated outcomes in Indian Ocean yellowfin tuna stock and harvests across five different levels of enforcement: no enforcement (*et* = 0), 25% enforcement (*et* = 0.25), 50% enforcement (*et* = 0.50), 75% enforcement (*et* = 0.75), and full enforcement (*et* = 1).

Skylight Adoption Analysis

Analysis Methods

The goal of this analysis is to understand the factors that may influence whether or not a country adopts Skylight and to identify potential countries for targeted philanthropic outreach. This analysis can also be adapted to understand how Skylight offerings can evolve to better attract non likely adopting countries, or countries with a significant need for monitoring support (see **Figure III**). By examining the common characteristics among Skylight adopters, we can identify trends across countries that actively engage with Skylight. Non-Skylight countries that share those Skylight-user characteristics can be considered 'likely adopters', as they exhibit similar trends to Skylight countries. These likely adopters may be good candidates for future philanthropic engagement within the illegal fishing detection and prevention space.

The first step in this analysis involves the identification of explanatory variables for Skylight adoption. We began by considering a comprehensive set of indicators from two sources: the World Bank and the Illegal, Unreported, and Unregulated Fishing Risk Index (detailed in the 'Data' section below). The full suite of 51 indicators included measurements of national governance effectiveness, IUU fishing risks and prevention efforts, and GDP. To narrow down this large set of indicators, we excluded indicators with NA values for more than 10% of the dataset, used real-world context to eliminate irrelevant indicators, and tested the remaining batch for collinearity and discarded highly collinear indicators. The remaining 12 key indicators were used in the model selection phase of this assessment (see **Table VI**).

Binomial logistic regression was employed to test various models and hypotheses, with the final model chosen using backwards model selection. Model selection was guided by Multi-Model Inference with Bayesian Information Criterion (BIC) scores as the selection criteria. Notably, no models fell within 2 delta BIC points from our best model, enabling us to focus the remainder of the analysis on this best model. Fit of the best model was then assessed using Area Under the Curve (AUC). The best model was used to populate a confusion matrix of predicted Skylight adopters and true adopters. In this matrix, all false positive countries—those predicted by the model to be Skylight users but are not—were identified as our likely adopters.

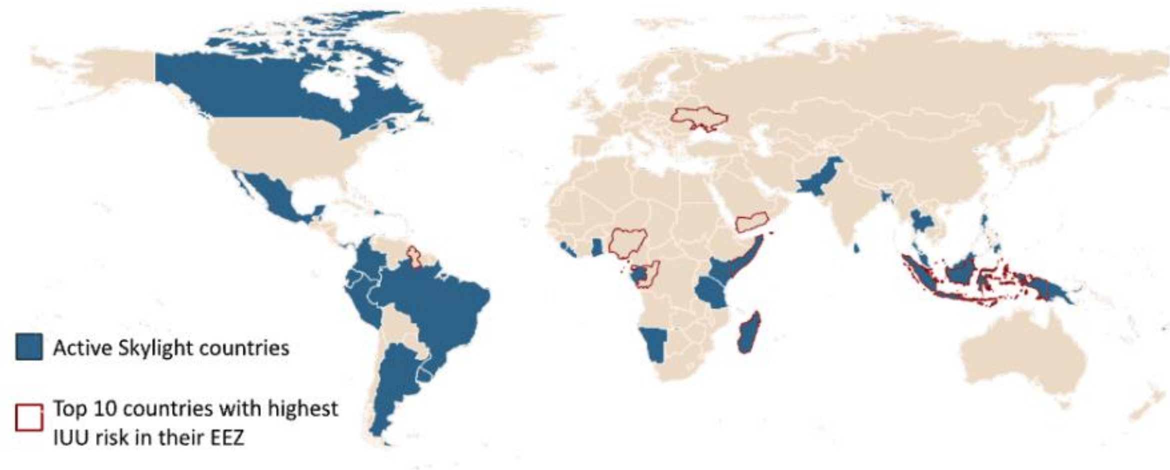


__Figure III.__ Map of active Skylight countries in blue and the top 10 countries with the highest IUU fishing risk in their EEZ outlined in red (IUU Fishing Risk Index 2023).

Data

Data for this analysis was obtained from 3 sources:

1. IUU Fishing Risk Index
2. World Bank Country Data
3. Skylight User Engagement Metrics

IUU Fishing Risk Index: This dataset was co-developed by Poseidon Aquatic Resource Management Ltd., a fisheries and aquaculture consultancy firm, and the Global Initiative Against Transnational Organized Crime (Macfadyen, G. and Hosch, G, 2023). The index consists of 40 IUU fishing indicators across 152 maritime countries from 2019 to 2023. The 40 indicators are grouped by which state has responsibility: the coastal state responsible for the EEZ, the flag state of fishing vessels, or the port state where the fish is landed. Indicators are also grouped by vulnerability to IUU fishing risk, known or expected prevalence of IUU fishing, and response to IUU fishing. Our analysis focuses on the indicators that we believe are most relevant to IUU fishing monitoring.

World Bank: We sourced three time series datasets from the World Bank including Governance Indicators, GDP, and World Development Indicators.

> **Governance Indicators:** An aggregate of data from 30+ think tanks, international organizations, non-governmental organizations, and private firms capturing household, business, and citizen perception of the quality of governance in more than 200 countries. This data is developed in part through survey and expert opinion and features 6 indicators. These indicators were highly collinear and therefore only one was included in the final set of 12 key indicators (Kaufmann, D. & Kraay, A, 2023).

> **GDP:** Data on the per capita gross domestic product of 200+ countries (World Bank Group, 2022).

World Development Indicators: This dataset covers many facets of global development. For our analysis, we utilized aquaculture and capture-fisheries data (Worldwide Governance Indicators, n.d.).

Skylight User Engagement Metrics: The Skylight team provided usage metrics for the countries that have been engaged with the Skylight tool. We used the weekly engagement metrics to determine which countries are actively Skylight users[1]. Note that the active user data was pulled in January 2024 and the list of active countries may have changed since then.

Table VI. The covariant inputs to binomial logistic regression analysis

Covariant	Definition	Causation Hypothesis	Data Source
Voice and Accountability	This indicator measures the overall levels of democracy in a country. Ranked on a scale of 0 - 100, with 100 being the most democratic.	Countries with higher values will be more likely to adopt Skylight because the government is more accountable to the people.	World Bank: Governance Indicators
Capture-Fisheries Production	This indicator measures the annual weight (tons) of fish caught at sea and brought to port legally in a country.	Higher quantities of sea-captured fish can be inferred to relate to a higher $ value. This will lead to higher Skylight adoption because legal fishing will be more valuable to protect in these countries.	World Bank: Developmen t Indicators
Ratio of Capture Fisheries Production to Aquaculture Production	This indicator measures the total capture-fishery production divided by the total aquaculture production in a country (in tons).	If a country has a more productive aquaculture industry than capture-fishery, they may have less motivation to put resources towards protecting capture fishery, which will lead to less Skylight adoption.	World Bank: Developmen t Indicators
Per Capita GDP	This indicator measures the per capita gross domestic product of a country (in USD).	Countries with a moderate GDP per capita will be likely Skylight adopters since they may have some resources available to invest in IUU fishing, but not enough to develop an entirely custom program.	World Bank

[1] The Skylight team defines active engagement as using the Skylight platform 3 weeks out of the last 5.

Covariant	Definition	Causation Hypothesis	Data Source
Dependency on Fish for Protein	This indicator measures the dependency of countries on fish as a source of protein, based on the volume of fish consumed per person.	Countries with higher dependency on fish for protein are more likely to engage with Skylight because they have more to lose from IUU fishing	IUU Fishing Risk Index
Designated Ports Specific for Entry by Foreign Vessels	This indicator measures whether the port country designates specific entry points for foreign vessels.	Countries that designate specific port entries for foreign vessels are more likely to be keeping track of foreign vessel activity.	IUU Fishing Risk Index
Party to the PSMA	This indicator measures whether countries have acceded to the FAO Agreement on Port State Measures.	These countries will be more willing to adopt Skylight because they have a demonstrated history of commitment to IUU prevention.	IUU Fishing Risk Index
Provision of Vessel Data for Inclusion in the Global Record	This indicator measures whether countries have provided data on their flagged vessels to the FAO for inclusion in the global record.	These countries will be more willing to adopt Skylight because they have a demonstrated history of global maritime transparency and cooperation.	IUU Fishing Risk Index
Ratification Accession of UNCLOS Convention	This indicator measures whether countries have signed on to the United Nation Convention on the Law of the Sea (UNCLOS)	These countries will be more willing to adopt Skylight because they have a demonstrated history of commitment to global maritime cooperation and standards for acts at sea.	IUU Fishing Risk Index
Size of EEZ	This indicator measures the size of a country's EEZ.	Countries with a larger EEZ are more likely to engage with Skylight, because they have more need for marine surveillance.	IUU Fishing Risk Index
Trade Balance for Fisheries Products	This indicator measures whether countries import a lot of fish compared to exports or export a lot of fish compared to	Countries with more fisheries exports will be more likely to engage with Skylight because they are more economically reliant on legal fishing.	IUU Fishing Risk Index

Covariant	Definition	Causation Hypothesis	Data Source
	imports (in value terms).		
Vessels on IUU Lists	This indicator measures how many vessels a country has listed on Regional Fisheries Management Organization (RFMO) IUU vessel lists.	Countries with high numbers of illegal vessels are less likely to adopt Skylight because they have potential economic ties to IUU activity and have a demonstrated history of inaction in IUU enforcement.	IUU Fishing Risk Index

IV. Results

IUU Fishing Dashboard

The latest version of our IUU Fishing Dashboard can be accessed through our public GitHub repository: https://github.com/sydneymayes/cirsea_dashboard. This repository reflects the most up to date data and code for the Shiny app. Based on feedback and interviews with fisheries management stakeholders, we will push changes to reflect best industry knowledge.

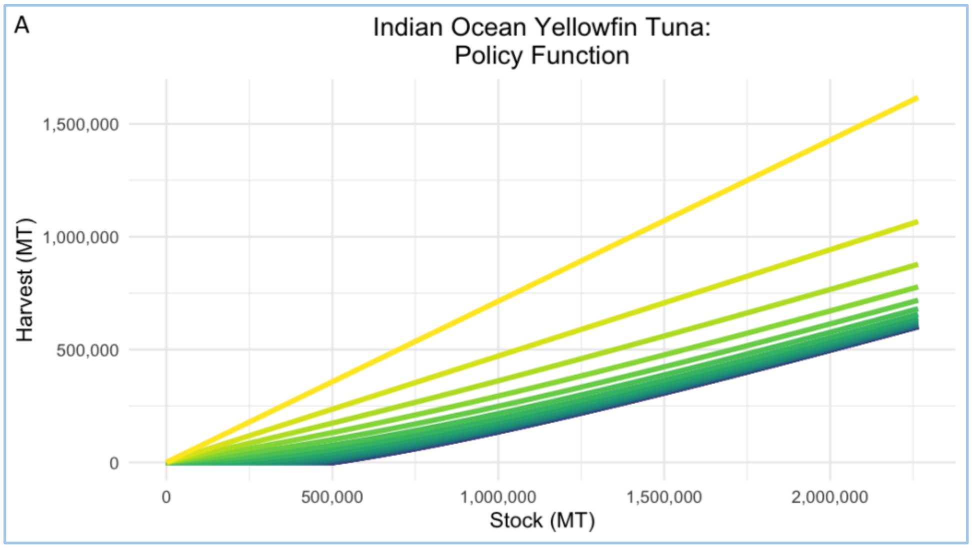
The app allows users to select from ten different IUU fishing events, select a jurisdiction (local, regional, or high seas), filter by cost constraints ($, $$, $$$), and specify data needs (eyewitness, image, location, video). Outputs are possible sensor and platform monitoring pairings and satellites, accompanied by brief descriptions. Other tabs of the application include more details about monitoring solution capabilities, caveats, and use case examples, as well as an introductory page providing background and context on the global IUU fishing problem.

Depending on our budget and discussion with Skylight, a version of the app may be hosted online. All questions related to the current status and accessibility of the app may be directed to our team, as future web-hosting capabilities are currently undetermined. Ultimately, we hope to share this tool broadly with global fisheries stakeholders to improve understanding of appropriate and effective IUU monitoring solutions.

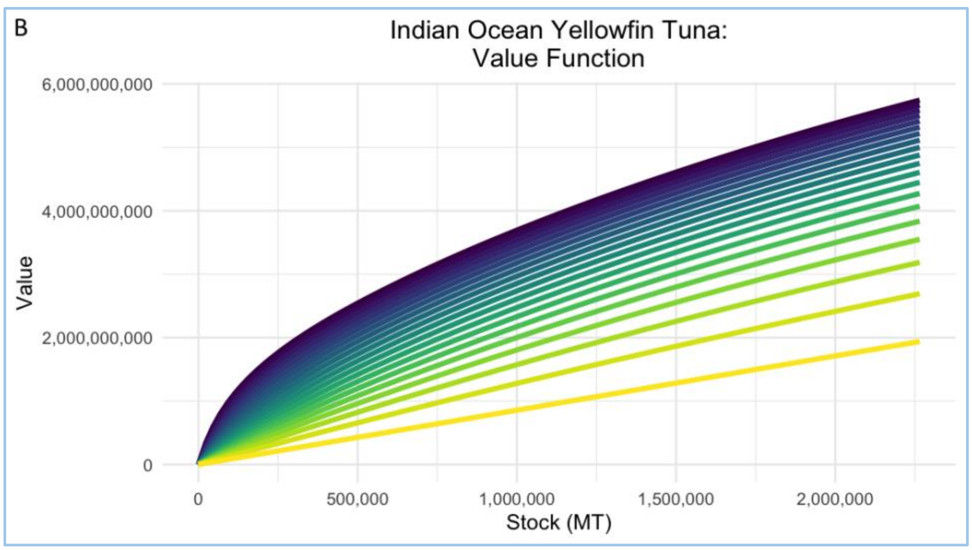
Bioeconomic Model

Part 1: Optimal Harvest

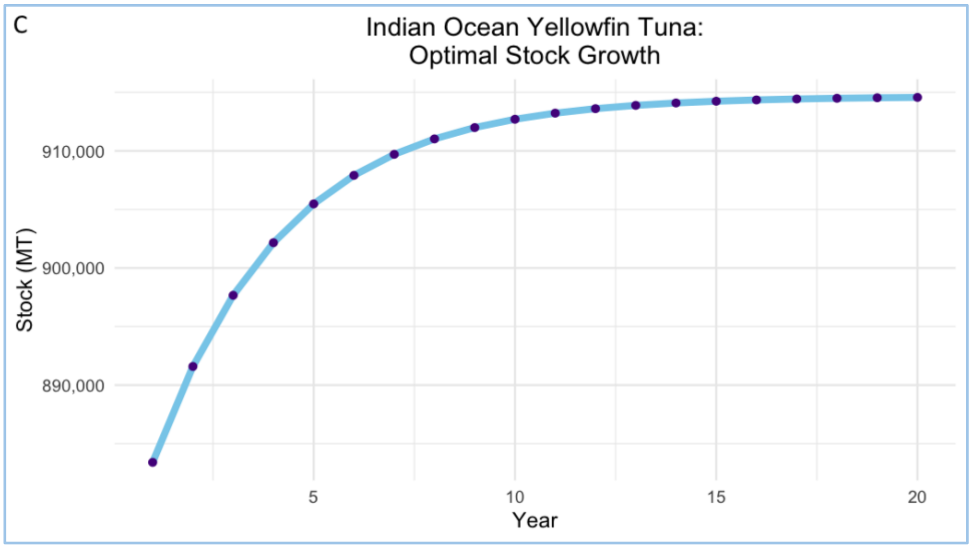
Graph A shows the results of the public profits value function iteration, assuming no illegal fishing. This function iterates through various harvest scenarios over time, with the initial runs shown in yellow. It ultimately converges on the *optimal policy function* (in purple), which is used to determine the dynamic economically optimal harvest, or legal harvest.



Graph B plots *value* (the sum of the *current profits* from harvesting plus the *discounted future value of fish*), given Indian Ocean yellowfin tuna stock (MT). Like the optimal policy function, Graph B also iterates until it converges upon the *optimal value function*.



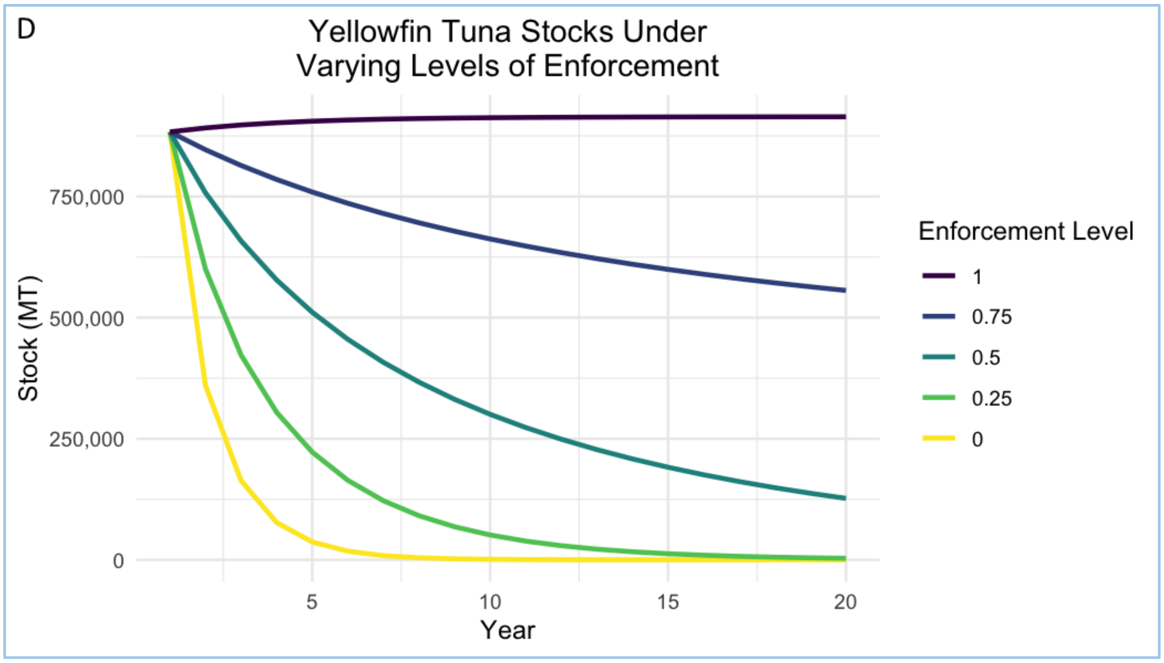
Graph C applies the *optimal harvest policy* identified to current Indian Ocean yellowfin tuna stock estimates (883,400 MT per the RAM Legacy Stock Assessment database). Under the optimal harvest policy, yellowfin tuna populations will be allowed to grow (e.g., harvest is less than annual growth) for roughly ten years. Eventually, the yellowfin tuna stocks approach a steady state where harvest and growth near an equilibrium.



Understanding the optimal harvest for a given stock level is crucial to differentiating between legal and illegal harvest. While the above graph depicts how optimal harvest supports stock growth over 20 years – starting at today's stock levels – the model produces a dataframe with 100 discrete stock values between 0 MT and 2,265,128 MT (carrying capacity), their respective optimal harvest level, and respective value. Using spline interpolation, a type of piecewise polynomial interpolation, the subsequent private profit optimization determines the optimal harvest for stock values outside of the dataframe, allowing us to adapt to dynamic inputs and appropriately identify and penalize illegal harvest.

Parts 2 and 3: Actual Harvest Under Different Levels of Enforcement

With the optimal policy function and the ability to interpolate legal harvest for any given stock level, we ran a second private profit optimization to determine *actual* fishing harvest. We carried out this optimization across five levels of enforcement: no enforcement (*et* = 0), 25% enforcement (*et* = 0.25), 50% enforcement (*et* = 0.50), 75% enforcement (*et* = 0.75), and full enforcement (*et* = 1). **Graph D**, below, shows how Indian Ocean yellowfin tuna stock responds to different enforcement levels. No enforcement represents the lower bound (yellow), where stocks drop to near-zero levels within six years. Full enforcement (purple) represents the upper bound, where stocks continue to grow from current stock levels (883,400 MT) over the coming 20 years.



In addition to stock dynamics, we evaluated how legal and illegal harvest changes across enforcement levels. **Figure IV** summarizes these results, with illegal harvest (in red) and legal harvest (in green) summing to total annual harvest. Together, Graph D and Figure IV illustrate how greater enforcement leads to higher stock levels and shifts harvesting dynamics from illegal harvest to legal harvest

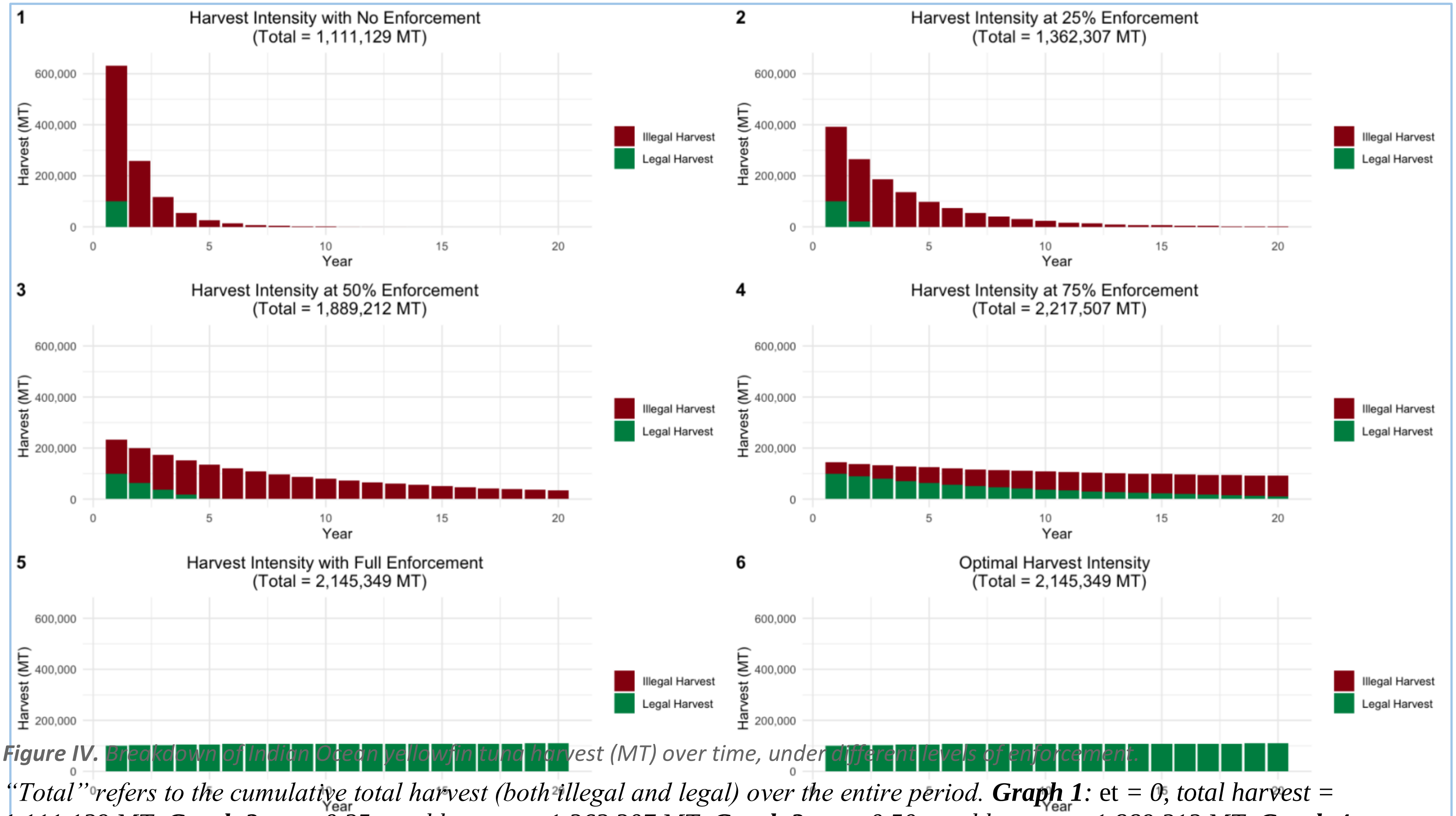


Figure IV. *Breakdown of Indian Ocean yellowfin tuna harvest (MT) over time, under different levels of enforcement.*

"Total" refers to the cumulative total harvest (both illegal and legal) over the entire period. ***Graph 1****:* et = *0, total harvest = 1,111,129 MT.* ***Graph 2:*** et = *0.25, total harvest = 1,362,307 MT.* ***Graph 3:*** et = *0.50, total harvest = 1,889,212 MT.* ***Graph 4:*** et = *0.75, total harvest = 2,217,507 MT.* ***Graph 5:*** et = *1, total harvest = 2,145,349.* ***Graph 6:*** *Optimal harvest according to the optimal policy function* (see *Graphs A – C above), total harvest = 2,145,349 MT.*

Lastly, for each level of enforcement we recorded the final biomass after 20 years of harvest, total harvest across all 20 years, and the subsequent breakdown of illegal harvest and legal harvest. Because the bioeconomic model is first and foremost a conceptual model, illegal harvest and legal harvest are summarized here as a proportion of total harvest. Our primary goal is to reveal how the *scale* and *magnitude* of illegal fishing changes as enforcement level improves, not the raw counts themselves.

Table VII. Stock dynamics and harvest across different enforcement levels (*et* = 0, *et* = 0.25, *et* = 0.50, *et* = 0.75, *et* = 1).

Stock Dynamics and Harvest Across Different Enforcement Levels

Starting Biomass (MT)	Ending Biomass (MT)	Illegal Harvest	Legal Harvest	Total Harvest (MT)	Enforcement Level
883400	0	91.04%	8.96%	1111129	**0**
883400	1738	91.08%	8.92%	1362307	**0.25**
883400	93331	88.52%	11.48%	1889212	**0.5**
883400	465059	61.71%	38.29%	2217507	**0.75**
883400	805522	0%	100%	2145349	**1**
883400	805532	0%	100%	2145349	**Optimal**

Enforcement level "Optimal" (light blue) refers to the optimal policy function. "Optimal" and "et = 1" share the same ending biomass, illegal harvest, and legal harvest. This is because the model is parameterized so that full enforcement (et = 1) yields near-optimal harvest levels.

Skylight Adoption Analysis

The indicators included in the best model from the Multi-Model Inference model selection method are listed in **Table VIII** along with the coefficients and significance level from the binomial logistic regression model.

Table VIII. Logistic regression analysis of predictors for Skylight use in coastal countries.

Outcome: Active Skylight User	Coefficient Estimate	Confidence Interval	*z*-value	*p*-value
Intercept	-1.417e+00	[-3.14 - 0.15]	-1.72	.086 .
Size of EEZ	4.964e-01	[0.07 - 0.98]	2.17	0.029 *
Voice and Accountability Estimate	8.467e-01	[0.09 - 1.73]	2.05	0.040 *
GDP per Capita	-8.924e-05	[0.00 - 0.00]	-2.66	0.007 **

. significance at .1
* significance at .05
** significance at .01

The confusion matrix depicted in **Table IX** provides a comprehensive overview of the model's predictive performance in classifying countries as Skylight adopters or non-adopters. This matrix compares the model's predictions against the actual Skylight adoption status of each country in the dataset. Specifically, it categorizes countries into four groups: true positive (correctly predicted as Skylight adopters), true negative (correctly predicted as non-adopters), false positive (incorrectly predicted as Skylight adopters), and false negative (incorrectly predicted as non-adopters).

Table IX. Logistic regression model accuracy in predicting Skylight use in coastal countries

		Actual	
Predicted	Skylight Adoption	0	1
	0	93	25
	1	**13**	18

Accuracy: 0.745
AUC: 0.8232

The false positive countries, or non-Skylight countries that the model predicted as Skylight adopters are: **Chile, Costa Rica, India, Jamaica, Kiribati, Marshall Islands, Mozambique, Palau, Senegal, Seychelles, Solomon Islands, South Africa, Tuvalu.**

Figures V(a), V(b), and **V(c)** show the distribution of indicator values across three different groups. Blue represents non-Skylight countries that were predicted by the model as Skylight adopters, green represents non-Skylights countries that were not predicted to be Skylight adopters, and pink represents actual Skylight adopters.

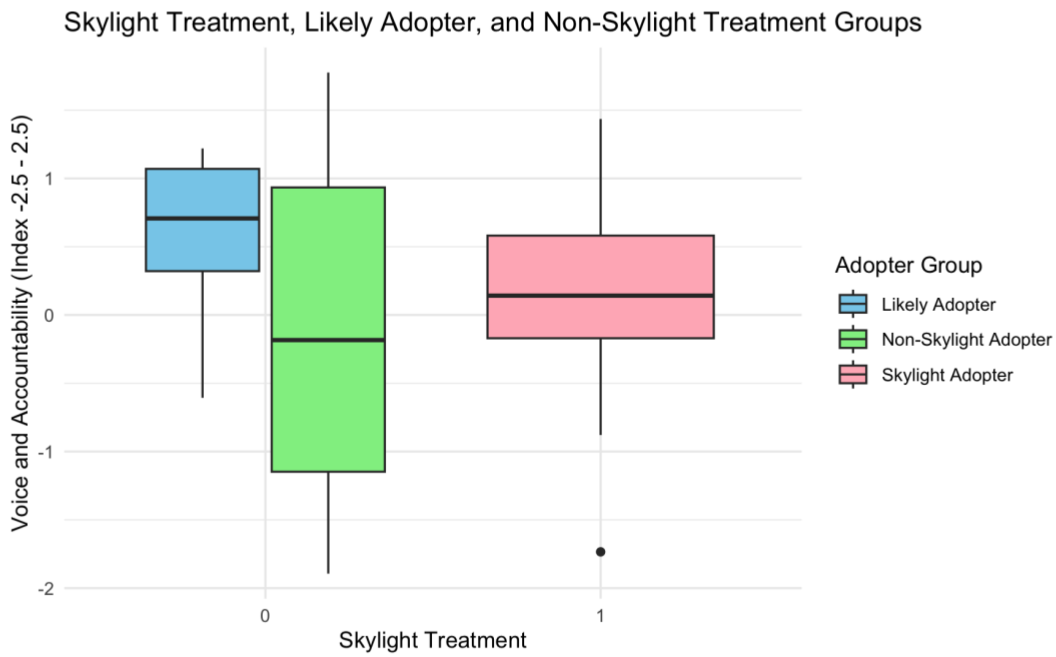


Figure V(a). *Voice and Accountability indicator distribution*

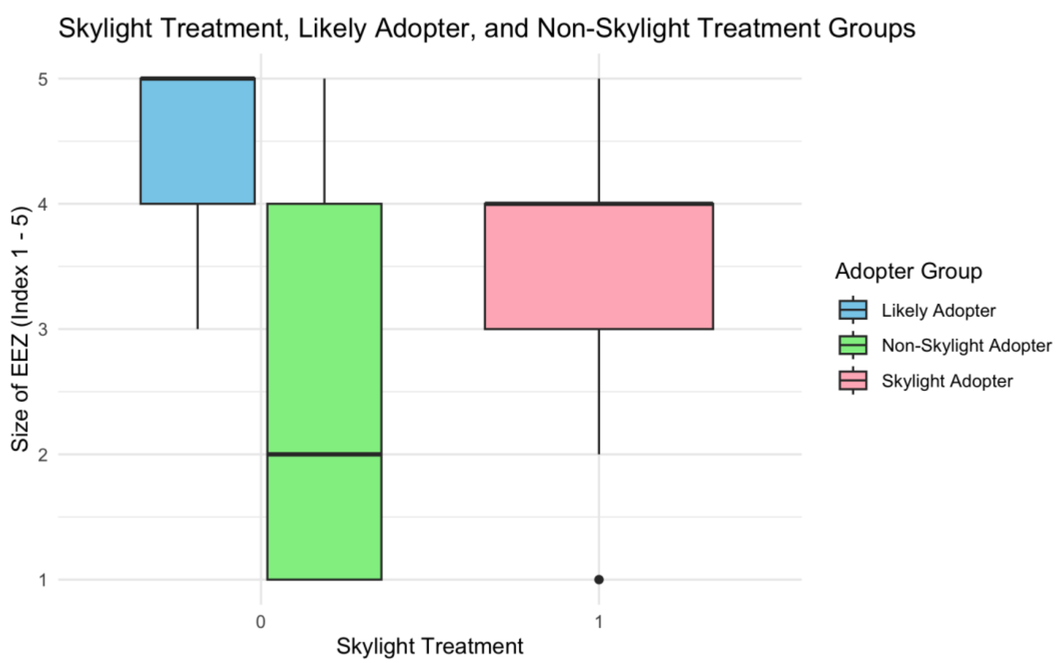


Figure V(b): *Size of EEZ indicator distribution*

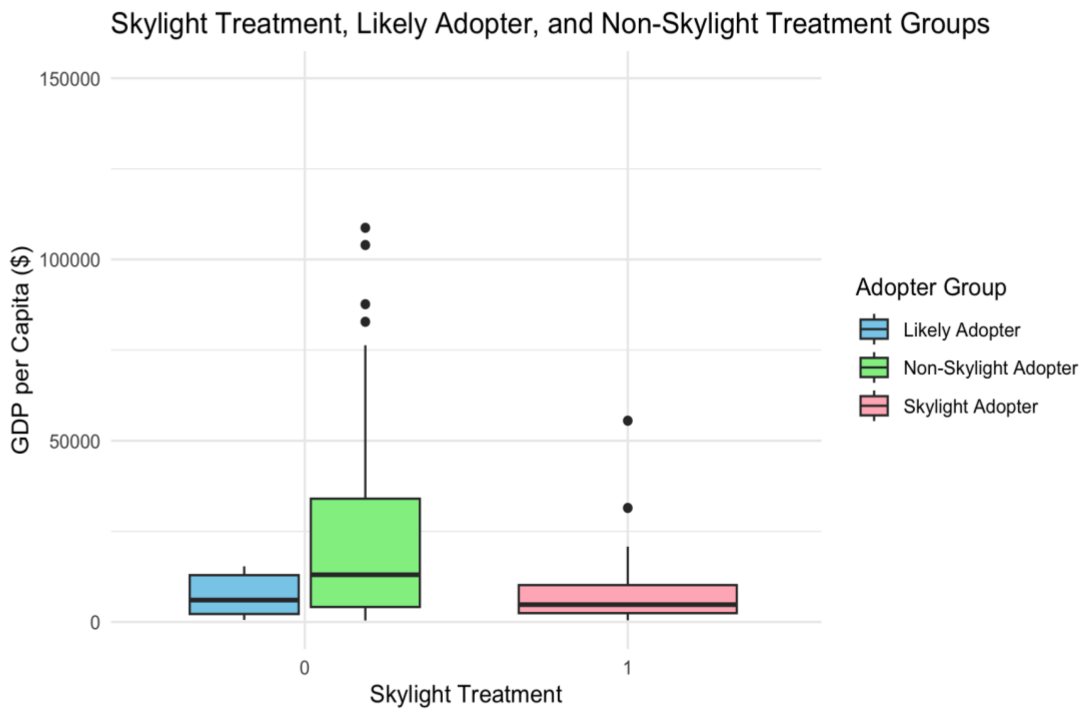


Figure V(c). *GDP per Capita distribution (up to $150,000)*

Figure VI visualizes the values of the three significant covariates across every country, with Skylight predicted countries outlined in blue and actually Skylight countries outlined in red. From this figure we can see the similarities between actual Skylight countries and predicted countries, and the differences between these countries and the rest of the world.

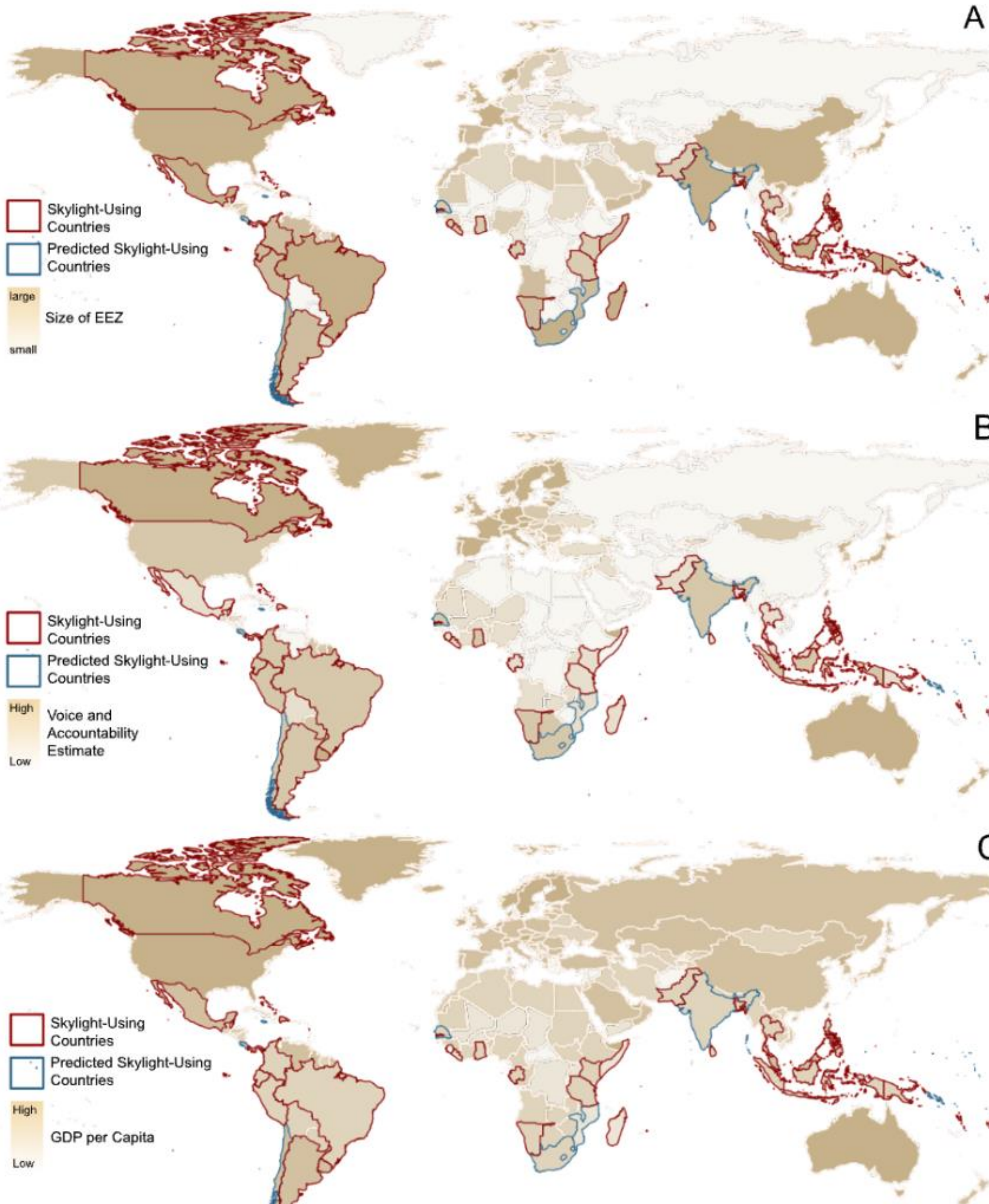


Figure VI. *Geographic visualization of the three key covariates. A: Size of EEZ; B: Voice and Accountability; C: GDP per Capita.*

V. Discussion and Conclusions

IUU Fishing Dashboard

The goal of this project component was to create a knowledge base and accessible tool for sustainable fisheries stakeholders to learn about suitable monitoring solutions for IUU fishing events. We recognize that there may be other types of IUU fishing events we have not addressed, but have included ten common occurrences in our Shiny app. Through an extensive review of the literature, we have attempted to provide monitoring solutions that best match a user's jurisdictional interests, cost constraints, and data needs.

While our web application is functional, informed by research, and producing outputs that we believe are logical, we recognize some limitations. First, we have not yet shown the app to stakeholders who may benefit from using the tool. Allowing them to trial the app and speaking with them to understand whether outputs are realistic and meet their needs will provide valuable information. Additionally, some monitoring technology categories are broad in the sense that there are many different models available (e.g., different types and sizes of manned vessels and aircraft may have different capabilities) but our data frames only contain one value for every sensor or platform. Future work may consider creating more specific categories of sensor and platform models to reflect more precise data and ultimately more accurate monitoring solution outputs. Finally, there are other monitoring strategies that the app does not yet represent, including scaled solutions. Technologies used for combating IUU fishing events are also evolving rapidly, driving changes in monitoring capabilities and costs. For our Shiny app to remain relevant and useful, periodically updating the data that informs our suggested monitoring solutions with new technological information will be critical.

The IUU Fishing Dashboard represents just one small resource to help address a wicked problem. Our hope is that this resource will improve access to information about methods for combating illegal fishing events. The monitoring strategies our app produces are not meant to be conclusive, nor will they be effective for every use case. Stakeholders will need to assess what strategies are best based on their own constraints, critical areas of focus, and enforcement options. We hope that our app helps inform the IUU fishing prevention space and will assist with important fisheries management decision-making.

Bioeconomic Model

The bioeconomic model demonstrates how improved enforcement results in better stock outcomes, reduced illegal fishing harvest, and higher total harvest.

Level of Enforcement and Stock

Enforcement level determines how long – and how well – Indian Ocean yellowfin tuna stock persists. The difference in outcomes between full enforcement **(*et* = 1**; stock at time t = 20 equals **914,558 MT**; harvest equals 109,037 MT) and zero enforcement (***et* = 0**; stock at time t = 20 equals **1 MT**; harvest equals 1 MT) is telling. Without enforcement, Indian Ocean yellowfin tuna goes extinct. With full enforcement, however, stocks can continue to grow well into the future.

Level of Enforcement and Illegal Fishing Harvest

Model results demonstrate an inverse relationship between enforcement level and the percent of harvest that is illegally caught. At lowest levels of enforcement (e.g., *et* = 0), the model predicts the vast majority of catch is illegal (≈ 91% of total harvest). While illegal harvest increases slightly by 0.04% when enforcement level increases to 25% enforcement (*see* Table VII, *et* = 0.25), this discrepancy is likely attributed to the fact that increased enforcement slows the decline of yellowfin tuna year over year, thereby extending the length of time that stocks persist and increasing the likelihood of harvesting at low stock levels. Despite this inconsistency, illegal harvest continues to decrease beyond 25% enforcement.

Level of Enforcement and Total Harvest

Another important insight generated from the model is that total harvest increases as enforcement level increases. An exception to this trend occurs at 75% enforcement (*see* Table VII, *et* = 0.75), where total harvest (2,217,507 MT) is ~ 3.36% greater than harvest under full enforcement (2,145,349 MT). This result may seem surprising at first glance, but only ~40% of the total harvest is legally harvested when enforcement equals 75%. If we extend the time horizon beyond 20 years, subsequent illegal harvest will eventually drive yellowfin tuna stock to crash.

Looking Ahead

The bioeconomic model, like the optimizations it relies upon, is dynamic. We anticipate integrating our model results into the IUU Fishing Dashboard and continuing to explore how changes in other parameters (i.e., fine amount, enforcement effectiveness) similarly affect the interplay between enforcement, stock, and legal, illegal, and total harvest. The bioeconomic model serves as a useful tool to examine the interplay between elements in a complex system where managers make stock-driven choices, while fishers make profit-driven choices. Ultimately, our results underscore the importance of enforcement in deterring IUU fishing.

Skylight Adoption Analysis

The indicators included in the final model were shown to be explanatory variables in predicting whether or not a country has adopted Skylight. Analysis reveals that Skylight adoption probability correlates positively with a country's level of democracy (or voice and accountability estimates) and the size of its Exclusive Economic Zone (EEZ), while displaying a negative correlation with per capita GDP. The association between EEZ size and Skylight adoption is logical, as this technology is only applicable to countries with an EEZ, with larger EEZs necessitating more robust monitoring. The slightly surprising finding of democracy being linked to Skylight adoption suggests that nations with high levels of citizen accountability are more inclined to invest in monitoring systems to mitigate resource exploitation and boost revenues for legal businesses. Notably, GDP emerges as the most significant covariate, indicating that higher GDP is associated with a lower probability of Skylight adoption within a country. These findings underscore the importance of targeting Skylight outreach efforts toward coastal countries with large EEZs, lower per capita GDPs, and relatively high levels of democracy.

The false positives in our model were used to address countries that fit the guidelines outlined above. These were determined as the countries that the model predicted to be Skylight countries but are not active Skylight users. These countries were Chile, Costa Rica, India, Jamaica, Kiribati, Marshall Islands, Mozambique, Palau, Senegal, Seychelles, Solomon Islands, South Africa, Tuvalu. Due to these similarities these countries share with Skylight adopters, we recommend that Skylight and other philanthropy organizations in the IUU fishing prevention space target engagement efforts towards these countries.

Figures V(a), V(b), and **V(c)** illustrate that the distributions of Skylight Adopter and Likely Adopter groups are more similar to each other than to the non-Skylight group for each variable, further affirming the relevance of the identified indicators in distinguishing potential adopters.

Although the best fit model achieved a 74.5% accuracy rate in predicting Skylight adoption, it misclassified 25 active Skylight users as non-adopters. This could have been influenced by the imbalanced dataset, which contains three times as many non-Skylight countries as Skylight countries. Nonetheless, with an Area Under the Curve of 0.8232, the model demonstrates robustness and reliability in its predictive performance.

Conclusions

Together, the IUU Fishing Dashboard, the bioeconomic model, and the Skylight adoption analysis represent a multifaceted approach to address the challenges and opportunities associated with IUU fishing monitoring and enforcement. These tools provide data-driven insights and accessible resources for sustainable fisheries management stakeholders. Supported by empirical modeling, data analysis, and a thorough literature review, this project offers a promising contribution to the global efforts to combat IUU fishing. Continued refinement and integration of these tools will support informed MDA decision-making and strategies to protect coastal economies, marine ecosystems, and the countless citizens that depend upon them.

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