Fisheries Network Analysis

DSAN 6400: Network Analytics

Morgan Dreiss Liz Kovalchuk

Illegal, Unreported, and Unregulated (IUU) fishing remains one of the most significant threats to the sustainability of global fisheries and ocean ecosystems. While various nations and Regional Fisheries Management Organizations (RFMOs) have implemented measures to regulate fishing activities, the fishing sector continues to exhibit highly complex and opaque networks of relationships among vessels, companies, and regulatory bodies. These complexities challenge efforts to monitor fishing activity and detect potential illicit practices, particularly in regions such as the Western and Central Pacific, where over 3,000 vessels operate under the governance of the Western and Central Pacific Fisheries Commission (WCPFC). Network analysis has emerged as a valuable tool for mapping and analyzing the relationships within fisheries systems, providing insights that are often obscured in traditional datasets. Prior research has demonstrated applications of network analysis in examining vessel interactions, trade flows, and social and governance structures related to fisheries management. This paper reviews the existing literature on network analysis in fisheries contexts and explores how these methods might be applied to publicly available fisheries data from the WCPFC region. This work seeks to establish a framework for future research aimed at identifying structural patterns, potential risk indicators, and opportunities for more effective fisheries governance and enforcement.

Keywords: Fisheries; Illegal, Unreported, and Unregulated Fisheries; IUU Fishing; IUUF; Network Analysis; Western and Central Fisheries Commission; WCPFC; RFMO; fishing vessel registry

Affiliations: Georgetown University - Data Science and Analytics Masters Program

Table of contents

1 Introduction

Over 90 million tons of seafood is harvested from our oceans every year ("Commercial Fishing. Global Fishing Watch" 2024), collected by nearly 3 million fishing vessels operating worldwide (Poortvliet 2024). With this immense level of fishing activity, there is a critical need for regulation to sustain fish stocks for future generations. While many nations and regions have implemented sustainable fishing practices and monitoring systems for decades, numerous countries and nefarious actors do not abide by these rules, contributing to growing global concern over Illegal, Unreported, and Unregulated (IUU) fishing.

This protein supply chain is unique in that it encompasses a diverse range of actors across the fisheries enterprise at multiple levels of procurement, production, and governance. Moreover, these actors are embedded in a complex web of regulatory frameworks that vary across jurisdictions and regions. Unlike domestic agriculture or meat production, commercial fishing often takes place hundreds—of even thousands—of miles away from the companies running operations and from the governmental bodies charged with oversight.

Understanding this complex system requires analytical methods capable of mapping the relationships and interactions among diverse stakeholders, vessels, and regulatory entities. With that in mind, this paper explores the potential of Network Analysis as a tool to show the intricate structures and connections within the fisheries sector.

This study reviews existing research and describes an initial approach for applying network analysis to publicly available fisheries data, focusing on the Western and Central Pacific region as a case study. While specific findings are beyond the scope of this project status assignment, this work sets the stage for identifying patterns and relationships that may inform future research, policy development, and strategies to combat IUU fishing.

1.1 Background

Certain fisheries, especially those which cross over multiple regions and jurisdictions, are governed by Regional Fisheries Management Organizations, or RFMOs. RFMOs are bodies that set regulations for fisheries and are responsible for holding their registered fishing vessels accountable for following the regulations set forth. RFMOs have designated regions and species within their field of management; see Figure Figure 1, which is a map of the five tuna RFMOs[1] that are responsible for managing fisheries covering 91 percent of the world's oceans ("What Is a Regional Fishery Management Organization. Pew" 2012).

For the purposes of this paper, we will be scoping the analysis to the RFMO responsible for the Western Pacific, the **Western and Central Pacific Fisheries Commission (WCPFC)**. In order for vessels to fish for highly migratory species of fish (i.e. all types of tuna, marlin, etc.) in the Western and Central Pacific, they must be registered with WCPFC and follow its regulations. The WCPFC Convention Area covers over 12 million square nautical miles, or 20% of the Earth's oceans (see Figure Figure 2).

There are currently over 3,000 vessels registered under the WCPFC, with the most prominent flag states[2] being China, Japan, Chinese Taipei (Taiwan), and the Philippines ("WCPFC RFV" n.d.). The WCPFC regulates when, where, what, and how these vessels are allowed to fish, but only on the High Seas outside any other country's Exclusive Economic Zone (EEZ)[3]. In

[1]Tuna is considered one of the most valuable fisheries in the world and all the tuna species are pelagic, ocean-going fish and considered highly migratory, making them a prime target for RFMOs.

[2]Flag State, or Flag State Jurisdiction, is defined as: "A State may exercise jurisdiction over a vessel that is registered with the State and flying its flag. This exercise of jurisdiction is based on the internationally recognized principle that a State may regulate the conduct of its nationals even when those nationals are acting outside of the State's territory." (National Oceanic and Atmospheric Administration 2024)

[3]Exclusive Economic Zone (EEZ): "A coastal State has sovereign rights to the management of natural resources and other economic activities within its EEZ. It does not have sovereignty within its EEZ, so foreign vessels possess the same non-economic rights within a State's EEZ as on the high seas." (National Oceanic and

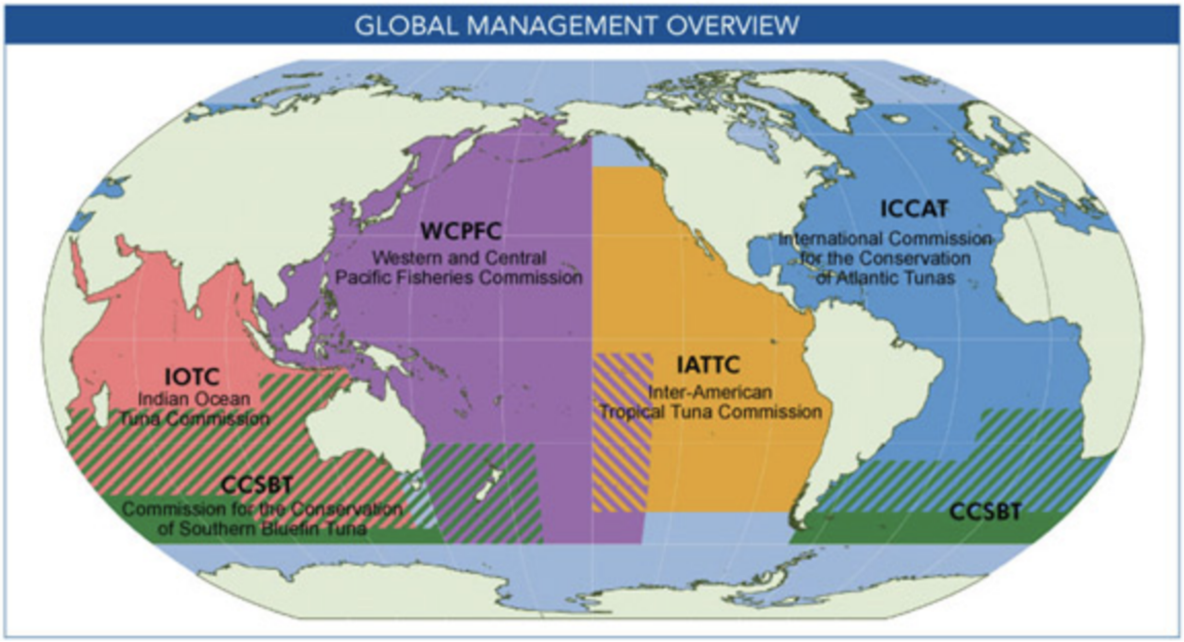

Figure 1: Global overview of tuna managing Regional Fisheries Management Organizations.

order for a vessel to be registered with WCPFC, it must also be flagged[4] in a country that is a member of the WCPFC[5].

With 26 member states and over 3,000 vessels, along with a large number of owners, operators, and corporations, the web of associations within the fisheries sector for just this RFMO is vast.

Using publicly available data on ship registration and associated information, we hope to examine the data for relationships that might indicate potential concerns or provide insight into the commercial fishing enterprise for this area of the globe.

Atmospheric Administration 2024) The EEZ extends from the country's baseline to 200NM (or when meeting another country's EEZ).

[4]Flag State, or Flag State Jurisdiction, is defined as: "A State may exercise jurisdiction over a vessel that is registered with the State and flying its flag. This exercise of jurisdiction is based on the internationally recognized principle that a State may regulate the conduct of its nationals even when those nationals are acting outside of the State's territory." (National Oceanic and Atmospheric Administration 2024)

[5]WCPFC Commission Members:

Members - Australia, China, Canada, Cook Islands, European Union, Federated States of Micronesia, Fiji, France, Indonesia, Japan, Kiribati, Republic of Korea, Republic of Marshall Islands, Nauru, New Zealand, Niue, Palau, Papua New Guinea, Philippines, Samoa, Solomon Islands, Chinese Taipei, Tonga, Tuvalu, United States of America, Vanuatu.

Participating Territories - American Samoa, Commonwealth of the Northern Mariana Islands, French Polynesia, Guam, New Caledonia, Tokelau, Wallis and Futuna.

Cooperating Non-member(s) - The Bahamas, Curacao, Ecuador, El Salvador, Liberia, Panama, Thailand, Vietnam.

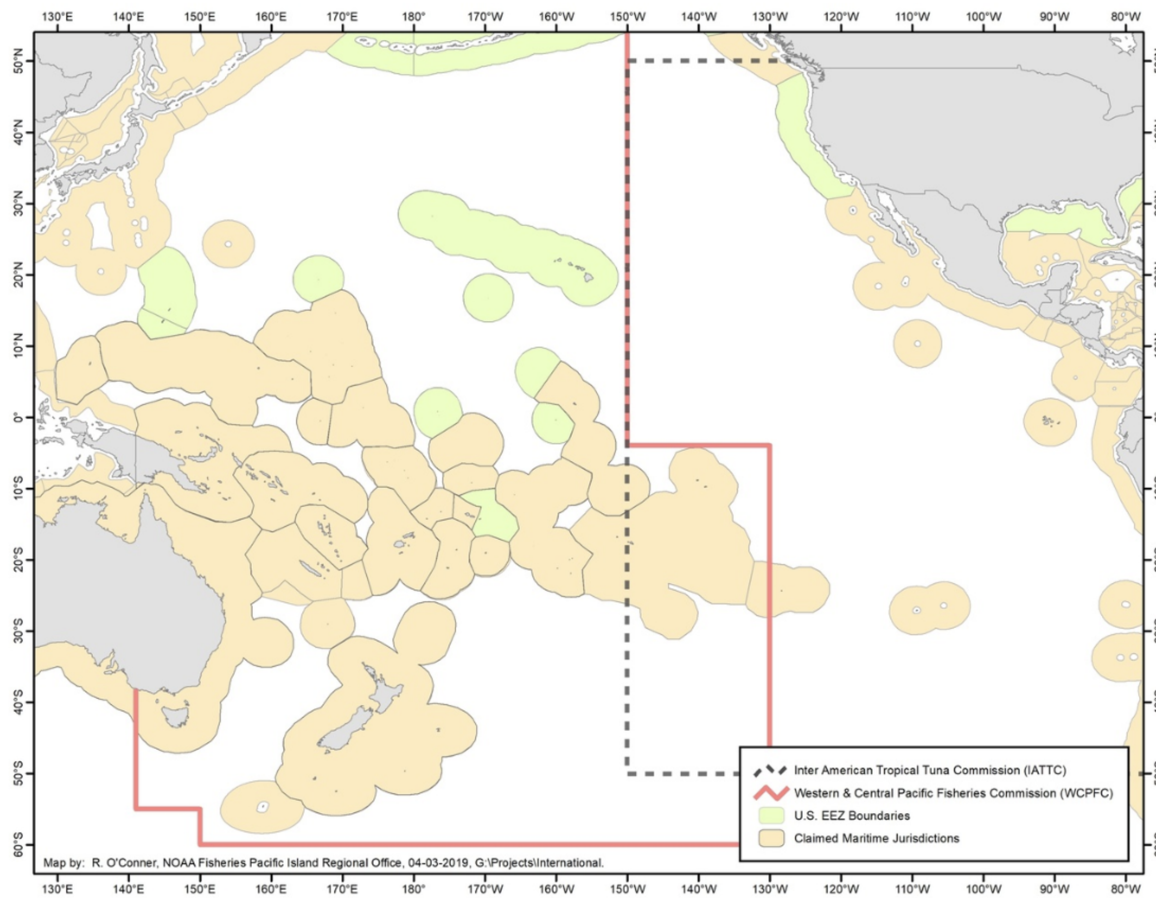

Figure 2: The WCPFC Convention Area spans the Pacific Ocean from roughly 141°E to 150°W.

1.2 Previous Work

Previous research has applied network analysis to study fishing practices and fisheries governance. Given the complex and layered relationships that exist between different entities and information flows, network-based approaches provide a way to model and visualize systems that would otherwise be extremely difficult to capture holistically. For instance, Dell'Apa et al. (2013) used Social Network Analysis (SNA) to analyze trade flows of spiny dogfish, revealing how global trade relationships impact regional conservation outcomes and suggesting that trade regulations could promote sustainability.

Network analysis has been used to relate information tied to vessels and their activities. For example, in Ford, Bergseth, and Wilcox (2018), researchers used SNA to identify key ships operating in the Indian Ocean fishing industry. By analyzing AIS data, they inferred relationships between vessels operating in close proximity and found that refrigerated cargo vessels (reefers) and bunkering ships played pivotal roles within the network, as evidenced by high eigenvector centrality scores. Network Analysis has also been used to understand vessel movements and behaviors outside of the fisheries scope. The highly cited Varlamis et al. (2021), explored the use of AIS data to build vessel-traffic networks. While their work focused more on visualizing maritime traffic patterns than directly addressing overfishing, it underscores how network-based data structures can enable analysis across diverse fisheries contexts.

Network analysis has also been applied to social and governance networks. For instance, Marín and Berkes (2010) examined co-management networks in Chilean small-scale fisheries, finding that power was highly centralized among government institutions and recommending policy changes to promote participatory governance. Such qualitative analyses underscore how network methods can extend beyond purely quantitative data to reveal institutional and social dynamics relevant to fisheries management.

The qualitative dimension remains important for future work that might follow quantitative analysis. As an example, Dell'Apa et al. (2014) expanded on earlier research to explore how stakeholder networks influence fishery management policies for spiny dogfish, highlighting the role of network structures in shaping effective governance.

Another study, Mulvaney et al. (2015), employed survey data to establish connections among stakeholders in the Great Lakes' local fisheries network. While the study highlighted methodological constraints due to reliance on survey responses, it also showed that informal relationships accounted for a significant share of network connections, revealing an under-explored layer of fisheries governance.

A particularly promising area involves transforming fisheries data into network structures to reveal hidden dynamics. A critical component of Nogueira et al. (2023)'s analysis of fisheries in the Azores was the conversion of time-series catch data into network graphs. This time-sensitive approach enabled identification of key species associations and critical fishing nodes relevant to sustainable management strategies. Such techniques illustrate the potential for network analysis not only to describe existing systems but also to support proactive recommendations for sustainability.

Across this body of work, researchers have applied diverse network approaches – from social networks and trade networks to vessel proximity networks – to uncover the structure and function of complex fisheries systems. These examples underscore the versatility of network analysis as a framework for exploring fisheries data. While each study focuses on a particular region or problem, collectively they demonstrate the value of network perspectives in understanding the multi-layered realities of marine resource use and governance.

This paper builds on these foundations by exploring how network analysis might be applied to the WCPFC fisheries context. However, our initial focus remains on developing methods and understanding the available data, rather than drawing definitive conclusions at this stage.

2 Data

Understanding the fisheries landscape in the Western Pacific requires integrating information from multiple domains. A large part of this analysis was creating this robust data set, which enabled the construction of a fisheries network and the application of network analysis methods to address the problem. Accordingly, we relied on datasets from international organizations, satellite-based monitoring platforms, and open-source geospatial repositories.

2.1 Data Collection

The first data source was the WCPFC's Registry of Fishing Vessels (RFV) ("WCPFC RFV" n.d.). This is a list of approximately 3,000 vessels that are authorized to fish within the WCPFC's Convention Area. The RFV contains the whole of the vessels' registration information, including official name, flag state, identification numbers, home port, vessel type, and owner information.

Since the goal was to look at the actual fishing vessel activity, rather than just the registration of vessels, a second primary data source was introduced to create the network. Automatic Identification System, or AIS, is a near real-time record of the location of vessels. AIS was originally a collision avoidance tool for vessels over 300 tons, but some fishing vessels also utilize it. While many AIS viewing and collection sources are paid services, this analysis utilized open-source AIS information from Global Fishing Watch (GFW) to identify vessels that fished within the Western Pacific.

GFW applies their own "fishing detection algorithm based on changes in vessel speed and direction", so that only the Apparent Fishing Effort was collected (Global Fishing Watch 2025b). Fishing vessel AIS activity was collected from the major fishing areas, EEZs and

High Seas Pockets[6], within the Western Pacific. The exact areas and their boundaries can be found in Section 5.1. The activity was collected for each individual area from 01JUL2024 to 01JUL2025, with each observation identifying the vessel and how many hours they exhibited fishing activity in that time period. GFW's map from this same period can be seen in Figure 3. The full breakdown of Global Fishing Watch's fishing vessel activity algorithm can be found in their 2018 paper, Kroodsma et al. (2018).

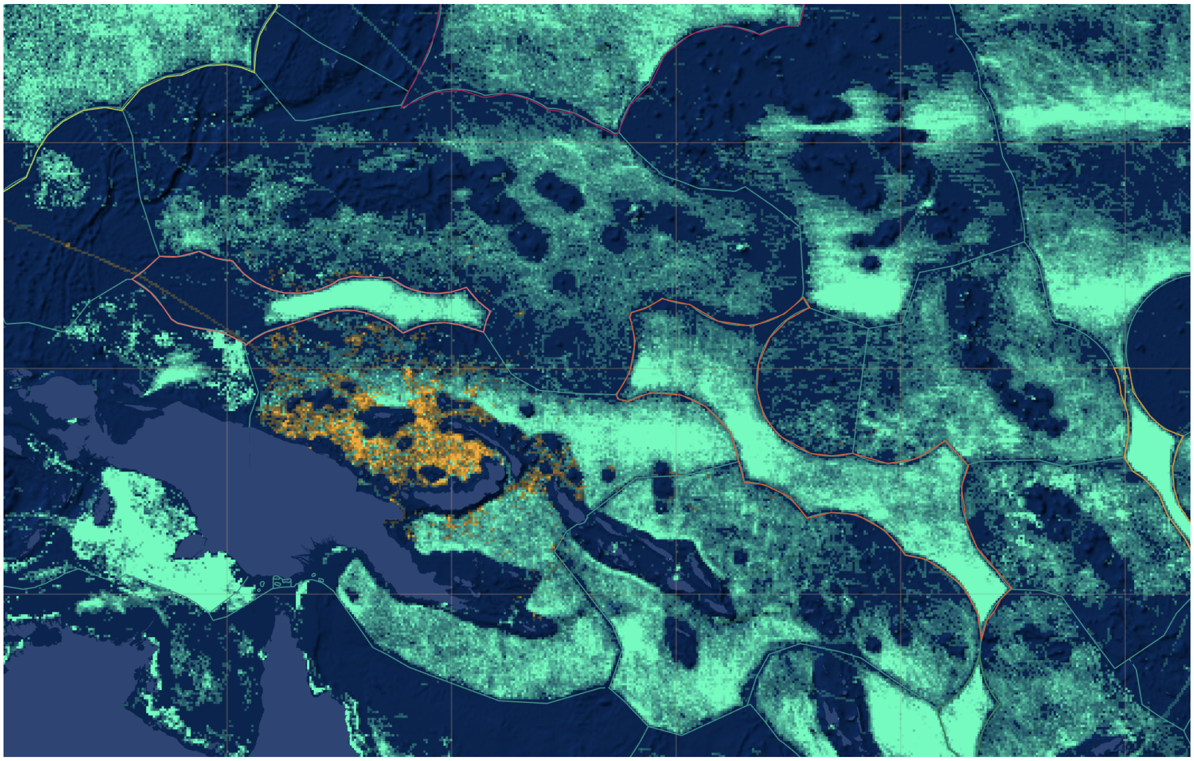

Figure 3: Global Fishing Watch Map with Apparent Fishing Efforts from 01JUL24 to 01JUL25.

It should also be noted that WCPFC also requires the use of Vessel Monitoring Systems, or VMS, for vessels fishing on the High Seas within the Convention Area. However, VMS is only accessible by those member states and agencies and organizations dedicated to fishers and is not publicly available. For that reason, VMS was not included in this analysis.

2.2 Data Cleaning

Before analysis, the data required several cleaning and preprocessing steps to ensure consistency and usability, along with preparing it for network creation. The Registry of Fishing Vessels was a complete data set, in that all the fields were filled out, but there was some variation of the

[6]High Seas Pockets are areas between county's Exclusive Economic Zones.

completeness within the fields. The field with the most inconsistency was the fishing vessels' owner's address field. Since the AIS data set that is be paired with RFV has a significant spatial aspect, the locations of the owners/companies were of interest. The inconsistencies with this field stem from the fact that owners are spread throughout Asia (and the world) and many countries have different ways of writing addresses. To create uniformity in the owner location, this field was cleaned utilizing OpenAI's API, specifically the gpt-4o-mini model's chat responses (OpenAI 2025), to extract the approximate latitude and longitude location of the owner/company.

For readability, additional cleaning and standardization was conducted on the RFV. The fishing vessel types were extracted from Food and United Nations (FAO) (2019) and the home port information was cross referenced with WCPFC's list of full port names (Western and Central Pacific Fisheries Commission (WCPFC) 2025). OpenAI's API was utilized again to extract the approximate latitude and longitude location of the home port as well.

2.2.1 Geo-Spatial Data Preparation

Given the spatial nature of the problem, a key objective of the analysis was to map the fishing vessel activity network in relation to each vessel's home port and ownership location. Achieving this required precise spatial coordinates for all network nodes.

To establish node locations, fishing area geometries were used as a foundation. For Exclusive Economic Zones (EEZs), centroids[7] were calculated from shapefiles provided by the Maritime Boundaries Geodatabase (Flanders Marine Institute 2023). High Seas Pocket geometries were manually delineated and extracted from the Global Fishing Watch map (Global Fishing Watch 2025a), and their centroids were similarly computed. Finally, the vessel ownership locations were calculated by spatial joins with the world's administrative boundaries of states and provinces (Earth and Society 2012). This allowed ownership locations to be grouped together on some level for easier visualization. Figure 4 shows the areas assessed.

2.3 Network Data Preparation

Before selecting final networks for analysis, we explored a wide range of potential node and edge combinations based on the available dataset. The goal was to evaluate which relationships offered the most meaningful insight into vessel behavior, ownership structure, and geographic clustering.

2.3.1 Potential Nodes

[7]Note: The centroids are used just for visual representation and no distances were computed from these figures.

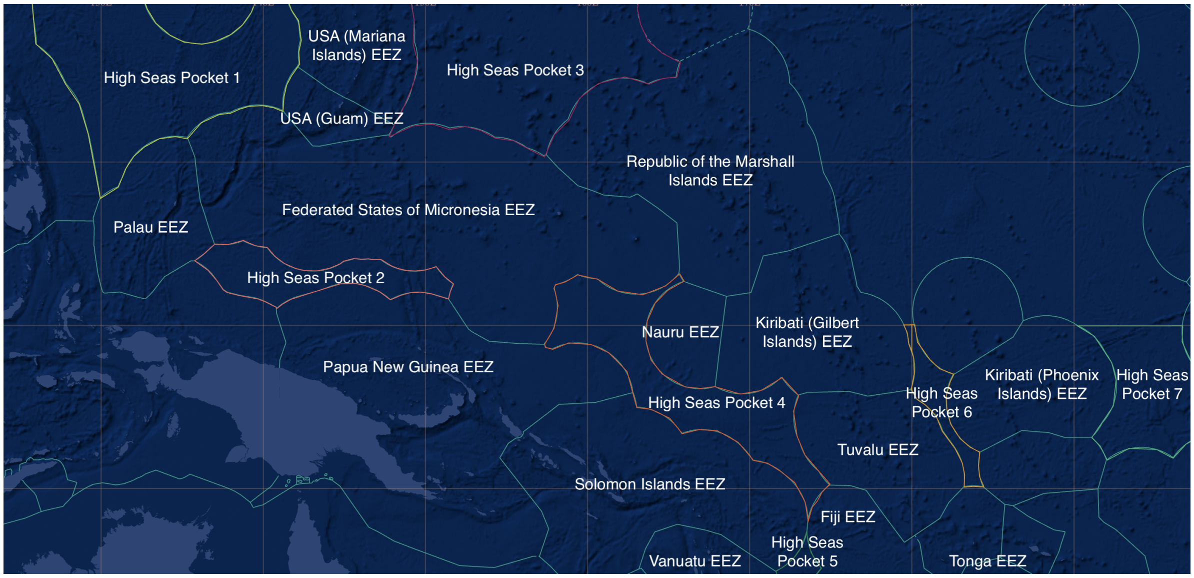

Figure 4: Fishing Areas assessed for AIS activity in the Western Pacific.

Node Type	Columns of Interest
Vessel	VID, Name of fishing vessel, Registration number, IMO
Owner	Name of the owner or owners, Address of owner
Master (Captain)	Name of master, Nationality of master
Port	Port of registry
Flag State	Flag of fishing vessel
Charterer	Name of charterer, Address of charterer
Fishing Methods	Type of fishing method
Authorization	Authorization number, Areas/species authorized

2.3.2 Potential Edges

From Node	To Node	Relationship Type
Vessel	Owner	"owned by"
Vessel	Flag State	"flagged under"
Vessel	Port	"registered in"
Vessel	Master	"operated by"
Vessel	Charterer	"chartered by"
Vessel	Fishing Method	"uses method"
Vessel	Authorization	"has authorization"
Owner	Address	"located at"

After exploratory construction and preliminary inspection of these pairings, we selected the following three relationship frames for quantitative analysis:

- Vessel-Vessel via Shared Fishing Areas
  - To examine spatial coordination and potential operational overlap
- Vessel-Vessel via Shared Ownership
  - To assess corporate control or flexibility/hierarchy of ownership.
- Vessel-Port
  - To evaluate the distribution of vessel registration.

These three networks provided the most interpretable structure and were well-supported by available data. Other potential edges such as vessel-to-charterer or vessel-to-master were excluded due to data sparsity or inconsistent reporting - this field can largely be filled out as the data providers choose.

2.3.3 Incorporating AIS

The final data set merged together the AIS data from the fishing areas and the vessel information from the RFV. To facilitate the network construction, each observation was a singular vessel fishing in a singular fishing area, with the vessel and area attributes included. Ultimately, this data set is an edge list with additional node and edge attributes. Here are the final fields of the dataset:

Table 3: Final Data Set Edge List Fields

Vessel Name	Flag State	Fishing Area	Fishing Hours
Vessel Type	Homeport Name	Homeport Province/State	Homeport Country
Owner Name	Owner Address	Owner Province/State	Owner Country
Owner Latitude	Owner Longitude	Homeport Latitude	Homeport Longitude

2.4 Network Construction

Table 4: Node and Edge Types for all networks

Node Type 1	Node Type 2	Edge Relationship	Edge Attribute
A	B	C	G

Node Type 1	Node Type 2	Edge Relationship	Edge Attribute
E	F	G	G
A	G	G	NA

3 Methodology

This study uses a mixed-methods approach that combines geospatial visualization and quantitative graph theory to analyze relationships among vessels, fishing areas, ports, and ownership groups in the Western and Central Pacific. The goal is to uncover non-obvious structure(s) in fishing activity and assess how vessels are organized.

To support this, we constructed three network frames:

- Vessel–Vessel (Shared Fishing Areas): A unipartite network where nodes are vessels and edges indicate co-occurrence in the same fishing area, weighted by the number of shared zones.
- Vessel–Vessel (Shared Ownership): A projection of a bipartite vessel–owner graph where vessels are linked if owned by the same entity.
- Vessel–Port: A bipartite network linking vessels to their home ports, reflecting administrative geography and potential regulatory hubs.

Each network was analyzed using centrality and community detection measures. Betweenness centrality helped identify potential bridge nodes that span otherwise disconnected parts of the network. A modularity-based algorithm was used to detect communities—clusters of vessels or ports that form tightly knit groups.

The vessel–fishing area network was designed to explore operational co-location and behavioral overlap, asking whether vessels tend to cluster in coordinated fleets. The vessel–ownership network provided insight into how fragmented or centralized fleet ownership is across the region. The vessel–port network aimed to reveal logistical and jurisdictional clustering and pinpoint influential port hubs.

All networks were constructed using Python's networkx library. A custom utility function (analyze_network) was used to compute summary statistics and generate visualizations. This multi-perspective approach enables a layered understanding of the Western Pacific fisheries system, with each network offering a distinct lens on vessel coordination and control. Similar to previous studies performed, we sought to understand relationships or other elements of underlying data that could tell us about the relationships between vessels and fishing practices.

3.1 Findings

While the analysis did not uncover direct evidence of illegal or unregulated fishing activity, it revealed meaningful structural patterns that provide a foundation for future investigation and monitoring.

3.1.1 Vessel–Vessel Network via Shared Fishing Areas

This network exhibited a highly interconnected structure, with 875 vessels linked by over 126,000 edges—indicating dense patterns of co-fishing activity. Centrality scores revealed a small number of vessels that act as structural bridges, connecting otherwise separate clusters. These vessels may represent highly mobile or multi-regional operators, possibly engaged in coordination across zones.

The top 10 vessels by **betweenness centrality** are shown below:

Vessel Name	Betweenness Centrality
ZHONGSHUI 917	0.0101
YI MAN NO.8	0.0101
ZHONGSHUI 927	0.0100
DE CHAN NO.26	0.0085
JIN FONG SHUUN	0.0074
MAN YING CAI NO.6	0.0074
CHIEN YUAN MING	0.0072
YI RONG NO3	0.0069
LIAOYUANYU101	0.0068
SHUN RONG NO.268	0.0064

Community detection identified three major vessel groupings, likely aligned with regional fleets, operational routines, or flag state affiliations. These structural separations suggest organized fishing behavior at scale, with a small number of vessels linking the system together. The visualization of this network is shown in Figure Figure 5.

3.1.2 Vessel–Vessel Network via Shared Ownership

This network presented a stark contrast: although the node set matched the previous network, it yielded only 1,204 edges and over 580 distinct communities. Most vessels were connected to just a few siblings under the same owner, and no vessels had meaningful centrality scores.

As all betweenness centrality values were effectively **0.0000**, this network confirmed that ownership structures are highly modular and fragmented—supporting the interpretation that firms tend to manage vessels in isolation, without cross-ownership coordination.

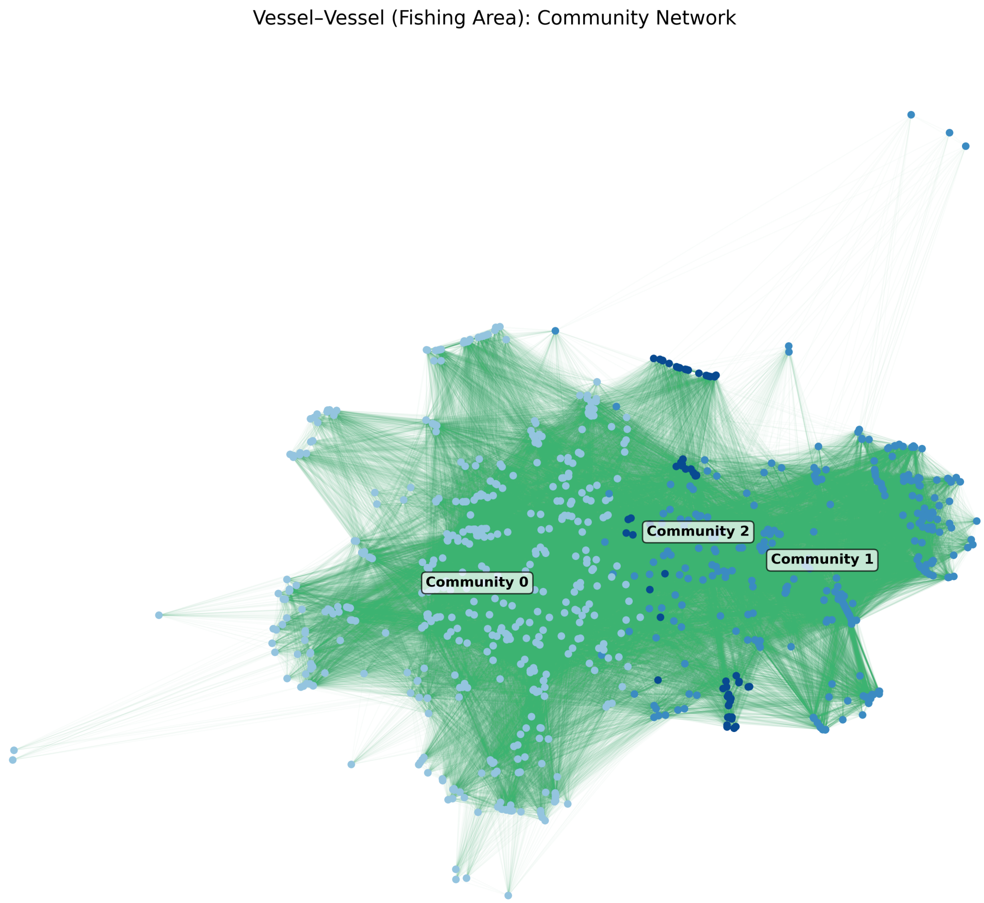

Figure 5: Vessel–Vessel Network with Community Detection.

3.1.3 Vessel–Port Network

The vessel–port network revealed moderate clustering and several key port hubs. Out of 957 total nodes and 882 edges, a few ports stood out—particularly **Kaohsiung**, which exhibited the highest betweenness centrality in the entire network. Other significant ports included **Zhoushan**, **Shidao**, and **Shekou**.

The top 10 nodes by **betweenness centrality** are shown below:

Node Name	Betweenness Centrality
Kaohsiung, None	0.1160
Shidao, CHN	0.0088
Zhoushan, CHN	0.0086
Shekou, CHN	0.0028
Busan, None	0.0027
Yantai, CHN	0.0015
HONG YANG 8	0.0014
HONG YANG 88	0.0014
HONGYANG8	0.0014
HONGYANG88	0.0014

Community detection revealed 79 port-based clusters, which largely aligned with national or sub-national jurisdictions. These clusters may reflect administrative boundaries, logistical corridors, or regulatory zones, but do not independently suggest problematic coordination.

3.2 Interpretation

Across all three networks, we did not observe clear signals of illicit coordination or suspicious centralization. Instead, the results reflect a complex but largely modular system where vessels group around geographic or ownership-based features in expected ways.

While exploratory, this analysis supports several key insights:

Central nodes such as Kaohsiung and a few high-degree vessels may serve as critical network connectors.

Ownership structures appear siloed, lacking the cross-fleet ties that might indicate centralized control.

Operational clusters align with known EEZs and flag states, reinforcing the territorial logic of fishing activity.

Given these observations, we interpret the results as establishing a structural baseline. The networks validate the underlying data relationships and may serve as a reference point for future anomaly detection, risk modeling, or governance design.

3.3 Geo-Spatial Analysis Results

Finally, a geo-spatial network was constructed utilizing the centroids of the areas and the approximate positions of the vessel's home ports. The geo-spatial visualization in Figure 6 with the fishing area nodes delineated from the home port nodes by color and the edge width characterized by the sum of fishing hours in that fishing area.

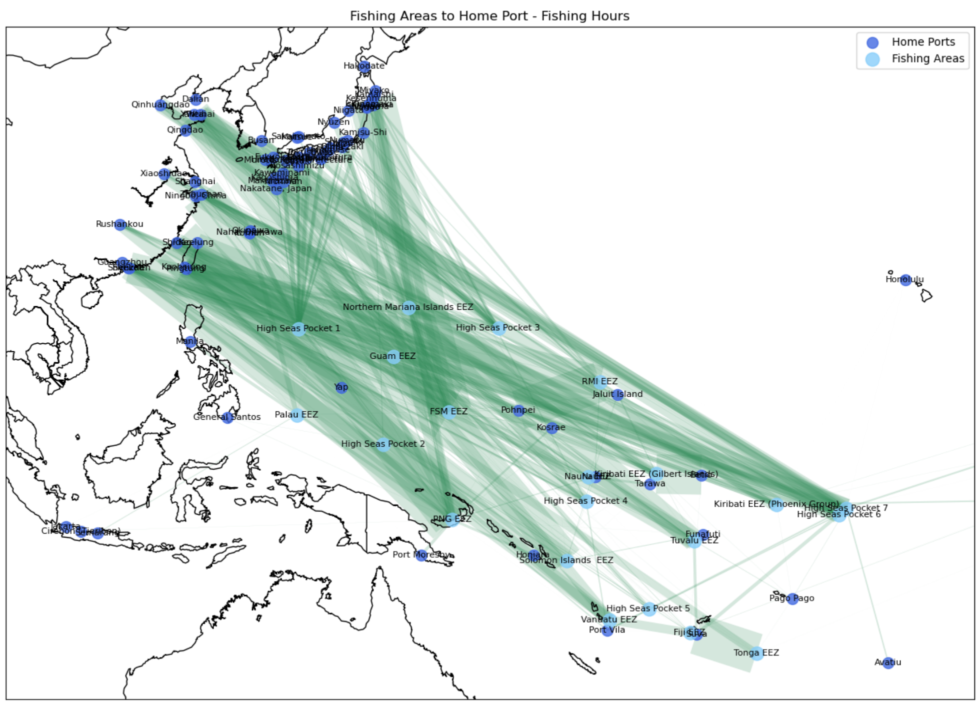

Figure 6: Fishing Area to Home Port Network Map.

This map alone is telling of the fishing vessel habits in the Western Pacific and clear patterns emerge. For example, port and fishing area pairs such as Pohnpei, FSM & the Marshallese EEZ and Suva, FJI & the Tonga EEZ show that almost the entirety of that area's fishing efforts are by vessels home-ported in those ports, while other fishing areas have more varied vessel connections. Many of the regional relationships are what you would expect, with vessels sticking to areas that are closer to their home ports, however there are a few exceptions. Namely, the Papua New Guinea EEZ seems to be a popular fishing area for vessels from China, Taiwan, and Japan, with very little activity associated with PNG home-ported vessels. And alternatively, the Kiribati EEZ (Phoenix Islands) seems to be favored by Chinese and Taiwanese vessels and not the Japanese fleets.

Utilizing a community detection algorithm, additional insight can be drawn from that network map, Figure 7. With just the fishing hours and their corresponding areas assessed, the algorithm found three communities. The communities describe the behavior of three distinct fleets of vessels: the Japanese Fleet, Chinese/Taiwanese Fleet, and Pacific Island Nation Fleet. While there are some miss-matches when looking geographically, this analysis shows that vessels from those ports may not exhibit the same behavior as those closest to it distance-wise, but their behavior is akin to one of the other fleets.

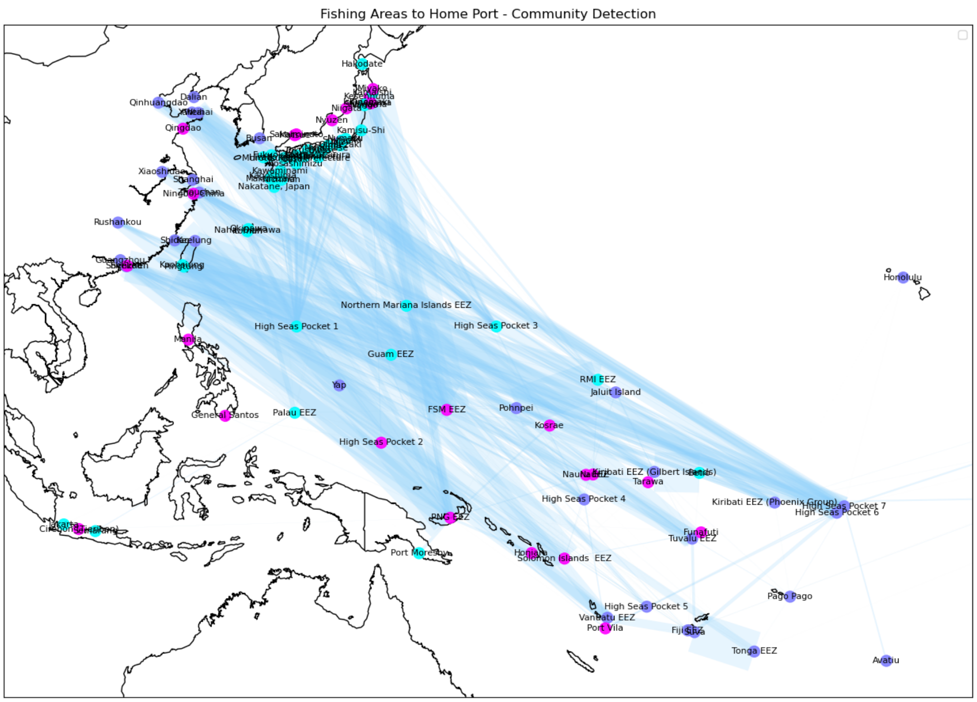

Figure 7: Fishing Area to Home Port Community Detection Map.

This analysis also looked at the relationship between vessel owner location and the home port of the vessel, however there was very little insights to be drawn, as the home ports were typically synonymous with the location of ownership. This is likely due to the fact that many companies have subsidiaries that located where their vessels are home-ported and that is what is listed on the vessel registration. This relationship between ownership location and home port makes analysis of ownership to fishing area redundant with our original geo-spatial analysis and was not conducted. The home port to ownership location is displayed in Figure 8.

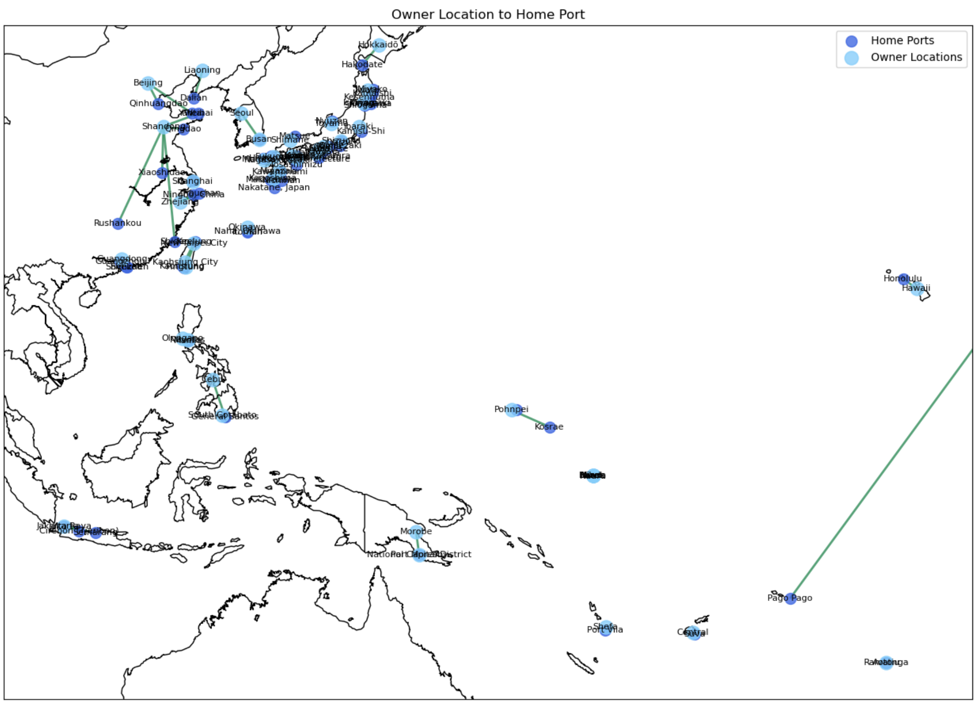

Figure 8: Home Port to Ownership Location Map.

4 Outlook

While this analysis does not make conclusive claims about illicit or unregulated behavior, it demonstrates the value of network-based approaches for mapping the structural landscape of industrial fisheries in the Western and Central Pacific. Through the integration of registry, ownership, and AIS-derived activity data, we were able to construct multiple interpretable network frames that revealed behavioral clustering, regional coordination patterns, and the modular nature of fleet ownership.

Additional analysis opportunities:

This analysis was conducted utilizing open-source AIS data, however these methods could produce more robust results if additional data is introduced. Specifically, if the data was expanded beyond AIS into RFMO's Vessel Monitoring Systems (VMS) and even electronic intelligence (ELINT) feeds (such as CRFS (2022)) further insights could be obtained.

Also one aspect that we did not touch on, but is relevant to this problem set is the role of fish carriers. Especially in relation to the geo-spatial analysis, where a vessel is home ported is not typically indicative of where the catch is landed. An additional analysis, using these same methods, focusing on fish carriers along with finding the proprietary information needed to determine where catch is actually landed would be highly beneficial to the fishing conservation community.

Ultimately, this work is intended to serve as both a baseline and a modular scaffold for future research. As more data sources become available and as monitoring technologies evolve, network analysis offers a scalable and adaptable method for surfacing systemic patterns in global fisheries governance.

5 Appendix

5.1 Appendix 1: Fishing Areas

The AIS data collected for the apparent fishing activity was broken down by area, primarily Exclusive Economic Zones (EEZ) but also High Seas Pockets. The centroids of the EEZs were computed from Flanders Marine Institute (2023) using geopandas. For this analysis, the following areas were observed:

Observed Area	Description	Centroid
Fiji EEZ	Exclusive Economic Zone of Fiji	177.689346, -17.94847097
Federated States of Micronesia (FSM) EEZ	Exclusive Economic Zone of FSM	150.3224817, 6.768434442
Kiribati EEZ - 1	Exclusive Economic Zone of Kiribati (Gilbert Islands Group)	173.8878893, -0.25912361
Kiribati EEZ - 2	Exclusive Economic Zone of of Kiribati (Phoenix Islands Group)	187.5460348, -3.731812109
Nauru EEZ	Exclusive Economic Zone of Nauru	166.1239638, -0.591130617
Palau EEZ	Exclusive Economic Zone of Palau	133.069498, 6.443930362
Papua New Guinea (PNG) EEZ	Exclusive Economic Zone of PNG	
Republic of the Marshall Islands (RMI) EEZ	Exclusive Economic Zone of RMI	167.4854677, 10.15136115
Solomon Islands EEZ	Exclusive Economic Zone of the Solomon Islands	163.6853914, -10.04465238
Tonga EEZ	Exclusive Economic Zone of Tonga	185.2341392, -20.22174869
Tuvalu EEZ	Exclusive Economic Zone of Tuvalu	178.1828785, -7.812542137
United States of America (USA) EEZ - 1	Exclusive Economic Zone of Guam	144.0026079, 12.9295752
United States of America (USA) EEZ - 2	Exclusive Economic Zone of Commonwealth of the Northern Marianas Islands	145.7393322, 18.28659832
Vanuatu EEZ	Exclusive Economic Zone of Vanuatu	168.5574292, -16.58523096

Observed Area	Description	Centroid
High Seas Pocket 1	Bounded by Japan's, USA's, Palau's, FSM's, and Philippines' EEZs	133.2661348, 16.03818414
High Seas Pocket 2	Bounded by FSM's, PNG's, Indonesia's, and Palau's EEZs	142.8799343, 3.058219655
High Seas Pocket 3	Bounded by 20° N to the North and RMI's, FSM's, and USA's EEZs	155.9543427, 16.04415883
High Seas Pocket 4	Bounded by FSM's, Nauru's, RMI's, Kiribati's (Gilbert Islands), Tuvalu's, Fiji's, Solomon Islands', and PNG's EEZs	165.9243784, -3.385867731
High Seas Pocket 5	Bounded by Fiji's, Vanuatu's, and Solomon Islands' EEZs	173.0194775, -15.37523716
High Seas Pocket 6	Bounded by the Equator (0°) to the North and Howland and Baker Islands' (USA), Kiribati's (Phoenix Islands), Tokelau's (New Zealand), Wallis and Fortuna's (France), Tuvalu's, and Kiribati's (Gilbert Islands) EEZs	-165.3957946, -4.886868152
High Seas Pocket 7	Bounded by the Equator (0°) to the North and Howland and Baker Islands' (USA), Kiribati's (Phoenix Islands), Tokelau's (New Zealand), Cook Islands' (New Zealand), Jarvis Islands' (USA), and Kiribati's (Line Islands) EEZs	-164.5540955, -4.161049605

References

"Commercial Fishing. Global Fishing Watch." 2024. October 24, 2024. https://globalfishingwatch.org/commercial-fishing/.

CRFS. 2022. "Gaining ELINT by Intercepting and Analyzing RF Radar Signals." CRFS. 2022. https://www.crfs.com/blog/gaining-electronic-intelligence-by-intercepting-and-analyzing-rf-radar-signals.

Dell'Apa, Andrea, Jeffrey C. Johnson, David G. Kimmel, and Roger A. Rulifson. 2013. "The International Trade and Fishery Management of Spiny Dogfish: A Social Network Approach." *Ocean & Coastal Management* 80 (August): 65–72. https://doi.org/10.1016/j.ocecoaman.2013.04.007.

———. 2014. "The International Trade and Fishery Management of Spiny Dogfish: A Social Network Approach." *Ocean & Coastal Management* 96: 165–72. https://doi.org/10.1016/j.ocecoaman.2014.05.007.

Earth, Natural, and North American Cartographic Information Society. 2012. "Admin 1 – States & Provinces (Cultural Vector, 1:10 m, Version 2.0.0)." ESRI Shapefile. https://www.naturalearthdata.com/downloads/10m-cultural-vectors/10m-admin-1-states-provinces/.

Flanders Marine Institute. 2023. "Maritime Boundaries Geodatabase: Maritime Boundaries and Exclusive Economic Zones (200NM), Version 12." https://www.marineregions.org/. https://doi.org/10.14284/632.

Food, and Agriculture Organization of the United Nations (FAO). 2019. "INTERNATIONAL STANDARD STATISTICAL CLASSIFICATION OF FISHERY VESSELS BY VESSEL TYPES." FAO Fisheries and Aquaculture Report. FAO.

Ford, Jessica H., Brock Bergseth, and Chris Wilcox. 2018. "Chasing the Fish Oil—Do Bunker Vessels Hold the Key to Fisheries Crime Networks?" *Frontiers in Marine Science* 5 (August). https://doi.org/10.3389/fmars.2018.00267.

Global Fishing Watch. 2025a. "Custom Map View: Fishing Effort and EEZ Boundaries in the Western Pacific." Interactive web map. https://globalfishingwatch.org/map/index?longitude=156.81440410472072&latitude=-1.6107084045585427&zoom=3.749255682384149.

———. 2025b. "User Guide — 'Activity – Fishing'." Web page, Global Fishing Watch user guide. https://globalfishingwatch.org/user-guide/#Activity%20-%20Fishing.

Kroodsma, David A., Juan Mayorga, Timothy Hochberg, Nathan A. Miller, Kristina Boerder, Francesco Ferretti, Alex Wilson, et al. 2018. "Tracking the Global Footprint of Fisheries." *Science* 359 (6378): 904–8. https://doi.org/10.1126/science.aao5646.

Marín, Andrés, and Fikret Berkes. 2010. "Network Approach for Understanding Small-Scale Fisheries Governance: The Case of the Chilean Coastal Co-Management System." *Marine Policy* 34 (5): 851–58. https://doi.org/10.1016/j.marpol.2010.01.007.

Mulvaney, Kate K., Seungyoon Lee, Tomas O. Höök, and Linda S. Prokopy. 2015. "Casting a Net to Better Understand Fisheries Management: An Affiliation Network Analysis of the Great Lakes Fishery Commission." *Marine Policy* 57 (July): 120–31. https://doi.org/10.1016/j.marpol.2015.03.008.

National Oceanic and Atmospheric Administration. 2024. "Jurisdiction over Vessels." https://www.noaa.gov/jurisdiction-over-vessels.

Nogueira, Brenda, Ana Torres, Nuno Moniz, and Gui M. Menezes. 2023. "Dynamics of Fisheries in the Azores Islands: A Network Analysis Approach." https://arxiv.org/abs/2309.09378.

OpenAI. 2025. "OpenAI API (GPT-4)." https://platform.openai.com/.

Poortvliet, Dave. 2024. "Sustainable Fisheries Management Begins with Vessel Tracking. Global Fishing Watch." October 24, 2024. https://globalfishingwatch.org/fact-sheet/sustainable-fisheries-management-begins-with-vessel-tracking/.

Varlamis, Iraklis, Ioannis Kontopoulos, Konstantinos Tserpes, Mohammad Etemad, Amilcar Soares, and Stan Matwin. 2021. "Building Navigation Networks from Multi-Vessel Trajectory Data." *GeoInformatica* 25 (1): 69–97. https://doi.org/10.1007/s10707-020-00421-y.

"WCPFC RFV." n.d. Accessed April 23, 2025. https://vessels.wcpfc.int/statistics/by-vessel-type.

Western and Central Pacific Fisheries Commission (WCPFC). 2025. "List of Ports for RFV." WCPFC. https://www.wcpfc.int/doc/list-ports-rfv.

"What Is a Regional Fishery Management Organization. Pew." 2012. February 23, 2012. http://bit.ly/102wBKa.