Introduction to the Modelling Approach as a Potential Tool to Estimate IUU Fishing Losses

What is a model?

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- At its core, a **model** is a simplified representation of reality.
- A good model strips away the noise to help us **understand**, **explain**, or **predict** how something works.

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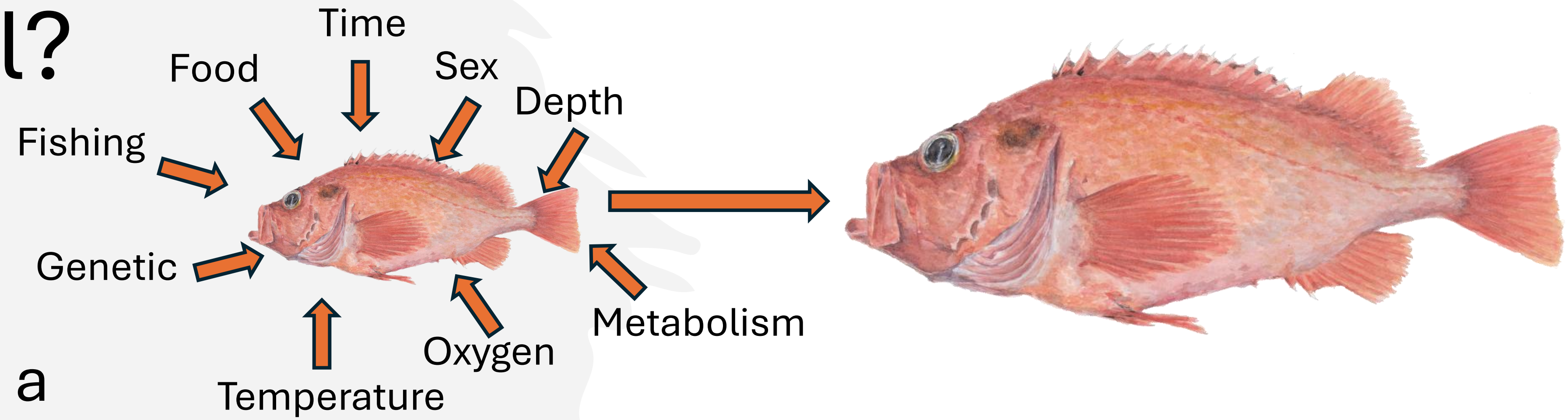
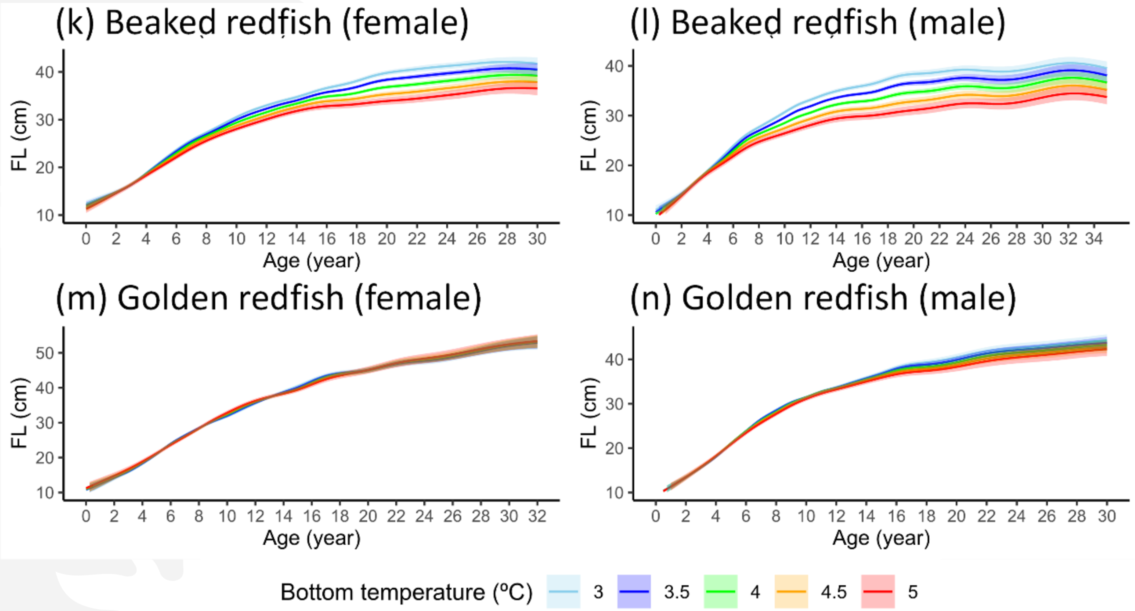


- At its core, a **model** is a simplified representation of reality.
- A good model strips away the noise to help us **understand**, **explain**, or **predict** how something works.

$$L = s(\text{Age}) + s(\text{BT}) + \textit{haul ID}$$

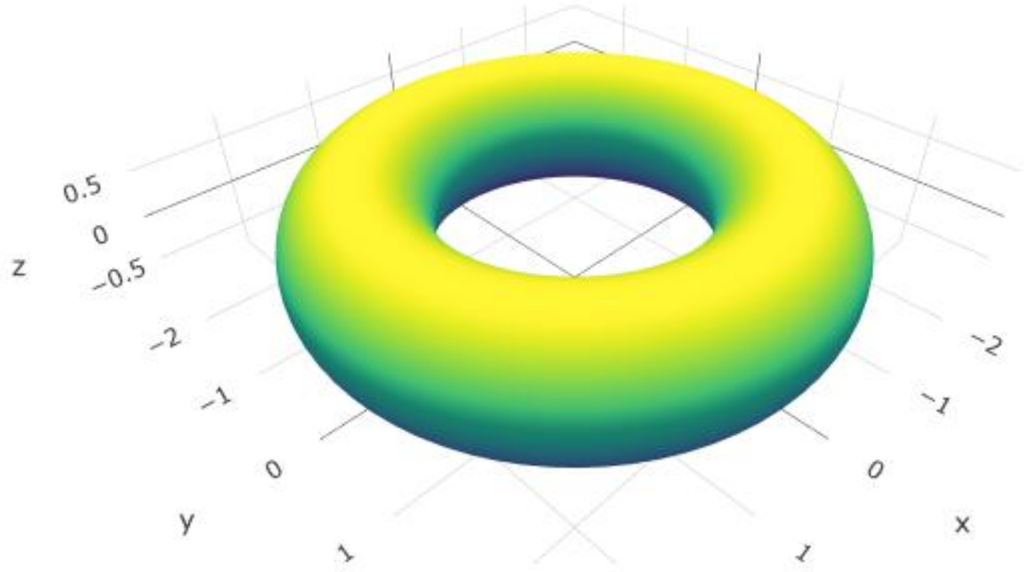


Mathematical & Statistical Modelling

- **Deterministic Models:** These assume perfect certainty. If you input X, you will always get exactly Y. (or input X, Y, R, Z to get r)

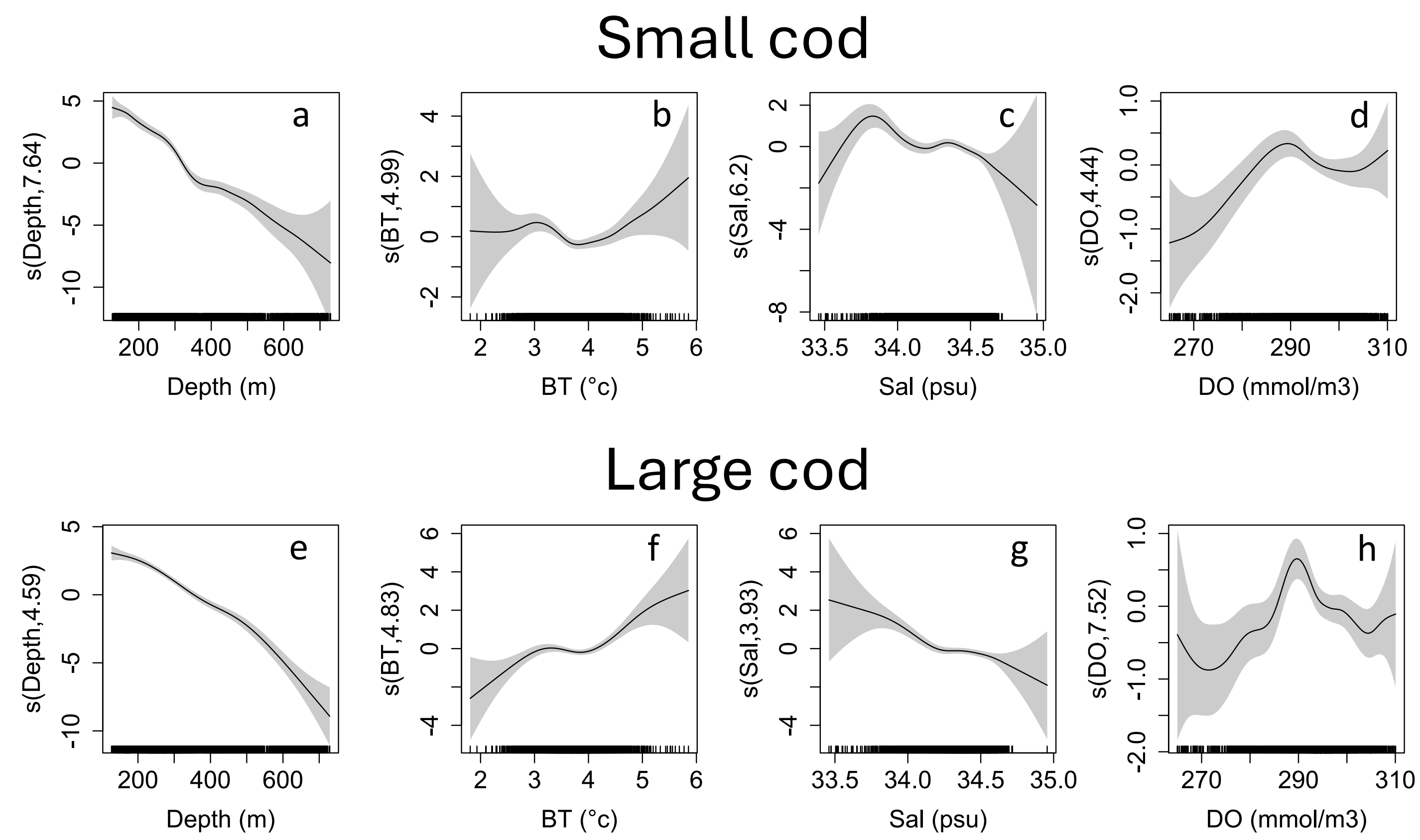
Deterministic 3D model: torus

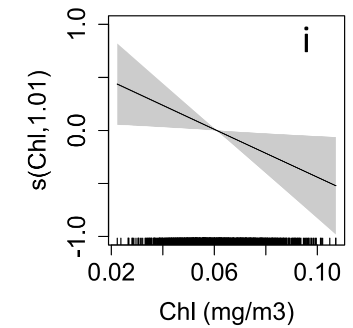
$$(\sqrt{(x^2 + y^2)} - R)^2 + z^2 = r^2$$



Mathematical & Statistical Modelling

- **Stochastic (Probabilistic) Models:** These account for randomness and uncertainty. They give you a range of likely outcomes rather than a single number.
    - Such as General Additive Model (GAM)





$$
\begin{aligned}
g(\eta) = \; & s(\text{depth}) + \\
& s(\text{BT}) + \\
& s(\text{salinity}) + \\
& s(\text{DO}) + \\
& s(\text{Chl}) + \\
& \textit{factor}\,(\text{fishing period})
\end{aligned}
$$

Mathematical & Statistical Modelling

- **Why Use a Modelling Approach?**
  - Test scenarios safely and cheaply
  - Identify key drivers
  - Forecast the future

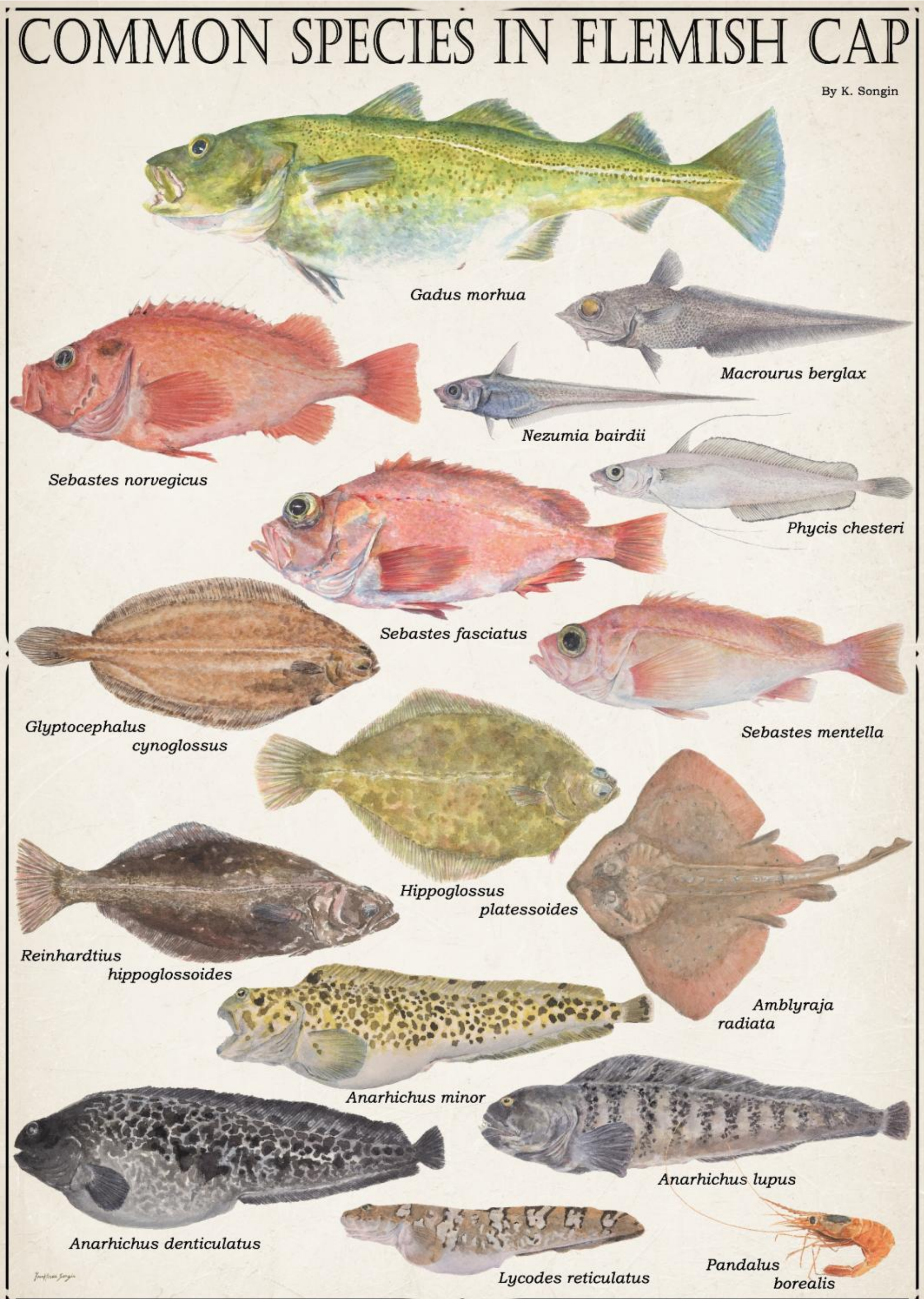
Modelling Process

- **Define the Objective**
- **Formulate the Model**
- **Parameter Estimation (Calibration)**
- **Validation**
- **Implementation & Scenario Analysis**

Modelling Process

- **Define the Objective (s)**
  - What specific question are you trying to answer?

    Example:
    - Does fish distribution in Flemish Cap change over time?
    - Do environmental factors affect fish distribution?
    - Does fisheries affect fish distribution?



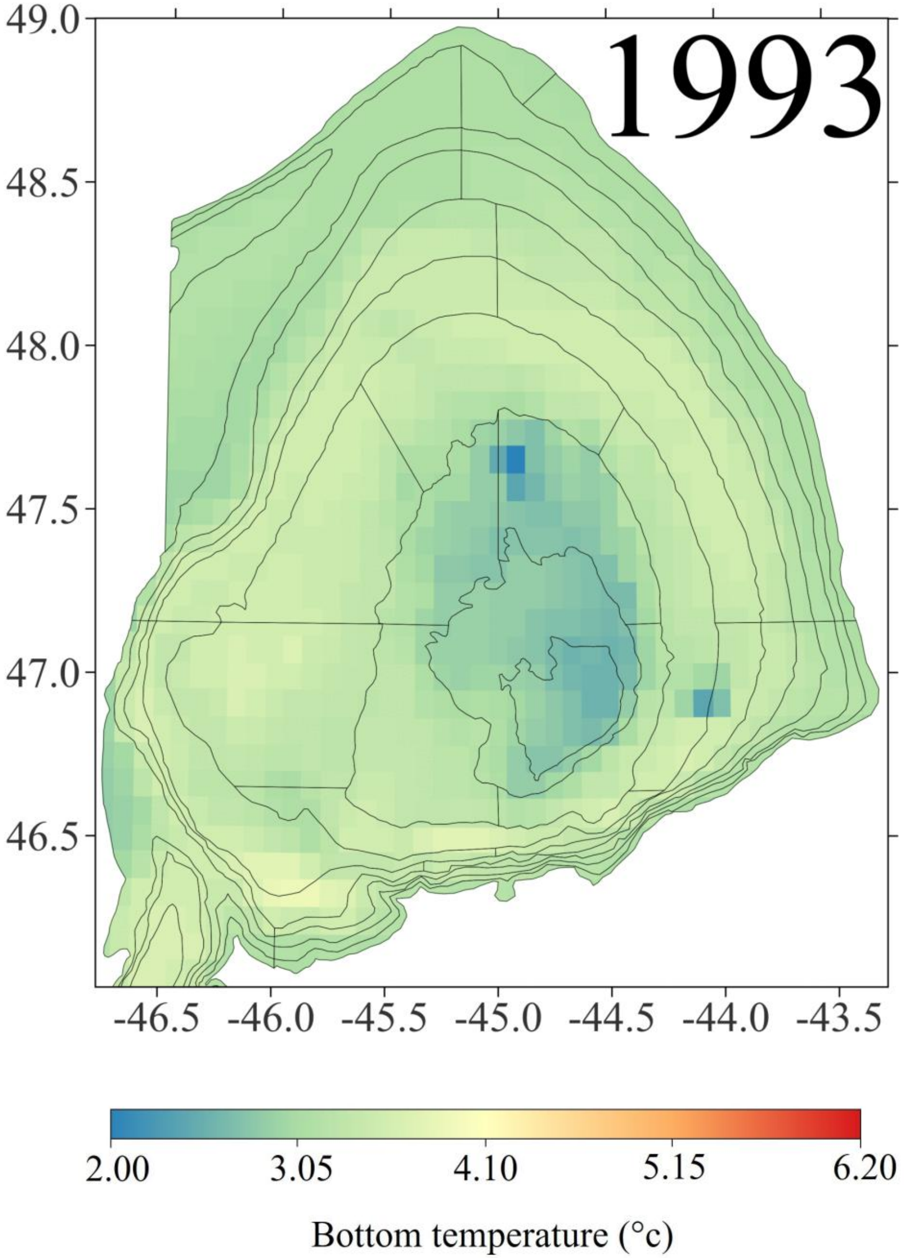
Modelling Process

- **Formulate the Model**
  - Determine the boundaries of the system. What variables matter? What are the assumptions?
  - **Example:** GAM

$$g(\eta) = s(\text{latitude}) + s(\text{longitude}) + s(\text{depth}) + s(\text{year}) + s(\text{BT})$$

$$g(\eta) = s(\text{latitude, longitude}) + s(\text{depth}) + s(\text{year}) + s(\text{BT})$$

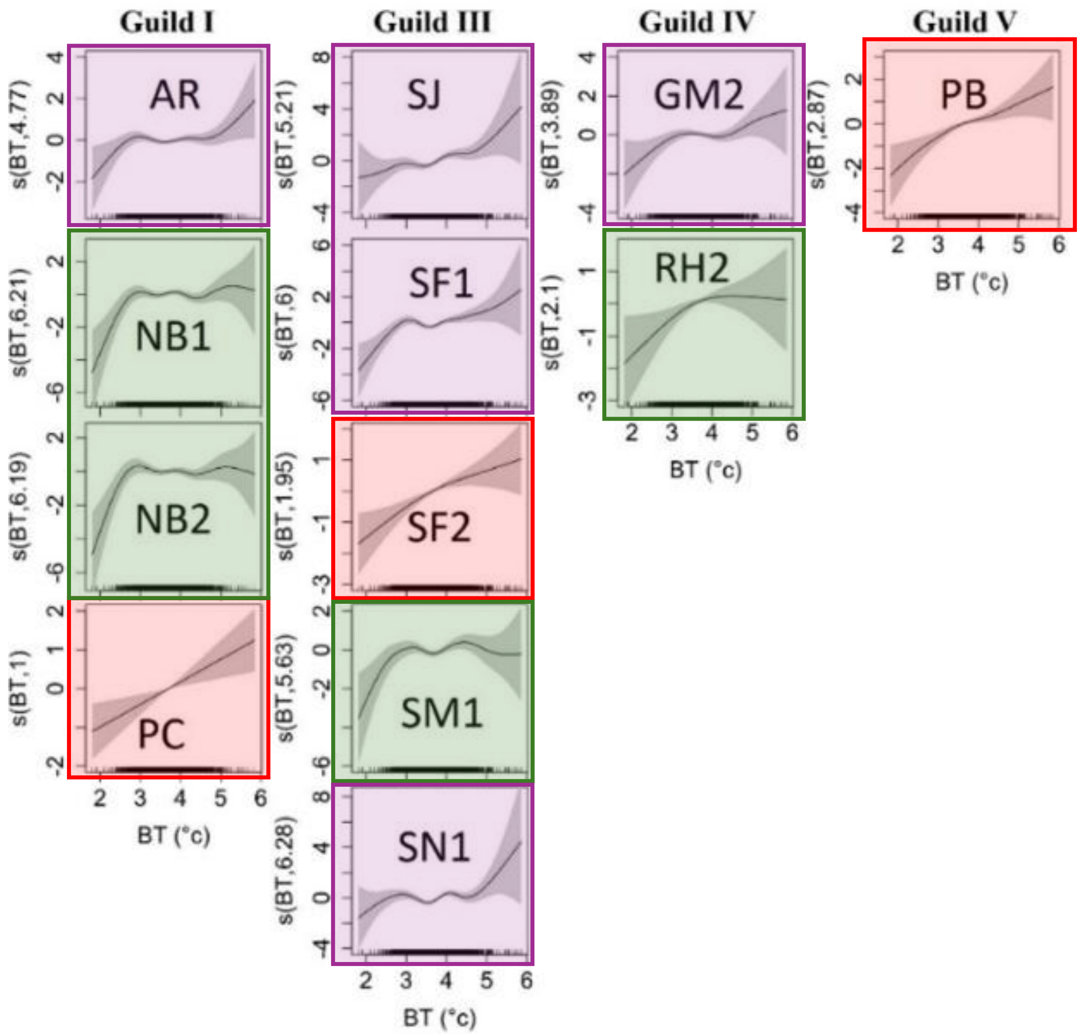
$$g(\eta) = s(\text{latitude, longitude, year}) + s(\text{depth, year}) + s(\text{BT})$$



Modelling Process

- **Parameter Estimation (Calibration)**
  - Feeding real-world data into the model to tune its settings so that its output aligns with known historical realities.
  - **Example:** GAM

Partial temperature effects on occurrence



Modelling Process

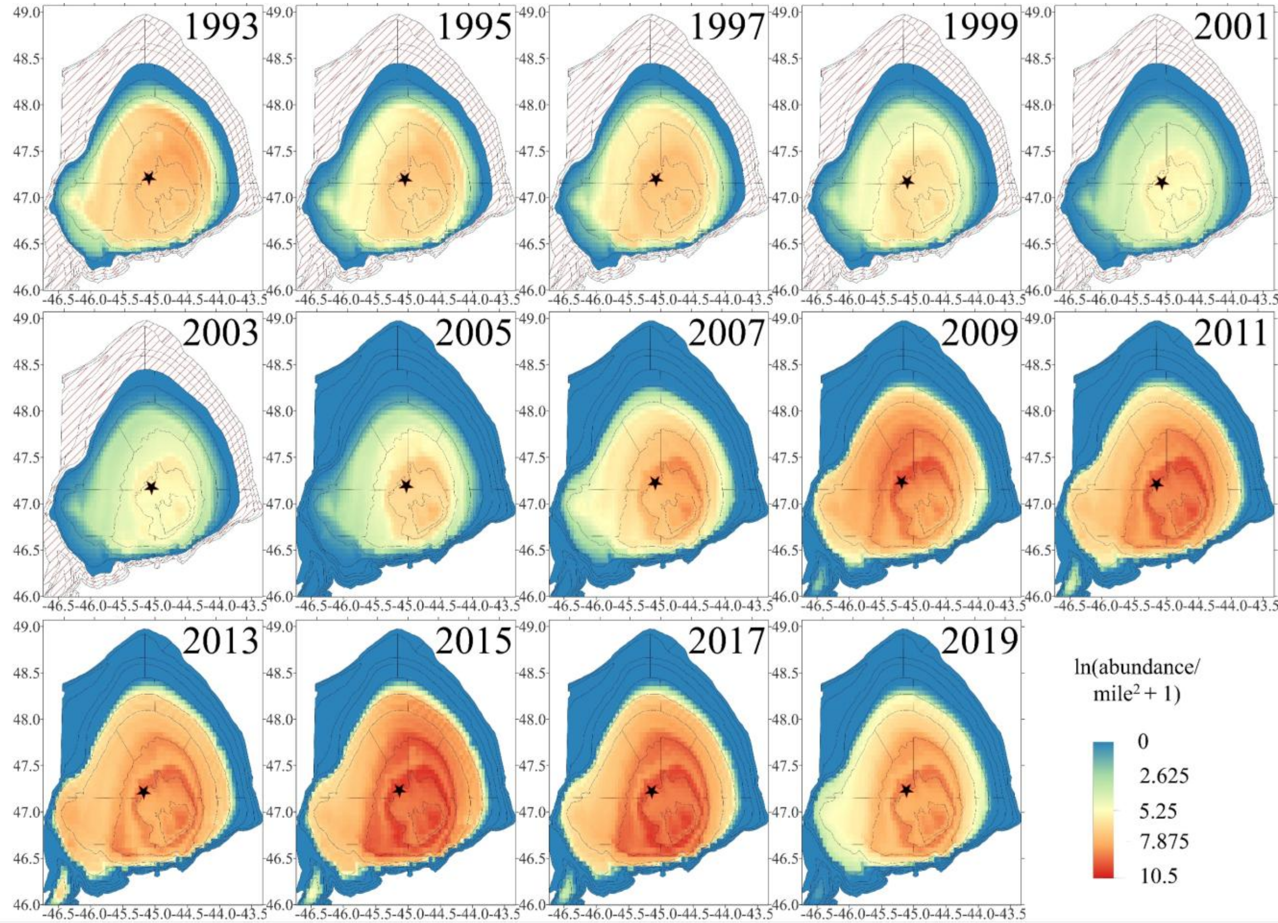
- **Validation**
  - Testing the model against a *new* set of data it hasn't seen before to ensure it actually works and isn't just "overfitted" to the old data.
  - **Example:**
    - Corelation between observations and predictions
    - Bootstrap
    - k-fold validation

Guild	Trophic species	Spearman´s ρ		
		Binomial GAM	Quasi-Poisson GAM	Delta GAM
I	*Gadus morhua* 1	0.80	0.76	0.81
	Amblyraja radiata	0.57	0.53	0.59
	Macrourus berglax 1	0.80	0.75	0.81
	Macrourus berglax 2	0.81	0.62	0.82
	Nezumia bairdii 1	0.73	0.70	0.79
	Nezumia bairdii 2	0.77	0.79	0.83
	Phycis chesteri	0.75	0.61	0.74
	Reinhardtius hippoglossoides 1	0.50	0.71	0.68
II	*Anarhichas lupus* 1	0.79	0.77	0.83
	Anarhichas minor 1	0.61	0.50	0.60
	Glyptocephalus cynoglossus	0.58	0.58	0.69
	Hippoglossoides platessoides	0.73	0.73	0.83
	Lycodes reticulatus	0.69	0.72	0.76
III	Juvenile *Sebastes* spp.	0.81	0.71	0.80
	Sebastes fasciatus 1	0.75	0.74	0.77
	Sebastes fasciatus 2	0.77	0.68	0.78
	Sebastes mentella 1	0.78	0.38	0.58
	Sebastes mentella 2	0.71	0.32	0.49
	Sebastes norvegicus 1	0.78	0.69	0.78
	Sebastes norvegicus 2	0.64	0.52	0.65
IV	*Gadus morhua* 2	0.80	0.64	0.81
	Anarhichas denticulatus	0.43	0.36	0.46
	Anarhichas lupus 2	0.69	0.58	0.73
	Anarhichas minor 2	0.61	0.53	0.64
	Reinhardtius hippoglossoides 2	0.74	0.75	0.87
V	*Pandalus borealis*	0.72	0.69	0.71

Modelling Process

- **Implementation & Scenario Analysis**
  - Running the model to predict scenarios/forecast/hindcast and inform decision making.

Large cod (>46 cm) distribution



Example

SCIENCE ADVANCES | RESEARCH ARTICLE

ENVIRONMENTAL STUDIES

Hot spots of unseen fishing vessels

Heather Welch[1,2]*, Tyler Clavelle[3], Timothy D. White[3], Megan A. Cimino[1,2], Jennifer Van Osdel[3], Timothy Hochberg[3], David Kroodsma[3], Elliott L. Hazen[2,1,4]

Illegal, unreported, and unregulated (IUU) fishing incurs an annual cost of up to US$25 billion in economic losses, results in substantial losses of aquatic life, and has been linked to human rights violations. Vessel tracking data from the automatic identification system (AIS) are powerful tools for combating IUU, yet AIS transponders can be disabled, reducing its efficacy as a surveillance tool. We present a global dataset of AIS disabling in commercial fisheries, which obscures up to 6% (>4.9 M hours) of vessel activity. Disabling hot spots were located near the exclusive economic zones (EEZs) of Argentina and West African nations and in the Northwest Pacific, all regions of IUU concern. Disabling was highest near transshipment hot spots and near EEZ boundaries, particularly contested ones. We also found links between disabling and location hiding from competitors and pirates. These inferences on where and why activities are obscured provide valuable information to improve fisheries management.

Example

Hotspot of unseen fishing vessels

Objective
- Identify IUU fishing from AIS gaps

Methods
- **Vessel data**
  - 28 *billion* AIS messages from 2017 to 2019
- **Classification using convolutional neural network**
  - fishing and non-fishing events
  - identify vessel gear types
  - vessel days, fishing days, and suspected disabling events

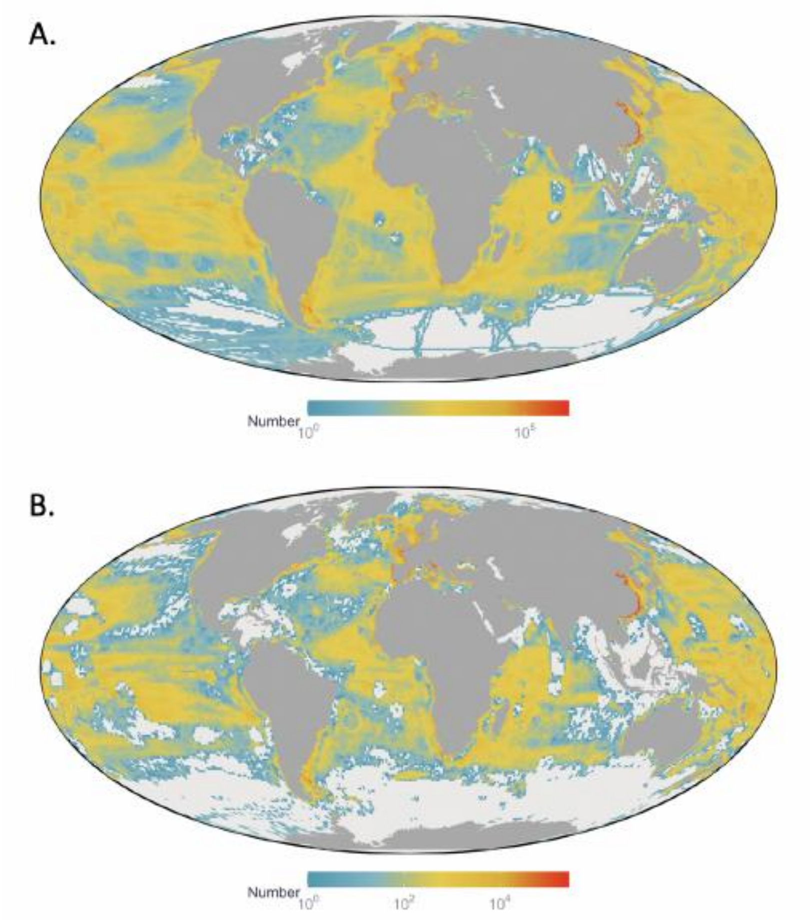


Figure S1. The Global Fishing Watch AIS dataset: vessel days (A) and fishing days (B).

Example

Hotspot of unseen fishing vessels

Methods

- **Modelling Drivers of Disabling Activity**
  - Boosted Regression Trees (BRTs)
    - Four behavioural drivers
      - distance to shore
      - loitering by transshipment vessels
      - distance to reported piracy events
      - distance to Marine Protected Areas (MPAs)

    - Four environmental driver
      - chlorophyll-a concentration,
      - eddy kinetic energy,
      - sea surface temperature (SST)
      - temporal SST variability

    - Models were constructed individually for 4 gears

Table S6. Boosted regression tree model performance metrics. Explained deviance is presented for the final models, while Area Under the Receiver Operator Characteristic Curve (AUC) and True Skill Statistic (TSS) are presented as the mean 75/25 cross-validation across 50 model iterations, ± one standard deviation.

		75/25 cross-validation	
	Explained deviance (%)	AUC	TSS
Full	26.21	0.81 ∓ 0.004	0.48 ∓ 0.006
Drifting longline	12.17	0.73 ∓ 0.005	0.33 ∓ 0.009
Squid jigger	47.08	0.91 ∓ 0.006	0.67 ∓ 0.018
Trawler	61.42	0.96 ∓ 0.004	0.79 ∓ 0.013
Tuna purse seine	16.53	0.76 ∓ 0.006	0.4 0.013

Example

Hotspot of unseen fishing vessels

Results

- The Global Scale of AIS Disabling

  Overall Activity Hidden:
  - Out of 3.7 billion fishing messages, the final dataset identified **55,368 suspected intentional disabling events** across 5,269 distinct vessels from 101 flag states.
  - More than 40% of vessels operating in the study area disabled their AIS at least once, obscuring up to **6% (>4.9 million hours)** of global commercial fishing activity.

Table 1. Dimensions of the suspected disabling dataset by gear type and flag state. The lower bound in the ranges for the total time lost and fraction of time lost to AIS disabling events result from capping suspected disabling events at 2 weeks. The upper bound includes all disabling events.

		AIS disabling events (*n*)	Time lost to AIS disabling events (days)	Fraction of time lost to AIS disabling events (%)
Gear type	Drifting longlines	18,641	32,826–83,202	2.0–4.6
	Squid jiggers	16,021	25,602–39,524	5.0–7.2
	Tuna purse seines	8620	19,945–44,735	10.7–20.6
	Trawlers	7913	14,980–22,823	3.5–5.0
	Other gear types	4173	7446–16,423	2.0–4.0
Flag	China	15,624	23,463–45,440	3.0–5.4
	Chinese Taipei	12,867	23,170–43,872	3.8–6.3
	Spain	4100	10,058–23,881	6.5–13.8
	United States	3543	8265–16,822	4.7–8.3
	Other flags	19,234	35,844–76,693	2.5–5.0
	All vessels	**55,368**	**100,800–206,707**	**3.2–6.0**

Example

Hotspot of unseen fishing vessels

Results

- The Global Scale of AIS Disabling
  Disabling hotspot:

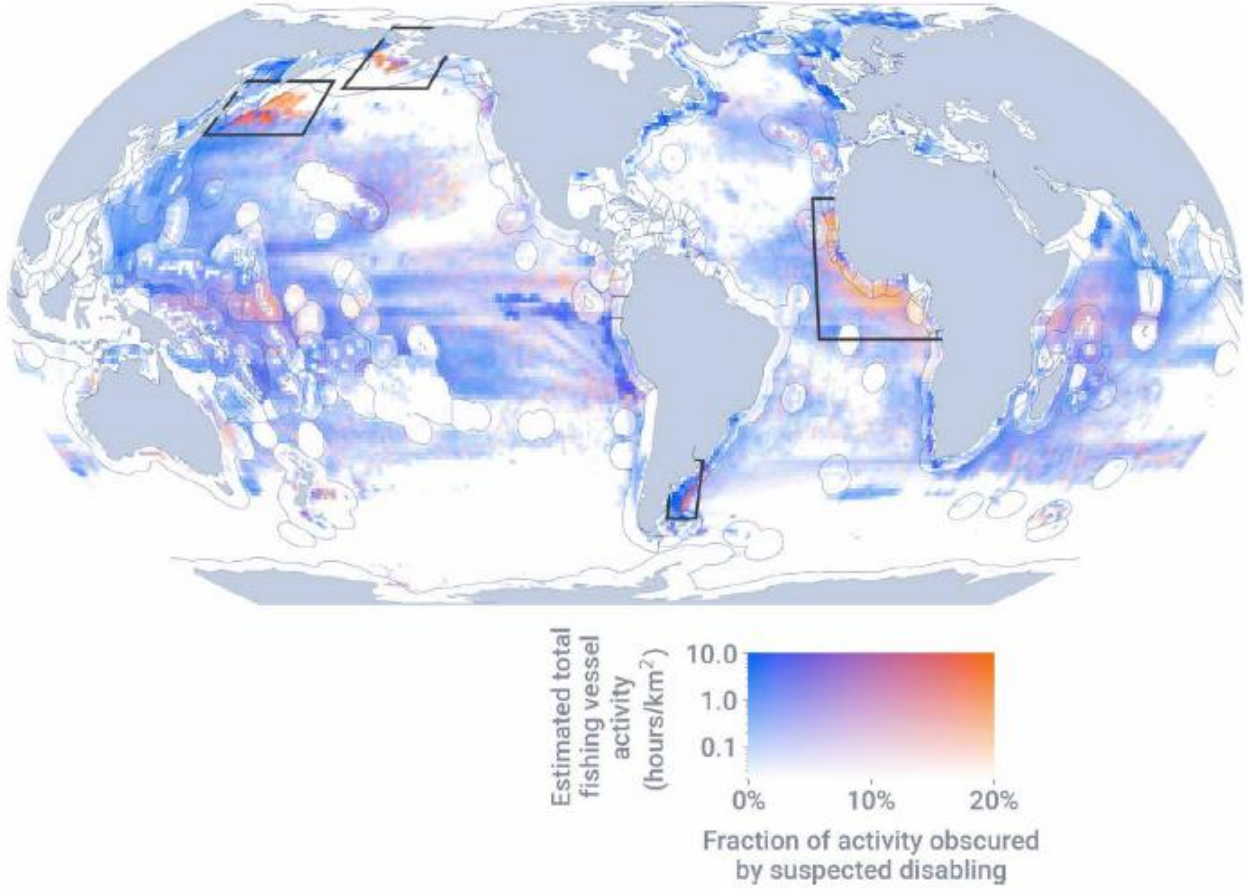


Fig. 1. Estimated total fishing vessel activity and the fraction of this activity obscured by suspected disabling events in areas with sufficient satellite reception quality (>10 positions/day). Areas with the highest fishing vessel activity and the highest fraction of activity obscured by disabling occur in three regions of IUU concern: near Argentina and West Africa and in the Northwest Pacific (black boxes). In contrast, fisheries in waters near Alaska, USA are some of the most intensively managed in the world.

Example

Hotspot of unseen fishing vessels

Results

- **Behavioural drivers**

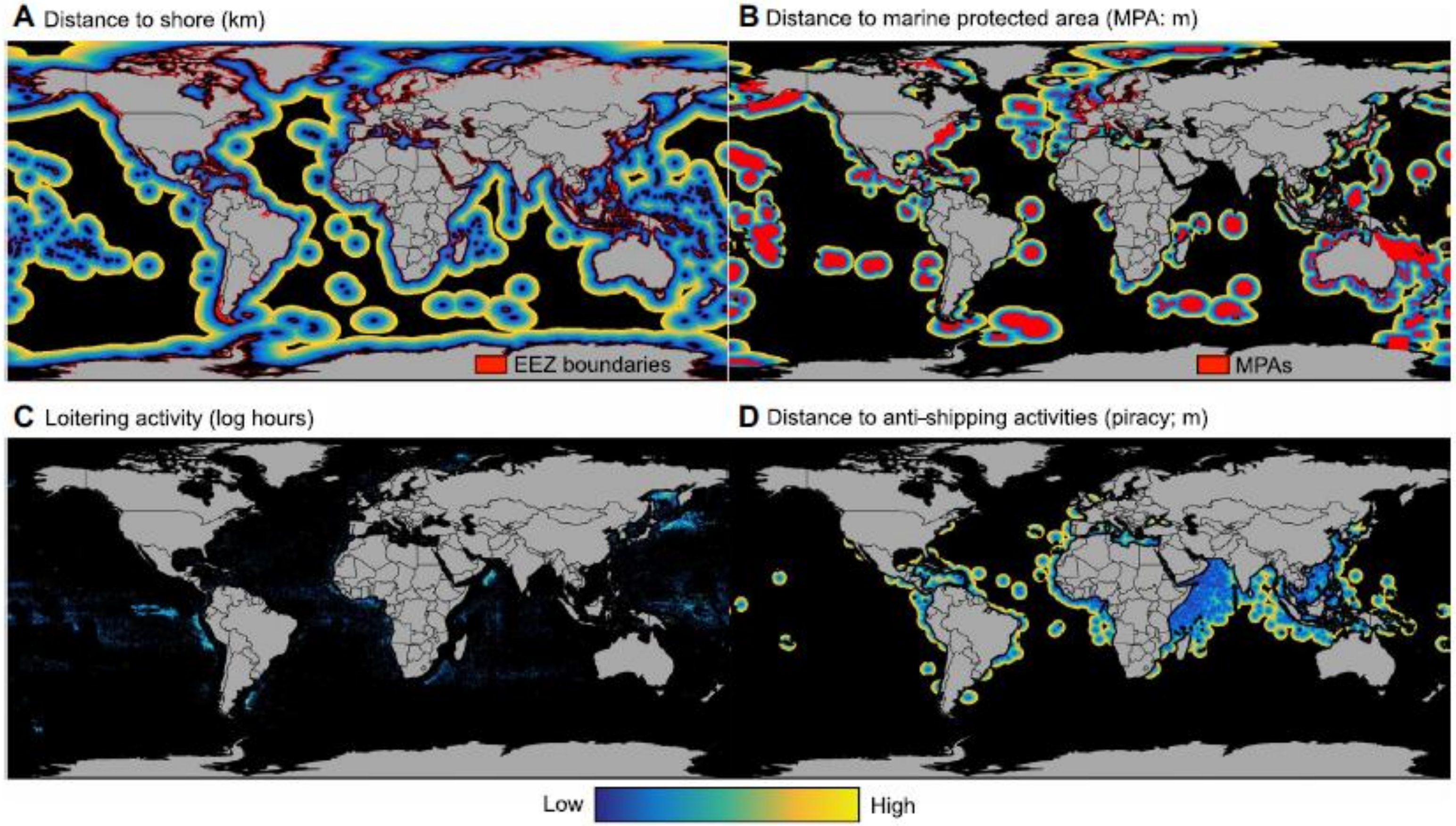


Fig. 6. Potential behavioral drivers of suspected disabling events. Panels show distance to shore (**A**), distance to marine protected areas (**B**), loitering activity (**C**), and distance to anti-shipping activities (**D**). Distance drivers (A, B, and D) are clipped to 400 km to constrain models to proximal effects.

Example

Hotspot of unseen fishing vessels

Results

- **Environmental drivers**

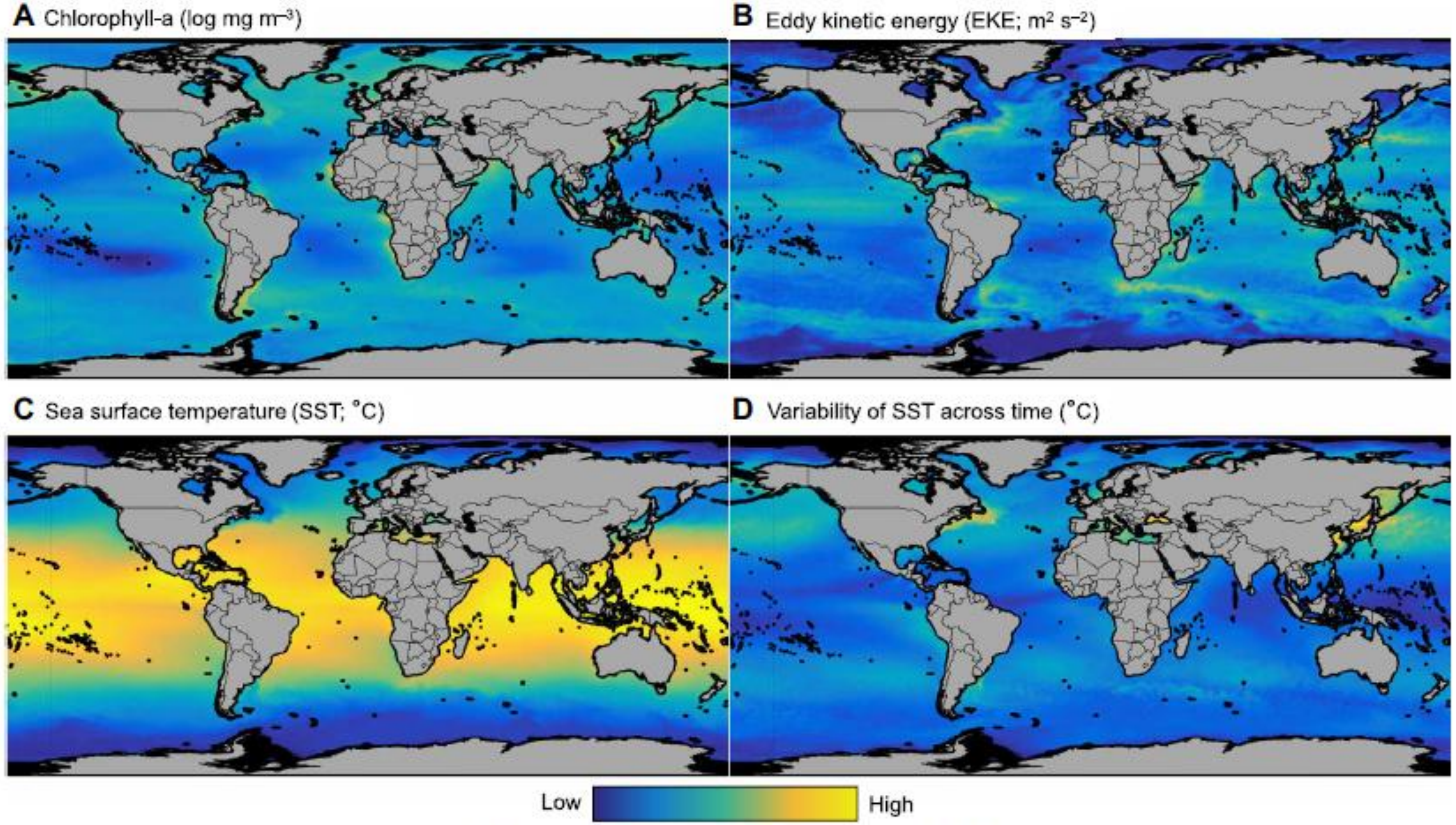


Fig. 7. Potential environmental drivers of suspected disabling events. Panels show chlorophyll (**A**), eddy kinetic engergy (**B**), sea surface temperature (**C**), and the variability of sea surface temperature across time (**D**). Drivers are average conditions across the 2017-2019 time series.

Example

PLOS | ONE

RESEARCH ARTICLE

Loitering with intent—Catching the outlier vessels at sea

Jessica H. Ford[1]*, David Peel[1], Britta Denise Hardesty[2], Uwe Rosebrock[2], Chris Wilcox[2]

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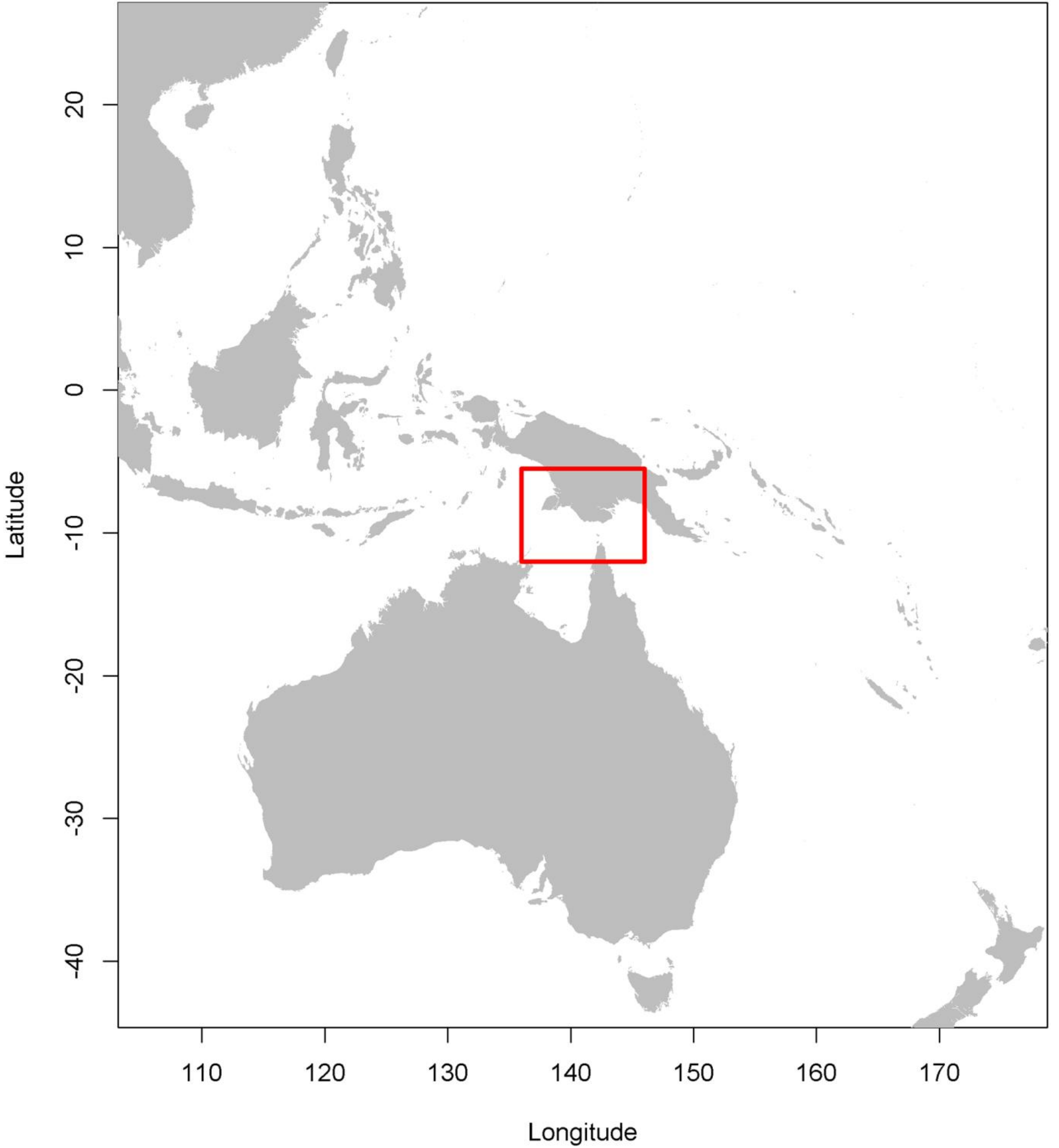
* Jessica.Ford@csiro.au

Example

Hotspot of unseen fishing vessels

Objective
- Identify IUU fishing from AIS data

Methods
- **Study area**
  - Arafura Sea
- **Vessel data**
  - 2.6 *million* AIS messages from 2015 to 2016
  - 2700 vessels of various types
- **Movement Metrics**
  - Time spent in a cell (seconds)
  - Distance travelled within a cell (meters)
  - Average speed inside a cell (knots)
- **GAM**
  - capture complex spatial and temporal trends
- **Anomaly Detection and Ranking**



Example

Hotspot of unseen fishing vessels

Results

- **Spatial Trends**: longer time spent in cells close to major land ports compared to the open ocean.

- **Flagged Track Profiling**: While normal tracks crossed a gridded cell in a direct, linear transit, <u>*anomalous vessels were flag-triggered for moving back and forth latitudinally or lingering for excessively long periods*</u>

- **Hotspots & Vessel Categories**: Out of the top 100 highest-ranked anomalous vessels, nearly half belonged to classes like tugs, pilots, military, or fishing vessels.
    - Tug and pilot vessel anomalies occurred mostly near ports
    - Fishing vessels were far more likely to behave anomalously near EEZ boundaries.

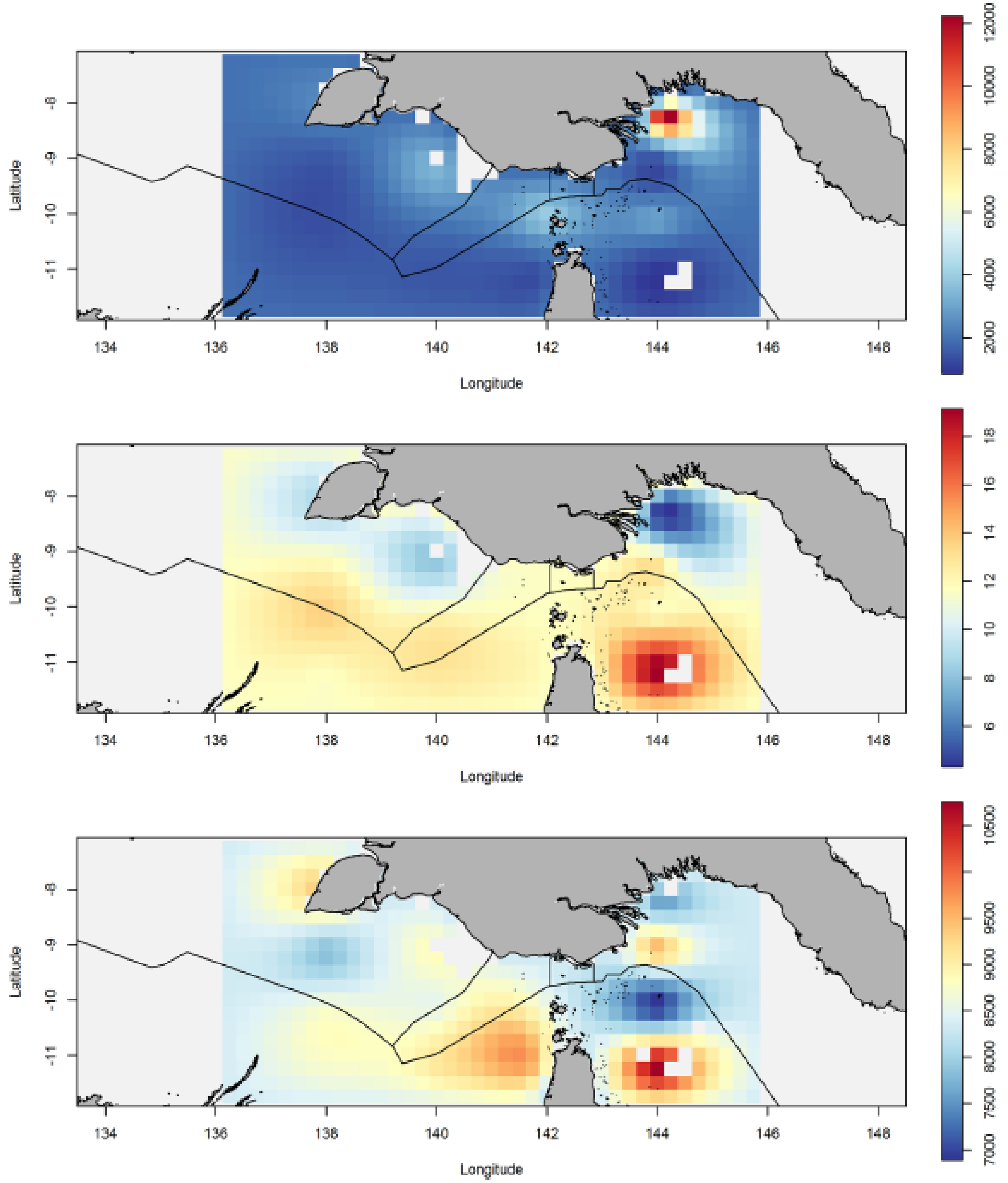


Fig 2. **2a)** Prediction surface for time loitering indicator. Scale shows predictions in seconds for time spent in cells. **2b)** Prediction surface for speed loitering indicator. Scale shows predictions in knots for average speed in cells. **2c)** Prediction surface for distance loitering indicator. Scale shows predictions in meters for distance travelled in cells.

Example

The Australian Journal of
Agricultural and
Resource Economics

Journal of the Australian
Agricultural and Resource
Economics Society

The Australian Journal of Agricultural and Resource Economics, 52, pp. 433–452

Economic and ecosystem impacts of illegal, unregulated and unreported (IUU) fishing in Northern Australia*

Sean Pascoe, Tomas A. Okey and Shane Griffiths[†]

Example

Hotspot of unseen fishing vessels

Objective
- Estimate both the direct and indirect impacts of illegal foreign fishing (IFF)

Methods
- **Study area**
  - Gulf of Carpentaria
- **Ecopath with Ecosim**
  - 83 functional biological groups
  - Fleets Modelled
    - Commercial
    - Non-commercial
    - Modelling scenarios with and without IFF
- **Data & Parameters**
  - 1990 as the base equilibrium year and tracked changes over a 15-year period to 2005

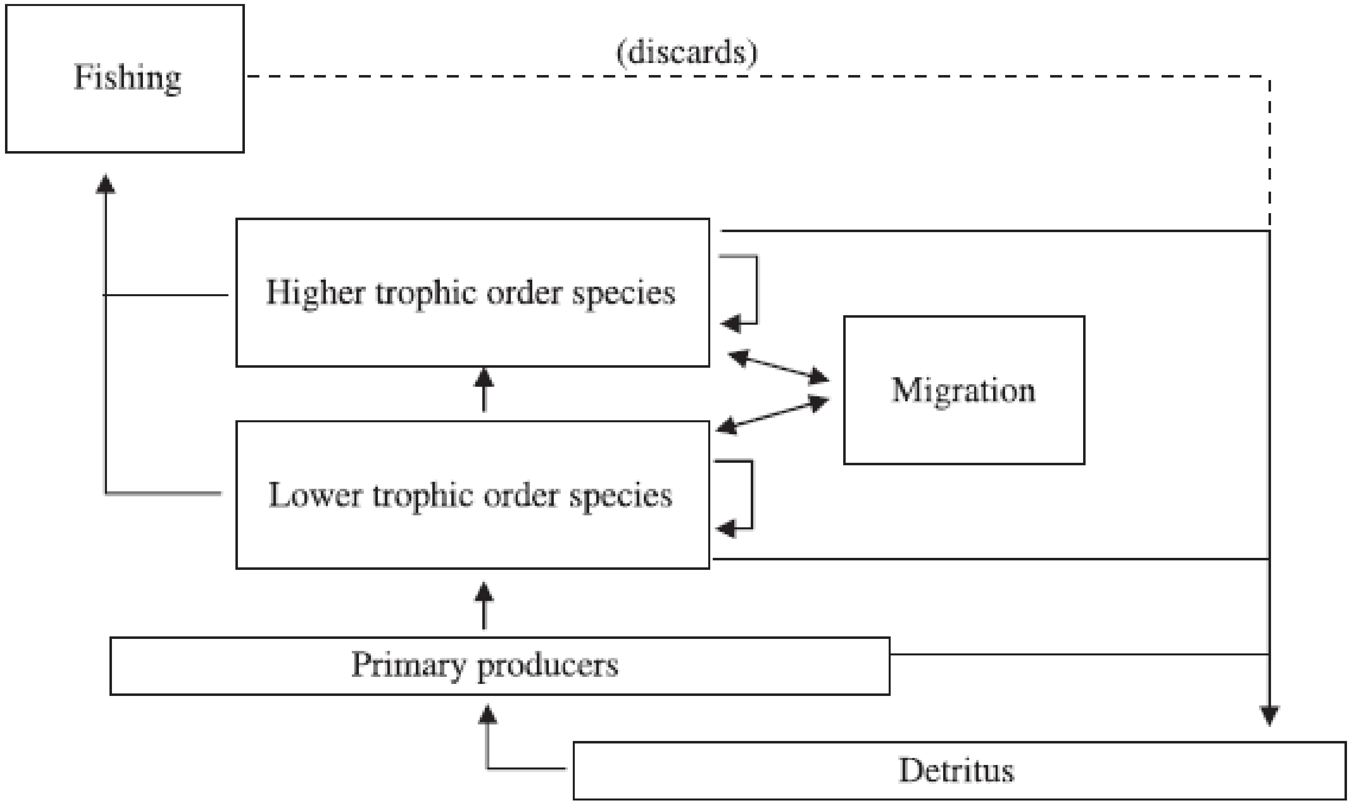


Figure 1 Diagrammatic representation of the EwE model.

Example

Hotspot of unseen fishing vessels

Results

- Mass balance

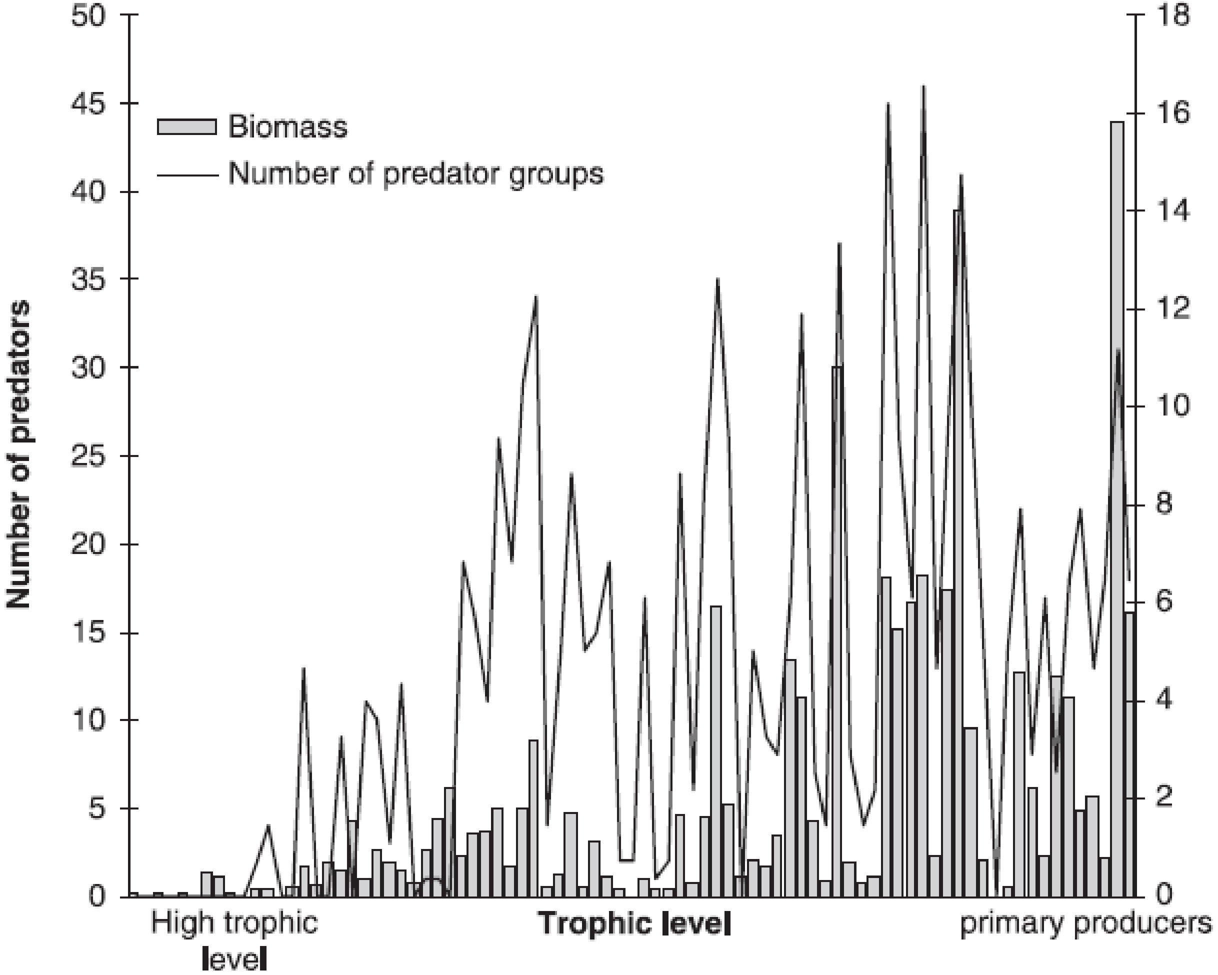


Figure 2 Relationship between trophic level, biomass and predation in the Gulf.

Example

Hotspot of unseen fishing vessels

Results

- IFF impacts on the ecosystem

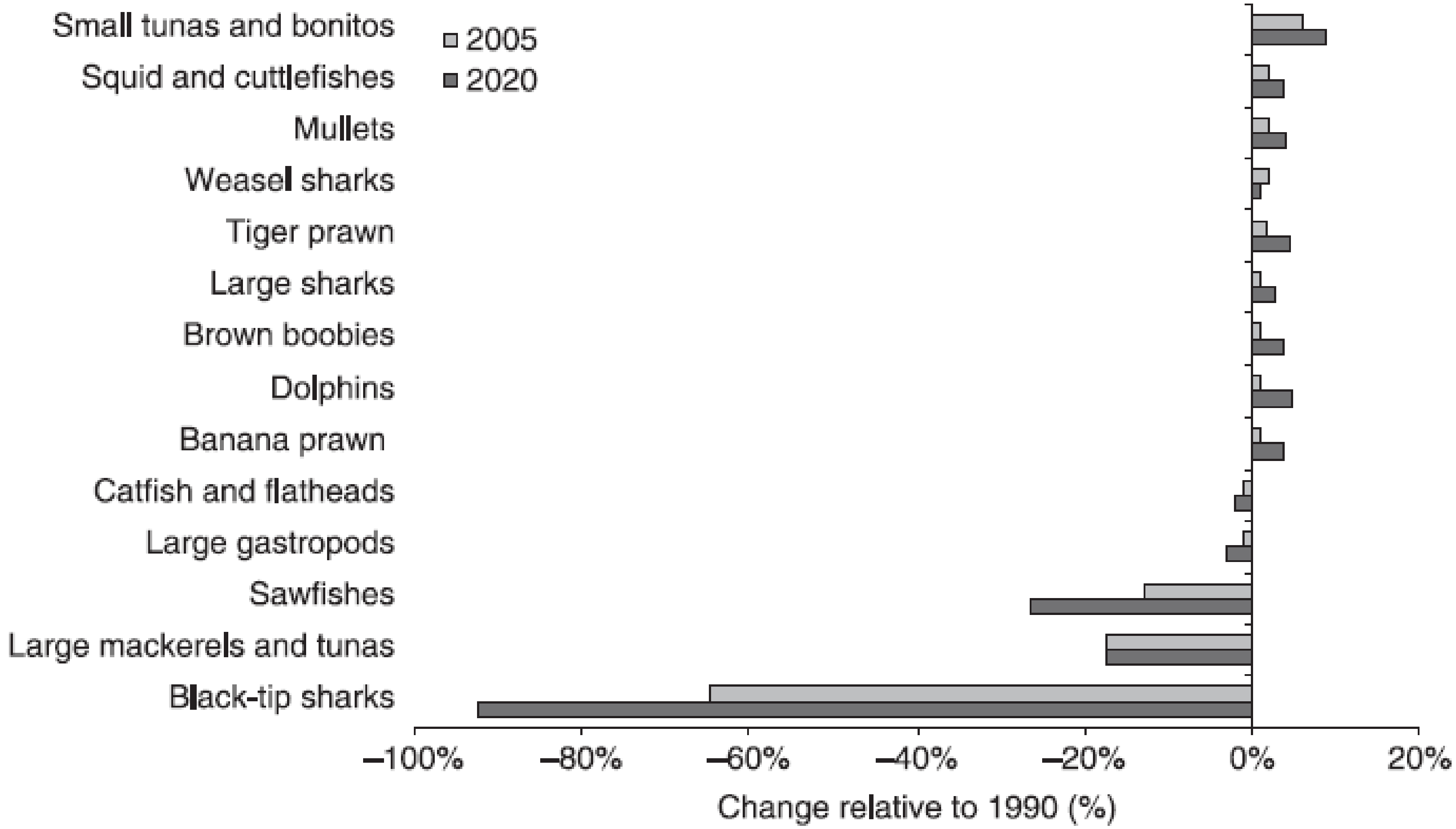


Figure 8 Estimated impact of IFF on stock biomass, 2005 and 2020.

Example

Hotspot of unseen fishing vessels

Results

- Economic impacts of IFF

Table 3 Estimated impact of IFF fishing on revenues and profits in 2005 and 2020

Fishery	2005		2020	
	Value of output (% change)	Profits (% change)	Value of output (% change)	Profits (% change)
Commercial				
• Banana	0.9	9.6	3.0	23.7
• Tiger	1.2	10.0	3.9	22.3
• Lines	–15.1	–579.6	–17.2	–574.2
• Nets	–6.2	–66.3	–10.2	–103.9
• Pots	0.7	7.7	1.6	17.0
• Fish trawl	0.2	1.7	0.8	6.8
• All fisheries	–1.1	–11.0	–1.3	–9.4
Non-commercial				
• Aboriginal	–3.3	NA	–5.2	NA
• Recreational	–0.6	NA	–0.4	NA
• Charter fishery	0.1	NA	–0.4	NA

NA, Not applicable.