# Tracking Overfishing: Visual Analytics of Suspicious Behaviors in Commercial Fishing Vessels


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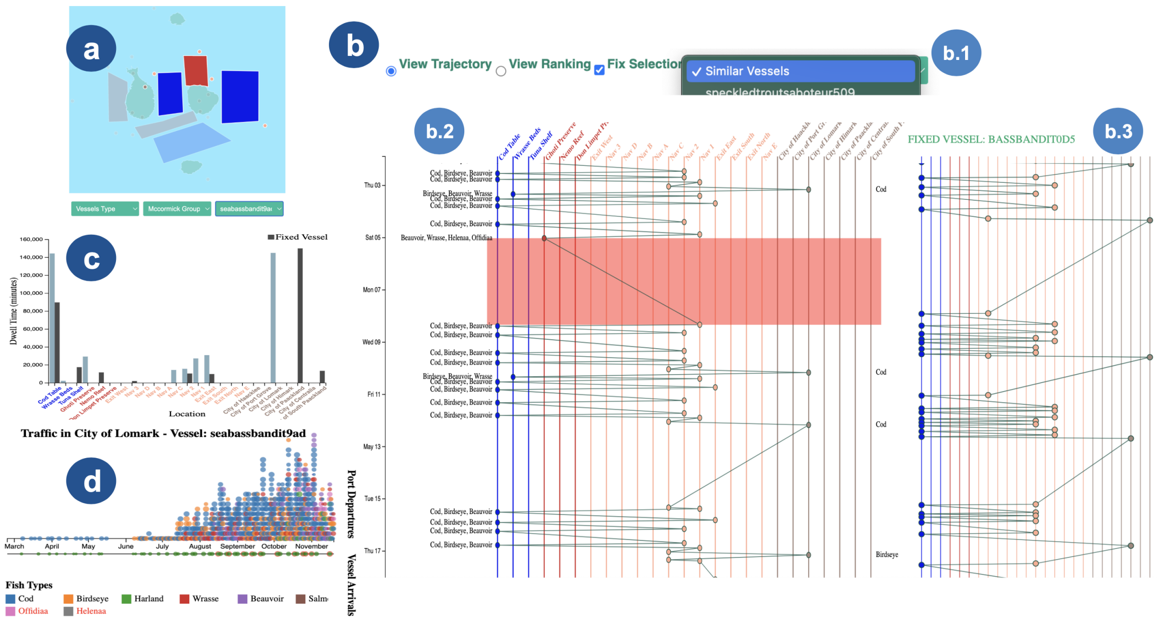



Figure 1: Overview of the implemented visualization system. (a) Oceanus map view highlighting vessels' transit locations; (b) Trajectory views: (b.1) Visualization options and list of similar vessels, (b.2) Trajectory of the selected vessel, (b.3) Trajectory of the fixed vessel; (c) Bar chart of total dwell time by location for selected and fixed vessels; (d) Time chart for the selected vessel.


## Abstract

The exposure of illegal fishing by SouthSeafood Express Corp highlights the urgent need for better tools to monitor commercial fishing in Oceanus. In response, we develop an interactive visualization tool for the VAST Challenge's Mini-Challenge 2. Our system analyzes the CatchNet knowledge graph, combining vessel tracking and port records from FishEye International, a non-profit dedicated to combating illegal fishing. The tool links vessels to probable cargos, identifies seasonal trends, and detects anomalies in port records. Detects suspicious activity of vessels, offering actionable insights to aid investigations and prevent future illegal fishing.



**Index Terms:** Illegal fishing detection, Visualization, Knowledge graph analysis.


## 1 Introduction

In the VAST Challenge 2024, understanding commercial fishing in Oceanus is crucial for assessing local fisheries' economic flows and sustainability. The recent discovery of illegal activities by SouthSeafood Express Corp. highlights the need for advanced analytical tools. To address this, FishEye International, a non-profit organization, processes vessel tracking data and shipping records into the CatchNet knowledge graph, which links vessels, places, and fish species through voyages, stops, and cargo movements

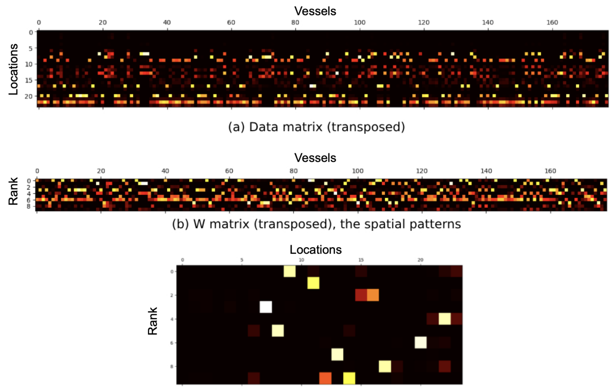
In Mini-Challenge 2, our task focuses on developing visualization tools for geographic and temporal analyses of CatchNet data. The main objective is to detect behavioral patterns indicative of illegal activities similar to those of SouthSeafood Express Corp. Additionally, we aim to help FishEye analysts understand the flow of commercially caught fish through Oceanus's ports, despite the data limitations, which include only port exit records rather than fish offloading records. Our solution, featuring three key visualizations (b, c, and d in Figure 1), introduces a method to estimate cargo based on probable fishing dwell before port arrival and identifies trajectory patterns by Nonnegative Matrix Factorization (NMF). Our visual analytics tool suggests fishing seasonal trends and enables the detection of anomalies in port exit records and vessel trajectories.

## 2 Approach

To tackle this challenge, we begin by analyzing the original graph, filtering, and sorting edges by date to construct the trajectories of each vessel. We adjust dwell values where we find significant discrepancies and categorize the locations into fishing areas, protected areas, ports, and navigation points. We also categorize fish species, emphasizing those exclusive to protected areas. Our analysis focuses on fishing vessels, estimating their loads and identifying behavioral patterns to detect similarities. Detailed explanations are provided below.

### 2.1 Fishing Catch Estimation

We estimate vessel overfishing using dwell time data and port departure records. We filter vessels that pass through a fishing or protected area within three days of arriving at a port, assuming that longer dwell times in these areas correlate with increased fishing activity. We then divide the cargo leaving a port by the number of




(a) Data matrix (transposed)

(b) W matrix (transposed), the spatial patterns

(c) H matrix, the coefficients by place for each pattern

Figure 2: a) Complete vessels-by-places matrix with rows as places and columns as vessels, showing total dwell time. b) and c) NMF of the data matrix using Rank 10.

filtered vessels, weighted by the time spent in areas where the associated fish could be caught. This estimate helps identify vessels with potential overfishing behavior, such as exceeding the average, although it has limitations.

### 2.2 Similarity between Vessels

We analyze ten months of vessel trajectory data, focusing on dwell times. By summing dwell times by location, we create a vessel-by-places matrix. We derive two matrices using NMF, as shown in Figure 2. Similarly to topic detection in text analysis, this method provides insight into how vessel activities are distributed across locations. We apply a similar interpretation to that of Garcia et al. [1]. Each row in $W$ represents a vessel's spatial pattern distribution of a vessel (columns in Figure 2(b)), and we measure the similarity between the vessels by calculating the Euclidean distance between these vectors.

## 3 Visualization Tools

The system generates detailed graphics of vessel trajectories, port interactions, and seasonal patterns, enabling the identification of suspicious activities and aiding in the prevention of illegal fishing.

### 3.1 Timeline Chart

**Port Arrivals and Departures:** By analyzing vessel arrivals, fish departures from ports, and vessel trajectories, we map the cargo transported by vessels and quantify it upon arrival at the ports. This analysis helps identify seasonal patterns and understand typical port operations. This view enables analysts to associate vessels with their probable cargo, offering a detailed view of how and when fish are transported. For instance, the timeline chart in Figure 3 illustrates the movement of cargo over time in a specific port.

**Detection of Anomalies:** The timeline chart reveals anomalies by plotting ports' outcomes and incomes, such as the July export of Sockfish, a protected species, from Paackland (Figure 3). By analyzing vessel trajectories and dwell times, the system identified vessels with fishing activities that exceeded expected patterns, indicating potential overfishing. These insights are crucial for guiding further investigations and supporting FishEye's mission to prevent illegal fishing.

### 3.2 Trajectory Chart

**Parallel Coordinates:** We use parallel coordinates to represent vessel trajectories, with each location on the map as an axis. We order the coordinates with the fishing areas on the left and the ports on the right, clearly describing vessel movements. This approach improves our understanding of vessel behavior (Figure 1(b)).

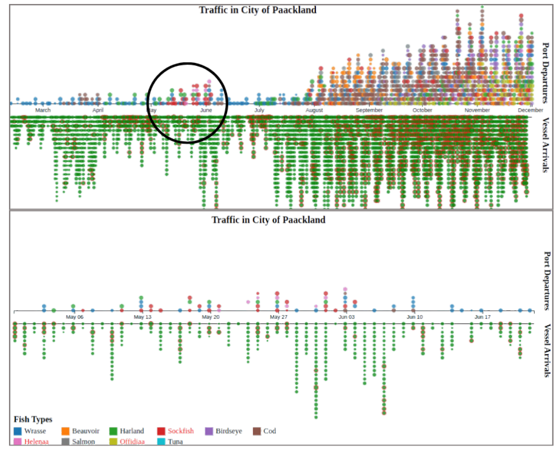



Figure 3: Timeline chart: The top shows the full flow of Packlnad city, with a black circle marking suspicious behavior. The bottom zooms in on the highlighted area.

**Similarities Analysis:** Our system allows users to fix a vessel and display its most similar ones. Selecting a vessel splits the trajectory chart, showing the selected vessel alongside the fixed one for comparison despite differences in duration or date (Figure 1(b.2)(b.3)). The bar chart then highlights comparability through similar dwell times and behaviors, regardless of location (Figure 1 (c)).

**Annotations** We highlight excessive dwell times in protected areas, which may indicate illegal fishing. We calculate the average dwell time in these areas and mark trajectories that exceed this with red boxes. In addition, we labeled the left side with the names of the fish associated with each fishing area through which the vessel passes and the right side with the potential fish transported to each port (Figure 1(b.2)).

## 4 Conclusions

We have developed an interactive tool that leverages the CatchNet knowledge graph to scrutinize suspicious behaviors and illegal practices within Oceanus' commercial fishing industry. This tool enables users to analyze seasonal fishing patterns, detect anomalies in port records, and link vessels with probable cargo. For example, the timeline chart (Figure 3 reveals fishing trends and periods of suspicious activity that can be identified using filtering tools.

Additionally, we employ advanced algorithms to identify vessels with similar behavioral patterns, which may indicate coordinated or repeated illegal activities. As shown in Figures 1(c)(b.2)(b.3), these patterns are detected without requiring exact location or temporal movement matches. This approach allows the tool to identify general behavior similarities.

Finally, despite limited catch data, our estimate provides insights into catch distribution, complementing the timeline chart. However, it fails to detect overfishing accurately, leading to false positives.

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## References

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