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Empirical Analysis of AIS Data's Ability to Detect Suspected Dark Oil Tankers in Russian Ports and Waters

An analysis in light of the Russian and Ukrainian conflict

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Abstract

This master´s thesis investigates the ability of AIS data to detect suspected dark tankers in Russian ports and waters in light of the ongoing Russian and Ukranian conflict. The thesis aims to serve as a stepping stone between AIS data and satellite data in detecting dark tankers and show the possibilities and limitations of AIS data. By employing a geospatial analysis approach, which includes polygon and hexagonal tiling, the study narrows the focus to specific geographic regions that exhibit potential signs of suspicious activities. The methodology involves an extensive filtering process to scrutinize tanker behavior, effectively reducing the scope of the investigation to 14,3 percent of the tanker fleet. While the model demonstrates success in flagging potential dark tankers, the intrinsic constraints of AIS data mean that conclusive evidence of illicit activities, cannot be ascertained without the corroborative power of satellite data. Additionally, the thesis undertakes a secondary empirical analysis to investigate the impact of the $60 price cap, set on December 5, 2022, on Russian port activities. The findings indicate a notable uptick in operations and a strategic pivot towards eastern Russia. This study also explores the intricate ownership structures of the vessels in question, shedding light on the complexities of maritime operations within a sanctioned environment.

Keywords – Shipping, Oil Tanker, AIS, Polygon Creation, Big Data, Embargo, "Dark tanker", Ship-to-Ship Transfer, AIS Manupulation, Geospatial Analysis

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1 Introduction

In the complex world of global affairs, a mysterious player has evolved at sea – the secretive "dark tankers". These ships operate discreetly, challenging conventional maritime norms, emerging in significant numbers from the Russia-Ukraine conflict and its aftermath.

Dark tankers, associated with covert activities, present unique challenges to international security and trade. Unlike regular ships, they intentionally conceal their details, such as ownership and cargo, sailing through international waters with a veil of secrecy (Basquill, 2020). This intentional lack of transparency enables them to bypass regulations and evade sanctions, posing a substantial threat to global maritime operations. These infamous vessels are known for engaging in various activities, from smuggling prohibited goods to avoiding taxes and facilitating unlawful trade in restricted regions. The consequences of their covert operations extend beyond the maritime domain, impacting economic stability, regional security, and the effectiveness of international sanctions (Basquill, 2020).

After the outbreak of heated conflict between Russia and Ukraine in February 2022, Western countries imposed sanctions to limit the power and penalize the Russian Federation (Nelson, 2022). A government-imposed restriction on trade was imposed on seaborne crude oil transports from Russia on December 5th, 2022. A price cap of 60 dollars per barrel was set by the G7 to support stability in global energy markets and to minimize negative economic spillovers of Russia's war. Anyone who provides services for shipments of Russian crude oil traded above the price cap would be eligible for sanctions. Support included trading and commodities brokering, financing, shipping, insurance, protection and indemnity, flagging, and customs brokering (Caprile & Delivorias, 2023).

The imposition of embargoes and sanctions laid the groundwork for the global emergence of the dark fleet, directing its course toward Russian ports and territory (Engebretsen, 2022). These vessels strategically turn off their transmissions to evade detection by Western monitoring when navigating within territorial waters of NATO member states-and other nations supporting the sanctions. The restrictive measures, namely sanctions and the embargo, render Russian ports and waters an ideal setting for researching dark tankers. The scene are particularly interesting regarding the location and detection of these vessels which will be addressed in this paper.

Understanding the operational tactics of dark tankers for detection purposes requires a close examination. They often employ strategies like turning off tracking systems, engaging in ship-to-ship transfers, and selecting remote locations for their hidden activities (Engebretsen, 2022). Their ability to adapt and exploit regulatory gaps highlights their resilience against traditional detection methods. The secretive nature of dark tankers requires a shift away from standard detection strategies. Traditional surveillance, reliant on routine tracking systems, proves inadequate in the face of these vessels' intentional efforts to remain hidden (Mazzarella et al., 2017). Addressing the dark tankers' locations requires the exploration advanced detection technologies and datasets.

Central to this endeavor is the Automatic Identification System (AIS), a tracking system used in the maritime industry to identify and locate vessels. AIS is mandatory under international SOLAS regulations for specific categories of vessels, such as crude oil tankers (IMO-A, n.d.).

Initially designed to enhance maritime safety, AIS operates through the maritime Very High Frequency (VHF) [1] system (Baric et al., 2016). They employ a specific communication protocol to define the transmitted information and the corresponding technological equipment. AIS transponders are designed for vessels to exchange critical data automatically. This data encompasses static particulars such as navigational information, dynamic insights derived from onboard sensors (e.g., vessel speed), and voyage-related data like draught, destination, and Estimated Time of Arrival (ETA). A primary function of AIS is facilitating information exchange between vessels operating within the same geographic area, reducing the risk of collision.

Figure 1.1 illustrates the transmission path of AIS signals. From vessels at sea, the signals are transmitted in given timeslots to satellites or ground receivers. This goes through a central maritime data aggregator before being available for the end AIS data user. For this thesis, we have been granted access to the United Nations Global Platform (UNGP) and its AIS database.

[1] VHF, Very High Frequency, denotes radio waves with frequencies ranging from 30 MHz to 300 MHz (Ekah et al., 2022)

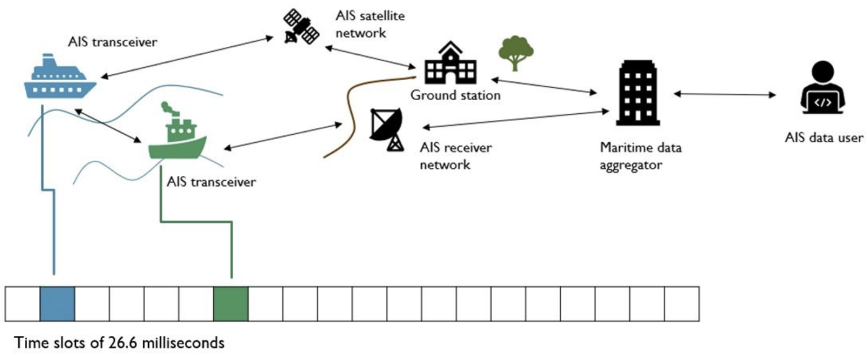


Figure 1.1: AIS Signaling (UNSD-A, 2020)

As recognized, AIS utilizes transponders on vessels, transmitting essential information such as identity, position, course, and speed. However, the adaptability of dark tankers in manipulating these systems necessitates a nuanced examination of AIS capabilities, limitations, and potential improvements. Since vessels can turn off their AIS transmissions to conduct illegal activities, this is a limitation to AIS and an essential factor for detecting suspected dark vessels. In addition, we cannot determine if their operations when "dark" are legitimate. Under our study, we interpret that vessels switching off their AIS in relevant locations have the possibility of going dark, which might indicate their engagement in illegal activities. This extended description stems from our acknowledgment of limitations in the Automatic Identification System (AIS), which, in turn, affects our ability to confidently predict the involvement of a specific vessel in illegal activities. Our approach narrows the entire tanker fleet to specific vessels during particular time frames and locations. This initial filtering serves as a foundational step, enabling researchers to conduct more in-depth analyses beyond the capabilities of AIS.

This thesis aims to create a methodology framework for detecting suspected dark tankers and serve as a stepping stone before implementing satellite technology or other data measures to verify the vessel's operational purposes. The challenge is to develop a detection model designed to address existing limitations and refine the precision of dark tanker identification. The model and its capabilities are thoroughly addressed to filter down suspected dark tankers from the global tanker fleet. It‘s creation involves synthesizing AIS data through big data analytics and spatial analysis. Combining these components aims to establish a comprehensive framework capable of filtering suspected dark tankers from routine maritime traffic. These filtered vessels will then be detected and flagged as suspected. For further research, satellite technology and AIS data can be merged for automatic detection (Mizukoshi et al., 2019). Moreover, satellite technology with capabilities to confirm the actions of the suspected vessels and uncover the vessel's true operational purposes is available ((Vake.AI, n.d.); (Windward.AI, n.d.)). The usage of AIS data and its ability to detect the suspected vessels are elaborated on, and we discuss the advantages and limitations of its usage, as well as essential notifications for further research.

In the scope of this thesis, we will address the suspected vessels "as dark" in an empirical analysis and analyze port activity based on AIS transmissions. We can then assume that our findings in the related period are made by "legitimate" vessels, and dark activity would be complementary. These assessments and results are compared to the expectations presented in a study by Babina et al. (2023). They analyze the economics of the Russian crude oil trade after the invasion of Ukraine in February 2022 and make short-term expectations for Russian crude oil exports and production. Following the empirical analysis, we take a deep-dive into the intricate ownership structure and registered flag concept of the suspected dark tankers. Complicated owner structures are characterized as a tactic by the dark fleet to hide their whereabouts and true vessel management (Engebretsen, 2022).

The remainder of this thesis is structured as follows: Chapter 2 reviews relevant literature. Chapter 3 introduces the framework and methodology for identifying suspected dark tankers through big data analytics and spatial analysis. In Chapter 4, we present our analysis and results. Chapter 5 presents our empirical analysis, treating the suspected dark vessels as dark vessels to analyze port activity and total ownership. In Chapter 6 we discuss the thesis methods and limitations. Chapter 7 contains our conclusions and suggestions for further research.

2 Literature Review

For the scope of this thesis, relevant literature involves research on the abilities and limitations of AIS, detection of dark vessels, sanctions and embargoes, and crude oil tanker trade research. There is limited research on our specific aim of developing a framework for filtering the search for detection of suspected tanker vessels. This thesis aims to fill a gap in the literature between AIS data and dark vessel detection by employing extensive geographical and vessel-specific AIS filtering.

The limited existing literature addressing the challenge of detecting vessels attempting to conceal their whereabouts by intentionally obscuring their AIS transmissions has explored various approaches. One paper exploited the *Received Strength Indicator (RSI)* available at the AIS base stations (BS) to detect whether a shortage of AIS messages represented an alerting situation or not (Mazzarella et al., 2017). They designed an anomaly detector to identify intentional AIS on and off switching before testing it on a real-world dataset. Our approach of building a model and testing on real data has the same research process. Mazarella et al., 2017 faced the difficulty of AIS messages from vessels being self-reported. Consequently, the key problem is the data's trustworthiness. Our thesis complements this research by using the problem of self-reporting transmissions as part of our detection method for suspected dark vessels.

Earlier research has also utilized the RSI from vessels at AIS base stations by examining the switching of Class-A AIS transponders from normal transmit power to low transmit power mode (Kelly, 2022). The paper analysed received RSI combinations at AIS stations with predicted signals and created a mathematical modelling and unique detection algorithm. However, this paper relies on the vessels being in coverage distance of AIS base stations. Our approach will depend mainly on Satellite-AIS (S-AIS), which has better coverage and can receive transmissions from vessels on a larger scale (Skauen, 2019).

Campbell et al., 2022 used several machine learning techniques to identify invalid AIS messages, which can be used for spoofing by dark vessels. Spoofing is a technique used by vessels to hide their real location and operations by transmitting misleading information (Balduzzi et al., 2014). They utilized K-means clustering, Decision tree (TR), Random Forest (RF), Feed-Forward Neutral Networks (FNN), Support Vector Machines (SVM), and Once-Class Support Machines (Ones-SVM). They found that DT, RF, and FNN best identified wrongful AIS messages. Another paper also detected AIS message falsifications and spoofing by checking messages and compliance with TDMA control (Louart et al., 2023). The two papers on falsification in AIS transmission findings can be used to identify spoofing and wrongful messages, but not to detect or filter for dark vessels' locations to a sufficient extent.

After we have built our model, we intend to employ and exemplify our methods on current activities surrounding the Russian embargo and price cap. As this thesis was written in the Fall of 2023, it has been approximately one year since the start of the embargo and one and a half years since the initial invasion of Ukraine. Consequently, there has been limited time to research the effects. However, in February 2023, a team using high-frequency Russian customs data found several effects and expectations we can use for our assessments (Babina et al., 2023). Our main focus points extracted from their findings are:

- Russia was redirecting crude oil exports to alternative markets such as India, China, and Turkey. Furthermore, they expected the effects to continue geographically.
- They expected Russian oil production and exports to increase to compensate for lost revenue by the price cap.

The paper encounters some main limitations that affect the reliability of its conclusions. Firstly, the Russian customs data used in the study are self-reported by Russia. This introduces a potential bias, as there is an incentive from Russia to overstate the effects of the sanctions. Such exaggeration may be intended to prevent the sanctions from worsening or, ideally, to encourage their improvement. Babina et al., (2023) validated the data by comparing it to data extracted from the *International Monetary Fund*, and the *UN Comtrade* and proved a high correlation. In addition, the customs data are based on invoices that may fluctuate the timing of imports or exports (Babina et al., 2023).

In addition to limitations in the data, the study only contained data up until 2023. It often takes time for the full effect of sanctions to materialize (Nelson, 2022). Our empirical analysis will examine the expectations of a future increase in oil production and a shift in ports used for exports. We will encounter these limitations using a different dataset (AIS) and a larger timeframe until May 31st 2023.

By using AIS, we will overcome some of the limitations encountered by Babina et al., (2023), as AIS data are broadly based on satellite receivers and offer extensive information on actual vessels location in high frequency (Smestad, 2015). The historical progression of AIS in tanker shipping reflects its evolution from a navigational aid to a multifaceted tool shaping operational practices. Initially adopted for safety purposes, AIS has become instrumental in addressing specific challenges unique to tanker shipping, particularly in oil transportation. The data extracted from AIS provides information on the true sailing distance between ports and provides adequate estimates of individual cargo sizes (see, e.g., Adland, Jia and Strandenes, 2017; Jia, Prakash and Smith, 2015). We will therefore contribute to the literature on the effect of the Russian embargo, and the specific paper from Babina et al., (2023) by using AIS data and a longer timeframe.

We are facing some limitations when we implement and build our research on AIS data. Silveira et al., 2014 and Emmens et al., 2021 prove that AIS, while being a significant tool for high-frequency research of the tanker market, also has its limitations. Harati-Mokthari et al., (2007) indicated that the destination identification in AIS could improve navigation safety, but data inconsistencies and vague or incorrect AIS entries for destinations were found.

When detecting suspected vessels going dark, there are some AIS data coverage limitations that must be encountered. When AIS was first implemented, it used VHF signals between base stations at the coast and vessels. This led to signals not being received when vessels were too far away (Carson- Jackson, 2012; Le Guyader et al., 2017; Šakan et al., 2018; Zhao et al., 2018). Between 2005-2008, S-AIS was implemented, solving some of the coverage problems but creating message collision problems (Alessandrini et al., 2018; Carson-Jackson, 2012; Høye et al., 2008). Silveira et al., 2015 and Emmens et al., 2021 found that AIS may lack significant coverage and provide wrongful or partial information, but more satellites are launched every year, improving the signal coverage (Skauen, 2019) However, closer to ports we face the possibility of message collision where clusters of vessels might have the same time slot for transmitting AIS signals. AIS does not function well in high-density areas (Carson-Jackson, 2012; Greidanus et al., 2015; Høye et al., 2008; Last et al., 2015; Tsou, 2010).

A significant limitation for analysing shipping and cargoes using AIS data is that the approach is only applicable where the cargo is observable and homogeneous (Adland et al., 2017). In our thesis, we will only analyse tanker vessels transporting crude oil in bulk, and the limitation will not affect our research. If future sanctions or embargoes against Russia or other countries were to be expanded to other commodities, it would be an essential limitation affecting, e.g., containerized cargoes where the content is generally unknown. Then, the usage of our methods and AIS data must be carefully evaluated before being effective and suitable.

Harati-Mokthari et al., (2007) researched the impact of humans on the accuracy of AIS data and found that the humanly inserted data such as destinations and draught is severely unreliable. Automatic transmitted data such as GPS were found to be highly reliable. The same paper showed that 80 percent of the AIS data contains errors. Human error is possibly a big problem in AIS transmission when transmitted manually (Harati- Mokhtari et al., 2007; Johansson et al., 2013; Tsou, 2010; Zhao et al., 2018; Alessandrini et al., 2019). Human error can also occur if the transmitter is installed or handled faulty (Harati-Mokhtari et al., 2007; Johansson et al., 2013).

During our process of detecting instances of suspected tankers going dark, specific filters and time thresholds are implemented to minimize unintended human errors that may occur. Manual interference, like shutting down the AIS to engage in illegal activities, has previously been explored (Mazzarella et al., 2015). Mazarella et al., (2017) used an anomaly detection algorithm and machine learning to identify AIS on-off switching. This thesis seeks for the vessels intentionally turning off their transmission, which is a substantial limitation in AIS data.

For data cleaning, AIS data is characterized by extensive volumes, and certain segments exhibit redundancy. Some papers have identified this concern as "data redundancy" (Pallotta et al., 2013) or labeled it as "noise" (Tsou, 2010). The process of cleaning AIS data is proved to be difficult (Zhao et al., 2018).

In conclusion, our exploration of the existing literature reveals that the identified limitations and complexities underscore the need for a robust and tailored methodology. The methodology, detailed in the following chapter, constructs a strategic approach to overcome the challenges highlighted in the literature review. We use the limitation of AIS transmission on and off switching in our model to detect suspected behaviour. To overcome the limitations of extensive volumes and coverage problems in the datasets, we apply geographical and vessel specific filters. As we shift our focus from theoretical considerations to practical implementation, the forthcoming methodology Chapter expresses the step-by-step procedures employed to extract meaningful insights from AIS data, offering a roadmap to address key issues when detecting suspected dark tankers.

3 Methodology

This chapter outlines the methodology and assumptions made for identifying suspected dark tankers from AIS data, through big data analytics and spatial analysis. The approach is structured into several stages: data collection, processing, filtration and combined spatial and temporal analyses. The filtration techniques in this methodology chapter displays important measurements to encounter key limitations of AIS-data.

Initially, the study involves acquiring and processing AIS data, focusing on identifying periods when vessels may purposely turn off their AIS transponders. The methodology leverages various data science and geospatial techniques. They include hexagonal tiling for spatial analysis and temporal pattern recognition to detect clusters of suspected dark activities.

Key elements of the approach include the use of advanced computational tools for data handling, spatial clustering to segment maritime space, and statistical analyses to uncover patterns in vessel movements. The integration of spatial and temporal data enhances the ability to scrutinize vessel behavior within specific maritime zones, identifying anomalies in standard tracking systems.

The methodological process can be split into three parts:

- *Establishing polygons in relevant areas*:
  In the first part, we aim to trim down the search area and create smaller hexagons for further analysis.
- *Filtering tankers based on vessel specific characteristics*:
  The objective is to trim the total fleet in the AIS dataset down to relevant tankers.
- *Determening suspected dark tankers*:
  After polygon creation and tanker specification, we aim to find clusters of areas where tankers may go dark within our polygons based on predefined thresholds.

The methodological overview is described, containing numerous sub-sections summarized in Figure 3.1 below.

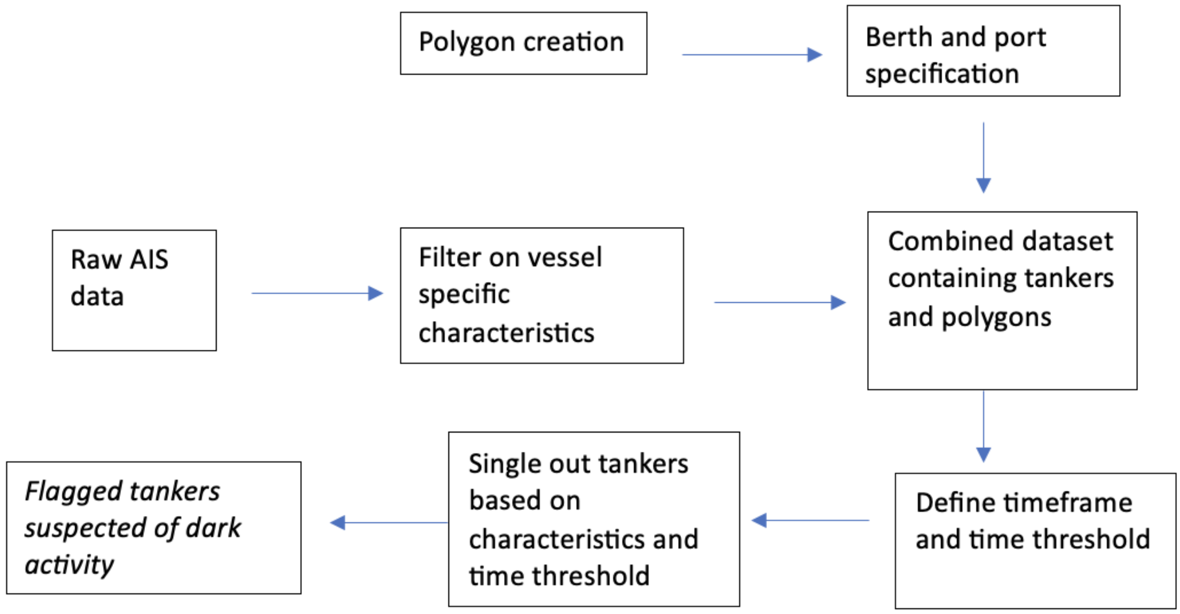


Figure 3.1: Data Flow Overview

3.1 Data Collection and Preparation

Given the vast number of vessels at sea, and the frequency of AIS transmissions, AIS datasets can quickly accumulate tens of billions of observations. Handling this type of data requires a well-considered data pipeline and a distributed computing environment to execute tasks within a reasonable timeframe with suitable processing capacity.

The AIS data from the United Nations Global Platform (UNGP) is stored in the AWS Simple Storage Service (S3)[2], and processing is done with a Spark Cluster[3] (similarly hosted on AWS). The system is based on a Kubernetes[4] cluster that reduces the complexity of running and managing the spark clusters, including the ability to scale up and down. We are then able to connect to the backend through the Data Mechanics Gateway API [5] (UNSD-C, 2022). This way, we can work locally in our Jupyter Notebook, integrated

[2]Amazon Simple Storage Service (S3) is a secure cloud storage service provided by Amazon Web Services (AWS) (Boisrond, 2021)

[3]Refers to a group of machines (nodes) that work together to process data using Apache Spark, an open-source, distributed computing system (Zaharia et al., 2010)

[4]Kubernetes is an open-source container orchestration system for automating software deployment, scaling, and management (Turin et al., 2020)

[5]An API, or Application Programming Interface, is a set of rules and protocols that allows different software applications to communicate with each other (Ofoeda et al., 2019)

with Ocean Spark. AIS data extracted from UNGP are provided by exactEarth [6], which combines its satellite data with terrestrial data from Fleetmon[7]. The company collects AIS messages from two different satellite constellations, totaling more than 65 AIS-equipped satellites, and also from the terrestrial-based network. The data contains live and global archive data from December 1th, 2018. In the data processing systems done at exactEarth, several validation tests are run to verify the accuracy of each AIS message (UNSD-B, 2020). This implies that the data available for us through the UNGP, is pre-cleaned by the service provider for advanced analytical techniques (UNSD-C, 2022).

Given the amount of data, we need to further filter our dataset to analyse and compute the aspired output, within a reasonable geographical structure.

3.2 Polygon Creation for Geospatial Analysis

For clustering and efficiency purposes, its important to establish precise search grids for ports and possible areas for potential dark activity. We design "polygons" as our search grids in relevant areas. By establishing these polygons we are able to remove noise from vessels outside of our areas of interest, reducing the dataset significantly. The creation of these polygons has also played an essential role in the use of time series and geospatial analysis.

Our analysis targets Russia's major oil exporting ports, with a specific emphasis on main oil exporters to Europe, in addition to the port of Kozmino in the North Pacific region. Port information has been retrieved from top exporting ports in Eastern and Western Russia, found in the Bruegel report from 2023 (Heussaff et al., 2023). This focus is designed to observe changes in production areas, especially those that are vital exporters to Europe. By selecting specific ports around the Russian-Pacific, Baltic, Arctic, and Black Sea regions, we have tailored our approach to concentrate on areas of high strategic importance.

To ensure a broader representation of port activity surrounding the areas, our study also includes additional ports that exhibit similar characteristics and significance within their

[6]exactEarth is a organisation in the field of global AIS vessel tracking, collecting comprehensive ship monitoring data (Miler & Bujak, 2013)

[7]Fleetmon, from KPLER, a company collecting real-time vessel position data (FleetMon, n.d.)

respective regions to ensure we get gain complete understanding. These supplementary ports have been identified, and their data was sourced from the World Port Index (WPI) database published by the National Geospatial-Intelligence Agency ("Maritime Safety Information", n.d.). Figure 3.2 refers to the port of Kozmino and our designed search area around the center of the port.

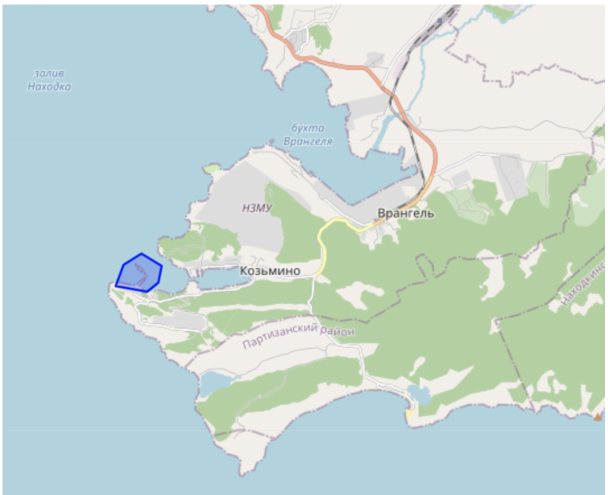
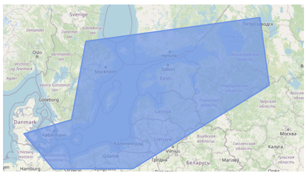
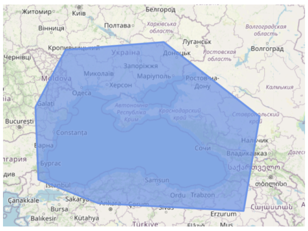


Figure 3.2: Port of Kozmino

The use of extended polygons around these ports serves multiple purposes. Primarily, it acts as an effective filter for our dataset, allowing us to eliminate excessive noise and focus exclusively on vessels of interest. This filter is instrumental in reducing complexity and enhancing the accuracy of our geospatial analysis. Furthermore, these polygons facilitate a more manageable and focused analysis of AIS signals and vessel movements. By confining our study to these selected areas, we can more effectively monitor and analyze the patterns of vessel activity. This is particularly relevant in observing changes in port activities, and in response to external factors such as the imposition of the Russian seaborne embargo. Figure 3.3 displays the areas defined as our polygons around strategic ports, where we retrieve AIS data for detection and analysis.



(a) The Baltic Sea



(b) The Black Sea

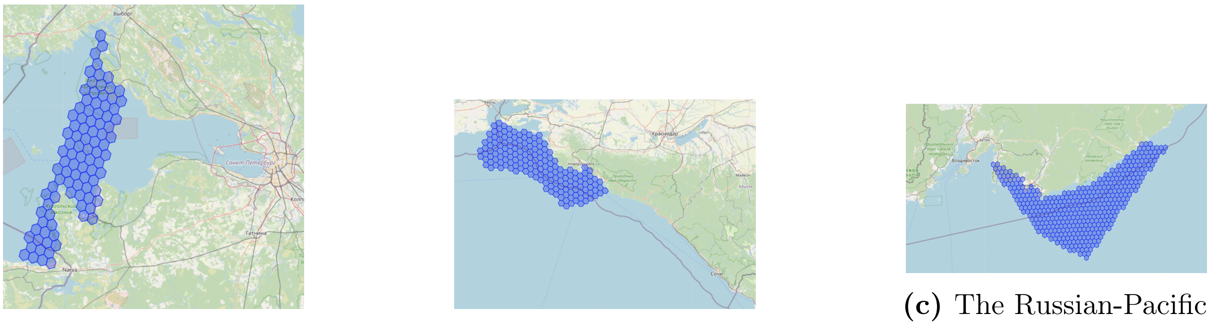
(c) The Russian-Pacific Sea

Figure 3.3: Areas of Interest Polygons

Our strategy to generate these polygons was to identify the regions where cargo activity was dense. For this purpose, we use AIS navigational status categories. AIS transmissions contains label information about the vessels current movements. The vessels should transmit correct signals for operations to avoid collision risk. Examples include whether a vessel is under sailing, is moored, is at berth or has restricted maneuverability. We use AIS navigational status "at berth" to identify operations while alongside a terminal and with "restricted maneuverability" to identify potential ship-to-ship (STS) operations. This is based on AIS data from before the invasion, when no incentive was in place to hide their activities. We use the defined polygons as geographical restrictions for our detection search after suspected vessels that go dark.

3.2.1 Partitioning the Hexagons

After identifying our areas of interest surrounding the ports, we generated a hexagonal grid within the regions of interest shown in Figure 3.4. This is done to partition areas for better visualization and clustering of dark events. The polygons are converted using the Python API of the H3 library accessible through the UNGP data library. The H3 geospatial indexing system is a discrete global grid system consisting of a multi-precision hexagonal tiling of the sphere with hierarchical indexes (“H3geo-A”, n.d.). The index offers sixteen distinct levels of cell resolution, which encapsulates the Earth with 122 cells at resolution $= 0$, extending to over 500 trillion at the highest resolution. Each cell within the H3 framework is uniquely identifiable by string and integer identifiers, streamlining the handling of large datasets. The hexagonal grid’s uniform shape, covers spherical surfaces like the Earth with hexagons of identical size. One of the main advantages of using hexagonal cells in grid systems, is that each cell is the same distance from its neighbors, which helps to keep measurements consistent ("H3geo-B", n.d.).



(a) The Baltic Sea **(b)** The Black Sea **(c)** The Russian-Pacific Sea

Figure 3.4: Berth Areas with Inserted Hexagons

To use the highest resolution possible, the areas of interest shown in Figure 3.3 are subdivided into specific zones, such as berth and port areas. This approach significantly streamlines the identification of hotspots, where a higher amount of incidents of suspected tankers going dark is observed. By focusing in these areas we can infer potential risk zones or areas of interest that need closer surveillance. The hexagons consistency in shape and size ensures that comparisons across different port areas are accurate and meaningful, enhancing our findings reliability. The polygons defining our entire areas of interest are outlined at a hexagonal resolution of four, which would mean that it fills the world with 288.110 hexagons ("H3geo-A", n.d.). The berth-specific polygons are outlined at a hexagonal resolution of six, consequently filling the area around the world with 14.117.870 hexagons, providing a detailed representation as shown in Figure 3.4.

3.3 Finding the Suspected Dark Tankers

3.3.1 Base Assumptions

Now that the search area and hexagonal grids are defined, we must filter the dataset on vessel characteristics to get the desired tankers capable of transporting our desired amounts of Russian crude oil. The filters and general idea of identifying suspected dark tankers set to the vessels and areas are determined based on our assumptions. This subsection will cover these assumptions and how they affect our analysis.

Assumption 1: Larger vessels conduct the transfers.

The first assumption covers the size of the tankers and how they are filtered and categorised. We filter based on size and DWT to remove noise from smaller vessels. By removing smaller vessels, we aim to concentrate on vessels most likely to carry a uniform and large volume of oil cargo. As seen in Figure 3.5, when focusing on the larger vessels, we filter out many of the tankers carrying refined products, while the thesis focuses on crude oil products.

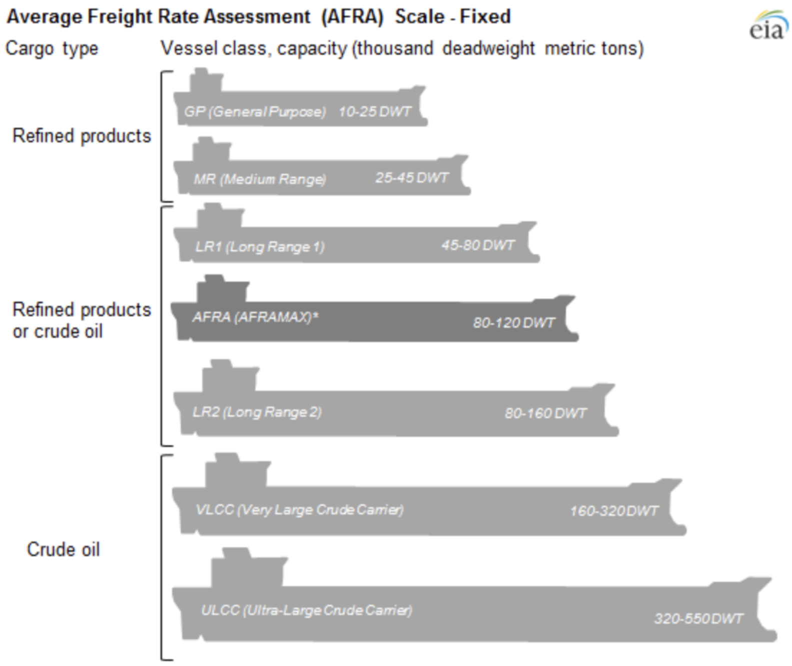


Figure 3.5: Vessel Sizes (EIA, 2014)

Assumption 2: From certain ports, straits and berths you cannot hide.

Our second assumption addresses the variety in effectiveness of suspected vessel detection, depending on geographical segments and AIS transmissions. The assumption is based on the fact that vessels deliberately turn off their AIS to avoid detection by Western monitoring systems. Particularly when they sail to and from Russian ports for the purpose of retrieving sanctioned oil shipments. This tactic is predominantly employed, as the vessels navigate through straits controlled by NATO member states and other nations enforcing sanctions. This allows them to reach their destinations without revealing their positions or movements. Given our defined areas, the assumption is that we expect to see suspected vessels going dark between straits and Russian ports.

Further, we incorporate a Speed Over Ground (SOG) criterion from the AIS transmission information. We set required sailing speed to more than three knots to distinguish between vessels actively navigating and stationary/moored vessels. This distinction is vital to focus our surveillance efforts on ships in active transit. Particularly those approaching or leaving Russian ports, and to avoid potential misinterpretations from non-moving ships.

Assumption 3: Tankers switch off their AIS to avoid being followed in real time.

The third assumption is that tankers switch off their AIS to avoid being tracked in real-time. The intuition behind this assumption is the potential desire for these vessels to evade real-time tracking, mainly when involved in STS transfers. During these crucial periods, leading up to and amid STS operations, vessels might be most inclined to conceal their location and activities. This is a substantial challenge in using AIS data to track maritime activities, as we cannot follow them while dark. Recognizing this limitation, our study does not account for potential spoofing or other forms of AIS manipulation. However, we aim to contribute to further research by identifying clusters of locations where we suspect tankers to commonly go dark. It's important to note that our reliance solely on AIS data is a limitation, as we cannot accurately track vessels that turn off their AIS or engage in spoofing.

3.3.2 Vessel Specific Criteria/Model Specification

After our base assumptions are made, we are ready to examine the next part of our model. The process of concentrating the dataset on our focused group of maritime vessels. These are earlier categorised as larger DWT oil tankers; Aframaxes and bigger ref. Assumption 1. The initial step involved extracting tanker-specific data from the broader AIS dataset. This process required a detailed examination of the vessel type attribute, explicitly targeting those classified as "Crude Oil Tanker" and "Crude/Oil Products Tanker." Such a classification ensured that the study was centered around vessels likely involved in the maritime activities of interest.

As stated, we target larger tanker vessels capable of carrying substantial volumes of Russian crude oil. So, as a secondary criterion, the DWT criterion of the vessels was utilized to refine the dataset. This parameter, denoting the carrying capacity of a vessel, served as a filter to focus on larger vessels that are more relevant in the context of maritime surveillance and monitoring. Specifically, the study targeted tankers with a

DWT exceeding 80,000, a threshold that helped isolate vessels of substantial size and operational capacity.

In line with our second assumption, we also applied a filter based on these vessels Speed Over Ground (SOG). We set a parameter for the SOG equal to or greater than three knots. Coupling this SOG criterion with the DWT threshold allows us to concentrate our dataset further. Concluding, we focus on larger vessels, specifically those with a DWT exceeding our minimum set capacity, and ensuring these vessels are actively moving at speed. This indicates operational behavior, thereby enhancing the relevance and accuracy of our analysis based on the mentioned assumptions.

Upon successfully identifying the relevant tanker vessels, the next step involved structuring this information into organized dataframes. These data frames were constructed for vessels identified by their unique identifiers - the International Maritime Organization (IMO) numbers and the Maritime Mobile Service Identity (MMSI) numbers. The IMO number, a unique seven-digit number assigned to maritime vessels, was pivotal in creating distinct records for each vessel (IMO-B, n.d.). We then merged the two datasets based on their vessel ID. We prioritized the IMO number, but used MMSI if IMO identification was not present to get all available vessels. IMO number is preferred over the MMSI as it is mandatory for all cargo ships carrying over 300 gross tonnage, and stays as a permanent indicator for each vessel (IMO-B, n.d.), as opposed to the MMSI identification.

This tracking and filtering process was instrumental in narrowing the dataset down to a manageable and focused subset. It could then act as fundamental groundwork for the subsequent analyses. By establishing these refined data frames, the study provided a robust foundation for in-depth spatial and temporal analyses of tanker movements. Furthermore, the vessels' behaviors in the context of identifying dark tanker activities within the maritime domain.

3.3.3 Determining Suspected Dark Tankers

When the tankers are correctly filtered to our purpose and polygons are specified, we can analyze and determine our suspected dark tankers. Our methodology for identifying these vessels is based on time thresholds, utilizing histogram analysis and specific time criteria derived from our dataset. The intuition behind the approach is tied to the limitations of draught and destination found by Harati-Mokthari et al., (2007), which could be alternative measures to detect vessels. Based on previous research, using determined time thresholds is the most suitable detector to catch signal anomalies from AIS data.

Model 1: Histogram Analysis

We employ a histogram analysis to understand the typical behavior of vessels within our areas of interest. We create histograms using combined IMO and MMSI data, considering various time intervals. As a part of our analysis, we want to understand the standard operational patterns of vessels within our polygons. To achieve this, we analyzed AIS data from the start of 2021 until the date of the embargo, December 5th, 2022. This pre-embargo period provides a comprehensive dataset to establish a benchmark for "normal" AIS signaling behavior. We included 2021 to correct for seasonalities and cycles which are typical for shipping markets (Stopford, 2009). This analysis is crucial as it sets the baseline against which we can compare future vessel behaviors to spot deviations or anomalies. We calculate the time difference between consecutive AIS signals for each vessel. This is achieved by comparing the timestamps of successive AIS transmissions. The time difference indicates the "normal" frequency at which vessels broadcast their position, speed, and other vital information.

To visualize and analyze these time differences, we construct histograms. In these histograms, the x-axis represents the time difference between AIS signals, and the y-axis displays the frequency of occurrences for these intervals. We divide the time differences into bins, each representing a specific time interval. This binning helps us to categorize and understand the distribution of time intervals in the AIS data.

From our histogram analysis, we retrieved values for the median, 95th and 99th percentile, intended to use as minimum thresholds for the detection model for suspected dark vessels. «Going dark» were defined as those vessels whose time difference between AIS signals is in the 99th/95th/median percentile. These percentiles is a statistical measure indicating that the time difference for the vessels is higher than 95/99 percent of all other vessels in the dataset. Such extended periods between AIS signals are categorised as abnormal, and the vessels are flagged for further investigation. Using PySpark[8] functions, we filter

[8]PySpark is the Python API for Apache Spark. Enabling you to perform real-time, large-scale data processing in a distributed environment using Python (Spark.apache, 2023)

vessels that meet this criterion and identify their last known positions before potentially going dark. This method involves partitioning the data by vessel ID and aggregating the data to understand the frequency and characteristics of the events. The final step consists of partitioning the filtered data by vessel ID and aggregating it to study the frequency and attributes of the dark events. This aggregation includes counting the number of times each vessel went dark, determining their last known coordinates, and identifying the timestamp of their previous AIS signal. This comprehensive analysis allows us to understand not just the occurrence of these cases, but also their context and potential implications.

Model 2: Maximum and Minimum Threshold

Our second model for flagging dark tankers uses maximum and minimum thresholds. The duration of ship-to-ship transfer defines the thresholds and finds future hot spots where this kind of activity can be present. The duration for completion of these transfers varies based on the quality of the cargo and weather conditions. Usually, transshipment is completed after 10-24 hours (Witkowska et al., 2017), which is the threshold we have set in the thesis.

Establishing Time Thresholds for STS Transfers

Minimum Threshold: The minimum time threshold is established based on the shortest expected duration of a typical STS transfer. This duration accounts for the time needed for vessels to maneuver into position, secure the transfer, exchange cargo, and disengage. The minimum threshold is crucial to filter out regular vessel activities shorter than a standard STS operation, such as brief docking or anchoring events.

Maximum Threshold: Similarly, the maximum time threshold is set based on the most extended reasonable duration for an STS transfer. This accounts for potential delays or extended operations but is calibrated to exclude unusually long periods that might indicate other activities or vessel statuses.

By applying these thresholds, we can help predict future hot spots of STS activity. We identify areas where vessels repeatedly "go dark" within these timeframes, suggesting potential locations for unauthorized STS operations. An overview of the flagging and detection module is shown in Figure 3.6 below.

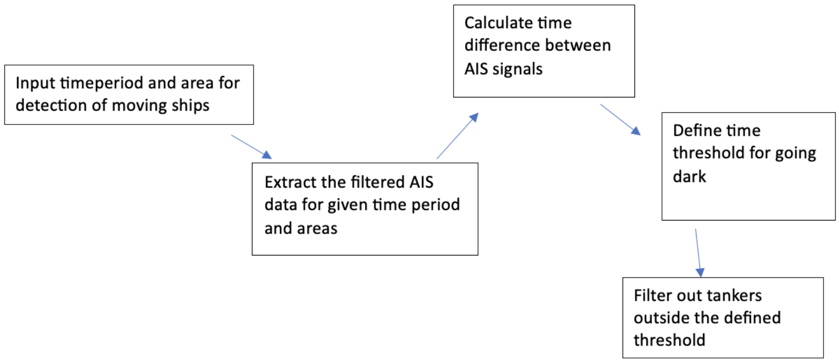


Figure 3.6: Methodology for Flagging of Suspected Dark Tankers

3.3.4 Orbis & the Integration of Satellite Data

Leveraging Orbis for Ownership and Vessel Information

To deepen our understanding of vessels and their associated entities, we leverage the Orbis database. A comprehensive global resource that provides intricate details on vessel ownership, management, and historical data (Orbis, n.d.). This information is crucial for our analysis, especially given maritime ownership's complex and often opaque structures. The AIS data alone cannot provide us with the nuanced information required to unwind the intricate layers of ownership. Thus, Orbis becomes a valuable tool in our investigative arsenal, enabling us to conduct thorough research on the vessels that are suspected to operate under the radar.

Ownership and Management Details: Orbis provides insights into the global ownership structures of flagged vessels (Orbis, n.d.). Understanding who owns and operates these tankers can be crucial in unraveling the networks behind potentially illicit maritime activities.

Verification of Flag and Name Changes: We use Orbis to double-check the flags under which these vessels operate and to track any changes in their names. Such changes can be indicative of attempts to evade detection or sidestep regulations.

Historical Analysis: The website also allows for a historical analysis of the vessels. Providing us with concrete information about their past activities and possibly suspected operations. This gives us a better understanding of vessels that may be objective to future sanctions.

Integration of Satellite Data

In the pursuit of identifying suspected dark tankers, our current approach is centered on an AIS-based analysis. While this method effectively flags potential dark activities, the scope of surveillance could be significantly broadened by integrating satellite data—an effective weapon to help distinguish genuine instances of AIS deactivation from data gaps or anomalies.

While our current system provides a solid foundation for monitoring, the additional layer of satellite data could offer a nuanced understanding of maritime behaviors. It could enable us to verify vessels suspicious activities more precisely and provide a detailed maritime domain awareness.

Considering satellite data integration into our surveillance framework remains a prospective avenue for future development. The integration of satellite surveillance in combination with AIS filtering has the potential to set a new benchmark in maritime transparency and security by closing the loopholes exploited by vessels going dark.

4 Analysis and Results

Chapter 4 delves into the findings of the suspected dark tankers. Section 4.1 details our approach for establishing time thresholds using histogram analysis, a crucial step in understanding tanker behavioral patterns. Section 4.2 shifts focus to the visualisation of suspected dark tanker activities, presenting quantity evolution and heatmaps highlighting areas of substantial activity. Finally, Section 4.3 conducts a sensitivity analysis on the time thresholds, assessing their impact and effectiveness in our overall analysis. This chapter contributes with detailed analysis and precise visual representations to give a thorough understanding of suspected dark tanker activities and their broader strategic impact.

4.1 Time Thresholds

Determining time thresholds for our suspected dark vessel detection model is crucial for rational and concise results. We decided to try several measurements to estimate legitimate thresholds, which we expected to be in the range of an average ship-to-ship transfer duration period, as clarified in the methodology chapter. We compute different estimates for our three relevant areas to adapt to geographical differences. Based on these results, we found integrating fixed minimum and maximum thresholds for our analysis beneficial. Differentiated percentile-based minimum thresholds resulted in approximately 50 percent of all tankers being suspected of conducting sanctioned activities. The sensitivity analysis in Section 4.3 further elaborates on the importance of finding accurate thresholds in our model. The following illustrated results are based on the pre-embargo period to set a benchmark for minimum thresholds in our vessel detection model for suspected dark tankers.

Figure 4.1 below is a histogram illustrating the time differences between AIS signals for filtered tankers within our designated polygon in the Baltic area. The histogram illustrates a 99th percentile time difference of 0.5 hours, 95th percentile time difference of 0,19 hours, and median of 0,11 hours.

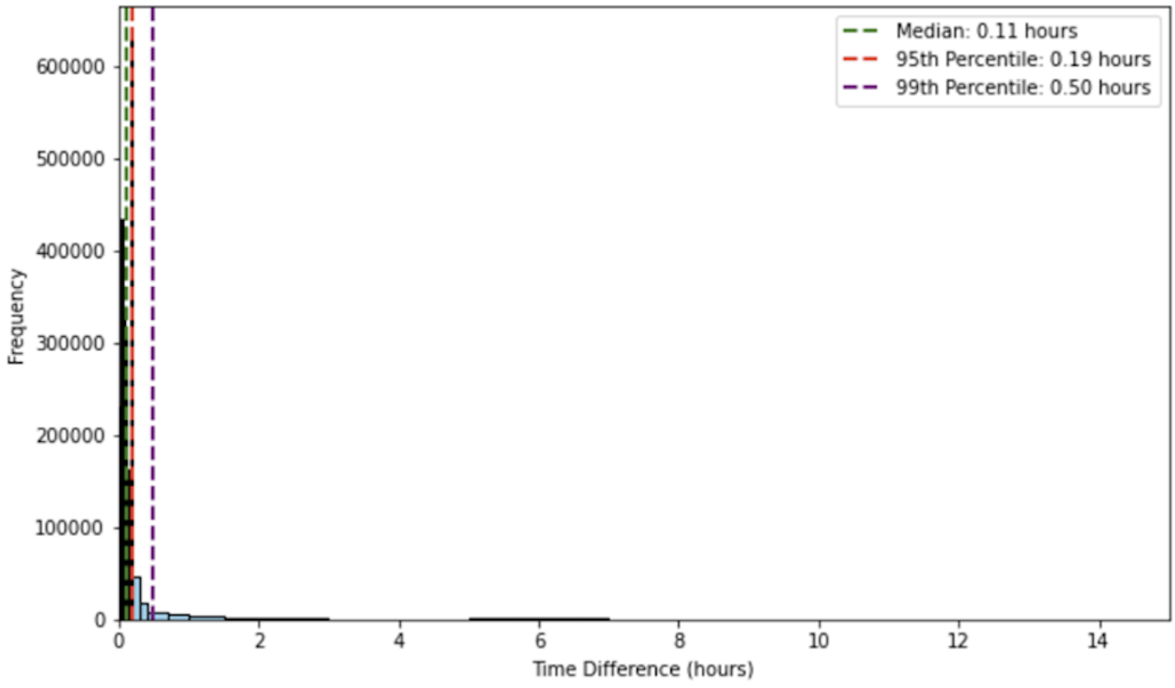


Figure 4.1: Histogram of Time Differences for the Baltic Sea

Figure 4.2 below is a histogram illustrating the time differences between AIS signals for filtered tankers within our designated polygon in the Black Sea. The histogram illustrates a 99th percentile time difference of 4,81 hours, 95th percentile time difference of 0,6 hours, and median of 0,17 hours.

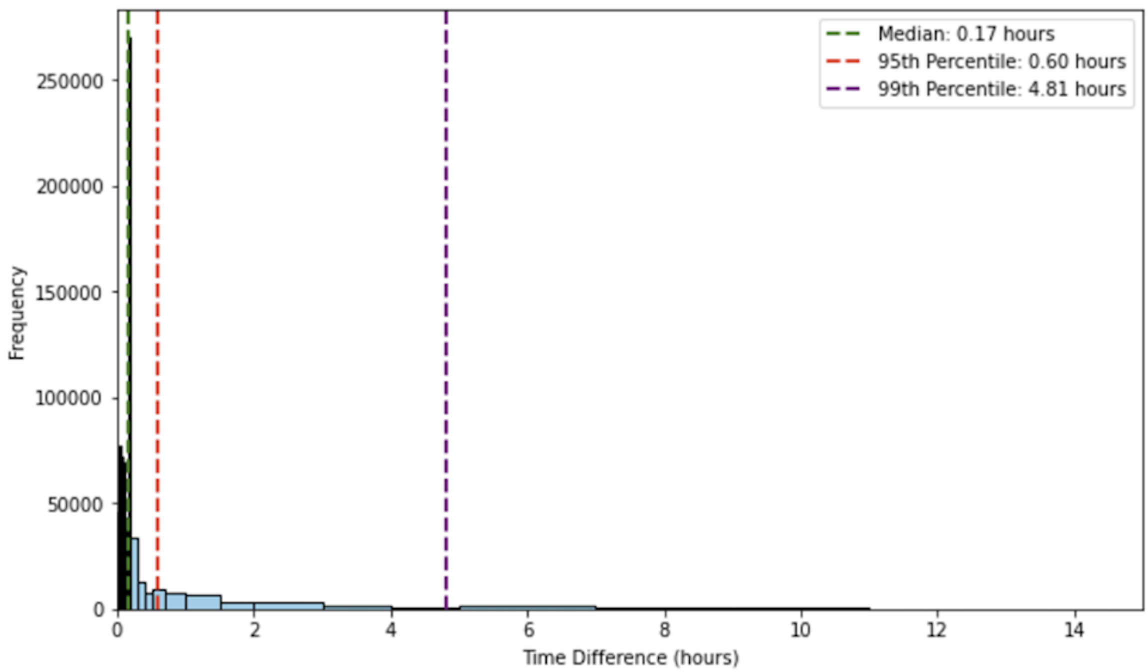


Figure 4.2: Histogram of Time Differences for The Black Sea

Figure 4.3 below is a histogram illustrating the time differences between AIS signals for filtered tankers within our designated polygon in the Russian-Pacific area. The histogram illustrates a median 99th percentile time difference of 4,16 hours, 95th percentile time difference of 0,55 hours, and median of 0,1 hours.

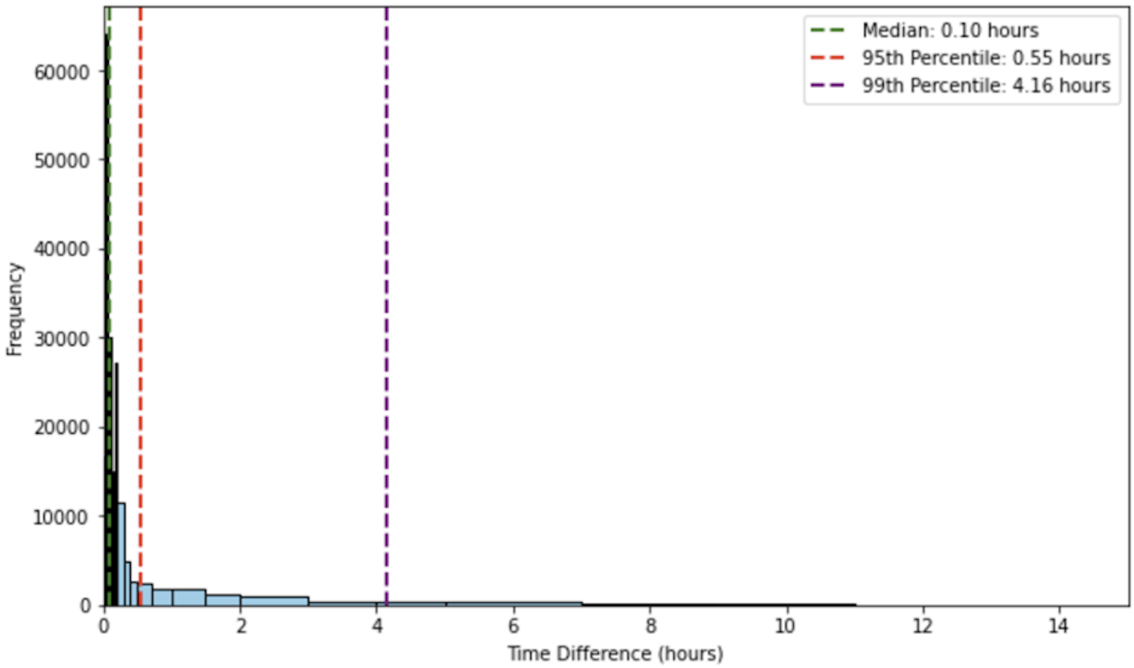


Figure 4.3: Histogram of Time Differences for the Russian-Pacific Sea

Table 4.1 displays the summary of the pre- and post-embargo results for our estimation of benchmarks. The illustrations for the post-embargo period can be found in Appendix A.

	Baltic	**Black Sea**	**Russian-Pacific**
Pre			
Median	0,11	0,17	0,10
95th	0,19	0,60	0,55
99th	0,50	4,81	4,16
Post			
Median	0,11	0,17	0,08
95th	0,18	0,95	0,30
99th	0,45	8,40	1,62

Table 4.1: Percentile Estimates

After examining the three categories for post-embargo percentiles, we find the 99th percentile most interesting. This is because we start seeing transmission times between AIS signals closer to what we expect for an average STS operation.

For the post-embargo period we found the 99th percentile for the Baltic area slightly decreasing from 0,5 to 0,45 hours. For the Russian-Pacific we saw a decrease from 4,16 to 1,62 hours. These decreases could be explained by seasonality or the shorter timeframes. They could also be related to suspected dark vessels. On the other hand, the Black Sea registered an increase in the 99th percentile by 3,59 hours. This increase could also be related to increased suspected dark tanker traffic, driving the threshold times upwards. These findings will be further addressed in Section 4.2 under suspected dark tanker activity.

The 99th percentile was intended as a minimum threshold for suspected dark vessel detection. However, we observed the results of the pre-embargo 99th percentile as a minimum threshold, to be too low for potential STS. They included excessive possibilities for ordinary ship operations inside the polygons.

Without a maximum threshold, moored, anchored or vessels that stopped transmitting because of in-sailing to port were included in our results and mistakenly suspected as a dark vessel. This also leads to an exaggerated amount of flagged incidents. When using a plausible STS timeframe as a minimum and maximum time threshold, we eliminate noise and focus on vessels with sufficient time to conduct STS transfers or in-port loading.

Because of the complications and noise using the 99th percentile, we have used maximum and minimum thresholds based on the average completion time for STS transfer. By using time thresholds based on estimates from Witkowska et al., (2017), we are left with the vessels that are in a plausible STS timeframe. These thresholds also correct for the wrongly flagged vessels in the 99th percentile. Because of this, Section 4.2 proceeds with the minimum ten and maximum 24-hour threshold.

4.2 Detecting the Dark Fleet

The filtering for the detection of suspected dark vessels is available in the methodology chapter. In this section the results from our detection process are presented. The first results illustrated are Figure 4.4; a time series analysis for all three polygons from the start of the embargo. The figure illustrates weekly new detection of suspected dark vessels for all three polygons. There are some overlaps of unique vessels across polygons, which are addressed. These are summarized in Table 4.5.

The visualisation in Figure 4.4 illustrates an apparent increase in weekly new suspected dark vessels from the initiation of the embargo on the 5th of December 2022 until the end of May 2023. We especially see more new suspected dark vessels building up in the Black Sea. There it increases steadily to a top of 18 weekly unique new incidents towards the end of our dataframe, maintaining a high trend, but high volatility. Figure 4.5 displays the same results with a 30-day rolling average for better visualisation of trends.

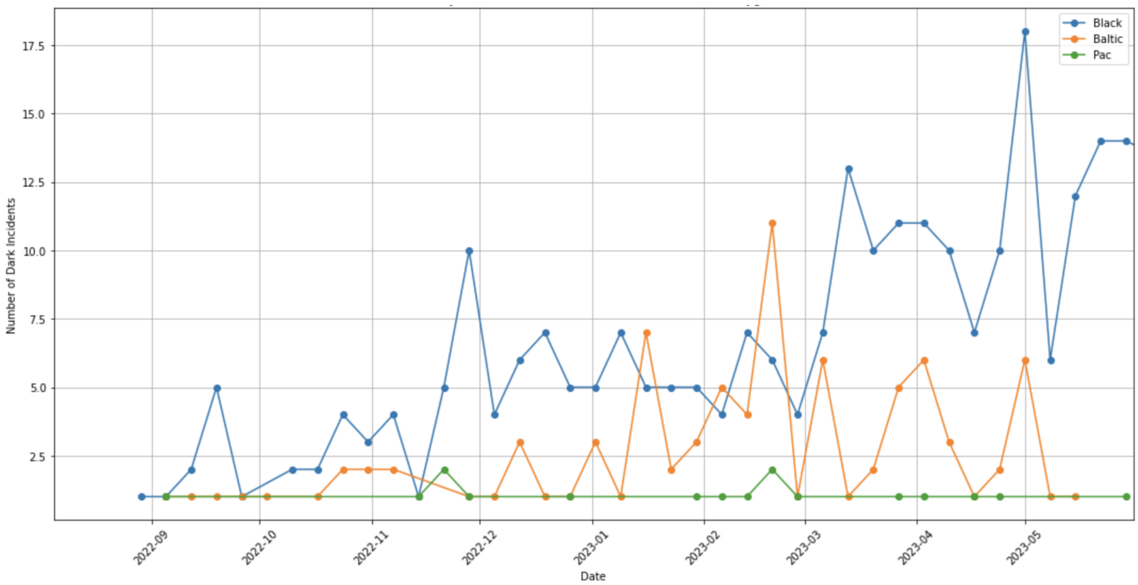


Figure 4.4: Suspected Unique Dark Vessel Detection Black, Baltic and Russian-Pacific Sea

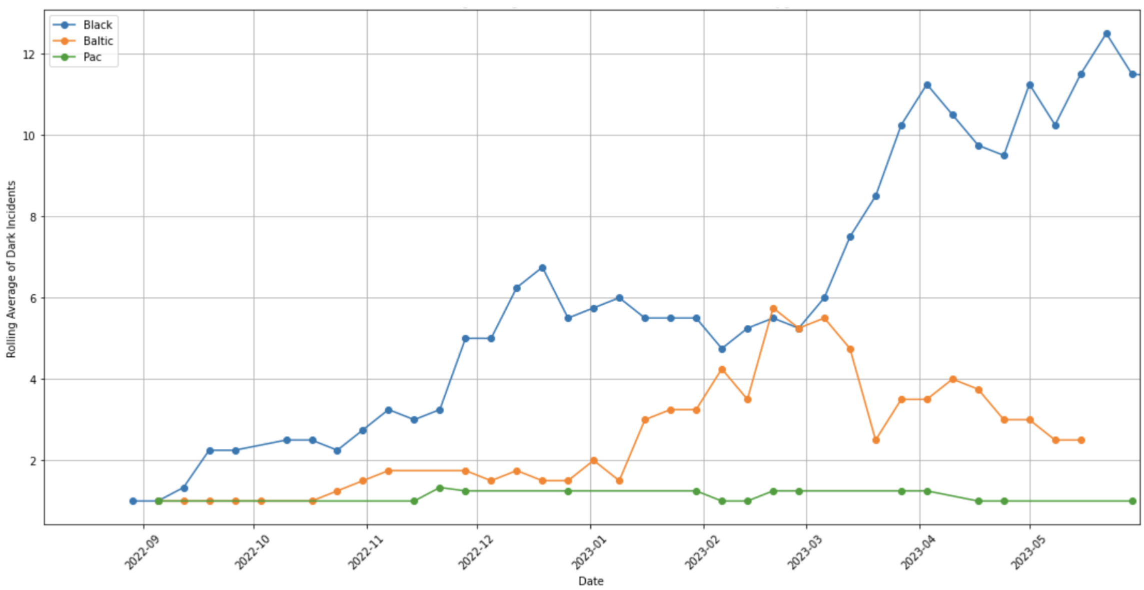


Figure 4.5: 30-Day Rolling Average, Unique Suspected Dark Vessel Instances Black, Baltic and Russian-Pacific Sea

Figure 4.4 and Figure 4.5 reveals a substantial surge in the weekly count of new unique vessels exhibiting suspected dark behavior, particularly notable during the second half of our timeframe. The figures show a spike in approximately week eight for the Baltic and Russian-Pacific. Around the same time as the G7 price cap was implemented on Russian petroleum products. In that specific week, we observed the highest number of weekly new suspected dark incidents for the Baltic with 11 instances, and in the Russian-Pacific with 2. We don't observe the same spike in the Black Sea for the week in question, but the week is the start of a period with continuous growth of new unique additions to the suspected dark fleet.

In addition to the intuitively visualized increasing trend in the Black Sea, the Baltic also displays an increasing trend. This is best visualized in Figure 4.5 with a 30-day rolling average. There is increasing volatility until the spike in week 8, 2023. We record a standard deviation of 1,90 before week 7, and 3,07 after week 7. Implying higher volatility in the post period. In support of this, six weekly incidents of unique suspected dark vessels were routinely recorded compared to the pre-embargo period and up until the spike in week 8. This results in a higher trend, with a weekly average of 3,54 for the Baltic. Before the spike, the average in our data period was 3,00. The Baltic has a more stabilized trend of new suspected incidents compared to the Black Sea, which is constantly increasing.

Opposed to the Baltic, the Russian-Pacific polygon displays a smaller cohort of new weekly vessels marked as potentially engaging in dark activities. This outcome aligns with expectations, given the fewer incentives for vessels to deactivate or use their AIS in the Russian-Pacific region. Vessels engaging in illegal activity and transporting Russian crude oil traded above the cap out of this area, don't need to pass through or by NATO countries or other countries in support of the current sanctions. This effect contrasts the Black Sea and the Baltic, where vessels pass by NATO countries and other Western countries supporting the sanctions. In the strait of the Baltic and the Bosphorus strait out of the Black Sea, the vessels are required to maintain a steady AIS transmission and can be easily spotted from land (Kpler, 2023). In addition, our defined polygon in the region doesn't include the strait out of the Russian-Pacific Sea, because we found it irrelevant to the area.

Aligning with the appearance of new and steady growth of the suspected dark fleet, we also see an increase in total suspected dark activity, better shown in Figure 4.6. From the statistics, we see much of the same increasing trends as in Figures 4.4 and 4.5.

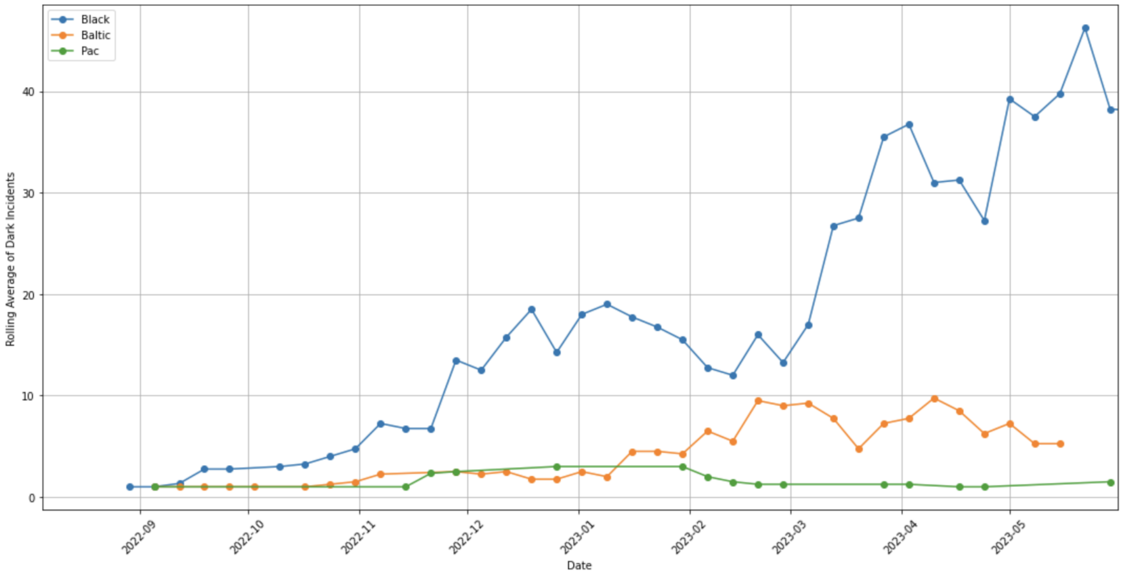


Figure 4.6: 30-Day Rolling Average, Weekly Suspected Dark Activity

The figure visualises an increasing trend of weekly suspected dark activity in the polygons. From the imposition of the embargo 5th of December 2022 and until May 31st 2023 we record 674 instances of suspected dark activity in the Black Sea. The weekly average is 26,64, compared to 6,07 before the embargo. In the Baltic the total suspected occurrences increases from 16 to 136, and in the pacific from 10 to 16. The low activity in the Russian-Pacific is, as earlier described, expected. The volatility also increases substantially for the Black Sea and the Baltic, from 8,20 to 15,81 and from 1,10 to 5,49 respectively. Table 4.2 displays the computed averages and standard deviations for the polygons before and after the implementation of the price cap 5th of December 2022.

	Baltic Sea	**Black Sea**	**Russian-Pacific Sea**
Average			
Pre-price cap	1,14	6,07	0,71
Post-price cap	5,44	26,64	0,64
Std.dev			
Pre-price cap	8,20	1,10	1,49
Post-price cap	15,81	5,49	0,91

Table 4.2: Averages and Standard Deviations of Dark Activity Before and After Price Cap Implementation 5th of December 2022

The increased dark activity could affect our estimated thresholds examined in Section

4.1. The more dark activity, the higher the percentiles will be. This also underscores the importance of using pre high-dark activity periods as benchmarks.

By examining the total suspected dark activity results, we measured a severe change in the amount of dark activity compared to the amount of unique suspected vessels. The findings of suspected dark activity per vessel are tabulated in Table 4.3. The table displays the Russian-Pacific registering a low count of suspected dark activity, with relatively fewer vessels to the activity. This results in a lower count of suspected dark activity per vessel, with each vessel going dark 1,33 times. For the Baltic Sea and Black Sea, we see a higher frequency of suspected tankers going dark multiple times, with an average of each vessel going dark 1,78 and 3,15 times, respectively.

Which for the Black Sea can be interpreted as;

- Each suspected vessel performs more dark activity, or
- the suspected dark activity is conducted by fewer vessels.

	Dark activity	**Dark Vessel**	**Frequency of going dark**
Baltic Sea	137	77	1,7792
Black Sea	674	214	3,1495
Russian-Pacific Sea	16	12	1,3333

Table 4.3: Suspected Dark Vessel Activity

Like our previous findings, this would suggest a higher level of suspected dark activity within the Black Sea and the surrounding Russian ports.

Table 4.4 displays the total count of unique suspected dark vessels recorded since the initiation of the oil embargo on December 5th, 2022, and until May 31st, 2023. For clarification, if a vessel has been detected twice or more inside the same polygon, the table counts it once.

Baltic polygon:	77
Black Sea polygon:	214
Russian-Pacific polygon:	12

Table 4.4: Number of Dark Tankers in Various Polygons

For our relevant timeframe from the implementation of the embargo until the 31st of May 2023, there are six instances of vessels being detected in two polygons. The instances of overlapping unique vessels suspected of going dark are visualized in Table 4.5. There are overlaps between the Baltic and the Black Sea. There is no registered overlapping of unique suspected vessels between the Baltic and the Russian-Pacific or the Russian-Pacific and Black Sea polygons within our timeframe.

Baltic & Black
9728241
9529475
9262924
9389071
9276597
9749556
Count
6

Table 4.5: Overlapping Vessel IDs and Count

The overlapping in polygons from Table 4.5 elaborates on the fact that there are 297 [9] unique vessels suspected of going dark. For our relevant tanker segment of vessels able to carry crude oil with a DWT of over 80.000, there are approximately 2077 vessels in the world's total fleet (DWT>80.000) (Banchero Costa, 2022). The portion of the total fleet which are categorized as suspected participants of the dark fleet by our model is approximately 14,29 percent[10] in the timeframe.

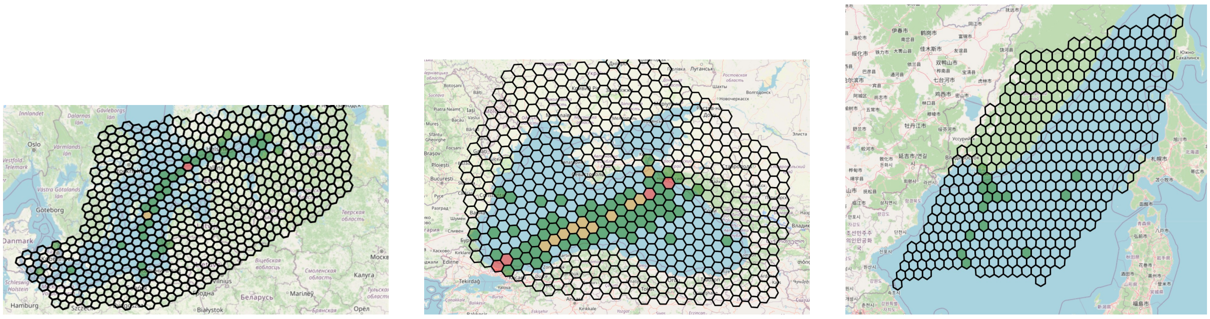
Our model for detecting suspected dark vessels has so far filtered the world's total tanker fleet down to 14,29 percent. For further geographical filtration we will now illustrate areas with heightened suspicion of illegal maritime activities. These incidents captured by our model are visualized in heatmaps for each of the three polygons. They demonstrate that we have geographical locations and coordinates for the unique vessels. In addition, we have the timestamps for when they go dark, which also substantially decreases the search windows for the suspected vessels. The vessel specifics are elaborated on in Section 4.4.

In the heatmaps depicting suspected vessels going dark, the hexagons are colored based on specific criteria, offering insights into the level of suspicion for illegal maritime activities. The colors indicate the quantity of suspected vessels within each hexagon, visually representing the density and intensity of potential dark vessel incidents.

[9](77 Baltic+12 Pacific+214 Black Sea) - 6 overlaps, equals 297 unique suspected vessels.

[10]297 unique suspects / 2077 total vessels in relevant fleet, equals to 14,29 percent of the total tanker fleet (>80.00 DWT) being suspected of dark activities.

Figure 4.7 illustrates the first series of heatmaps. Red indicates areas where the count of suspected vessels going dark exceeds or equals to 20. Orange represents areas with counts between 10 and 20 suspected vessels. Green denotes areas with at least one suspected vessel but fewer or equals to 10. This color scheme allows for a nuanced understanding of varying levels of suspected dark vessel activity, with red signifying higher concentrations and green indicating lower but still noteworthy instances.



(a) The Baltic Sea **(b)** The Black Sea **(c)** The Russian-Pacific Sea

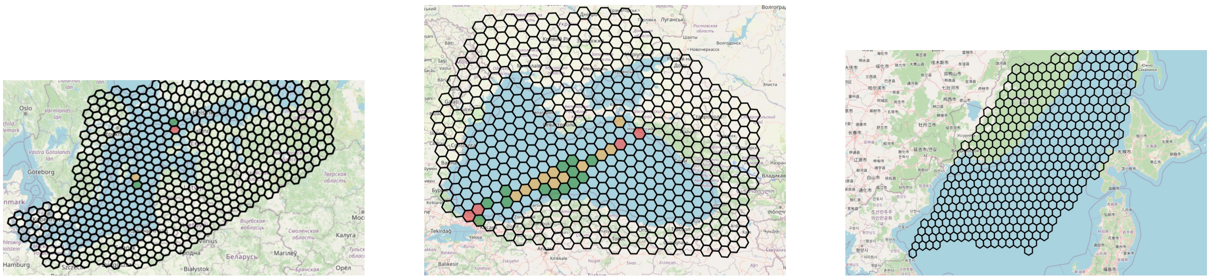
Figure 4.7: Polygon Heatmap Suspected Vessels Going Dark

Our visual geographical findings in the presented heatmaps indicate some specific areas with higher concentrations of unique suspected dark vessel incidents. An especially high concentration of vessels is seen in Figure 4.8b Black Sea, out of the Bosphorus strait and into the Black Sea. In line with assumption two, and as mentioned earlier, vessels pass by NATO countries when sailing through the strait and are visible from land. They are therefore required to have continuous AIS transmissions. However, they can interrupt the transmission when entering the Black Sea and navigating towards ports exporting Russian crude oil. The whole sailing route from the Bosphorus strait and into Novoryssisk port is highlighted, with "red" hexagons (>20 unique vessels detected) out of the strait and before the port of Novoryssisk.

For Figure 4.8a The Baltic Sea, we see the same pattern as in the Black Sea, with a continuous highlighted route from the strait out of Sweden/Denmark and towards Russian ports. A specifically dense area of suspected dark vessels is before the Viro strait, connecting Finland and Estonia. We expected to see such high density of detected suspected vessels going dark after passing through the strait into Russian waters, not before.

For Figure 4.8c the Russian-Pacific Sea, we see hexagons being marked as green (>5 unique vessels detected) without specific patterns. They turn green close to our suspected port of Kozmino, but because of the area's maritime structure and the lack of incentives to go dark, we see few highlighted hexagons and little density.

Figure 4.8 illustrates the second series of heatmaps, with a stricter lower criteria for highlighting. Now, green represents areas where the count of suspected vessels going dark exceeds or is equal to 5. In this series, the requirements for turning green are more conservative, highlighting areas with a moderate to higher concentration of suspected dark vessel incidents. Figures 4.8 (a) The Baltic Sea and (c) The Russian-Pacific Sea have significantly less graphics illustrated now. The Russian-Pacific Sea has none. In Figure 4.8b The Black Sea, we still see the contours of the sailing route between the Bosphorus strait and the port of Novoryssisk. The change in criteria didn't affect the yellow and red hexagons severely present in the polygon.



(a) The Baltic Sea **(b)** The Black Sea **(c)** The Russian-Pacific Sea

Figure 4.8: Polygon Heatmap Suspected Vessels Going Dark w/ Reduced Criteria

Both color scheme series aid in visually identifying regions with heightened suspicion of illegal maritime activities. Distinctions in color intensity provides a quick reference to the relative magnitude of suspected incidents within each geographical area. To analyze how the number of suspected dark tankers changes with the choice of thresholds, the next section contains our sensitivity Analysis.

4.3 Sensitivity Analysis

Based on our analysis of time thresholds in Section 4.1, we presented our analysis and results for detecting suspected dark tankers in Section 4.2. To underscore the importance of relevant thresholds in the detection process, we will now give our results for the sensitivity analysis, showing the variance of results for different estimated thresholds. This aspect will be further elaborated on in our suggestions for further research.

In the histograms presented in Section 4.1, we showcased the 95th, 99th, and median minimum thresholds. We encountered an unlikely high number of suspected vessels when considering the 95th or 99th percentile of time between AIS transmissions for each polygon as the threshold. The time between signals was too short and did not have a maximum threshold, making it improbable to detect vessels suspected of engaging in illegal activities within such timeframes.

Figure 4.9 visually illustrates the variation in results, demonstrating the sensitivity of the outcomes to the choice of thresholds. The poles labeled Min/Max represent the minimum 10 hours and maximum 24-hour thresholds discussed in Chapter 4. The poles named 99th and 95th percentile represents the results of suspected dark vessels for each region without a maximum threshold. The percentile gaps between transmissions are only used for minimum thresholds. Notably, there is a substantial change in the Baltic region when adjusting the threshold, mainly due to the difference from 0.19 for the 95th, and from 0.5 for the 99th, to our set minimum threshold of 10 hours. This visualization underscores the importance of selecting an appropriate time threshold for analyzing the time between AIS transmissions.

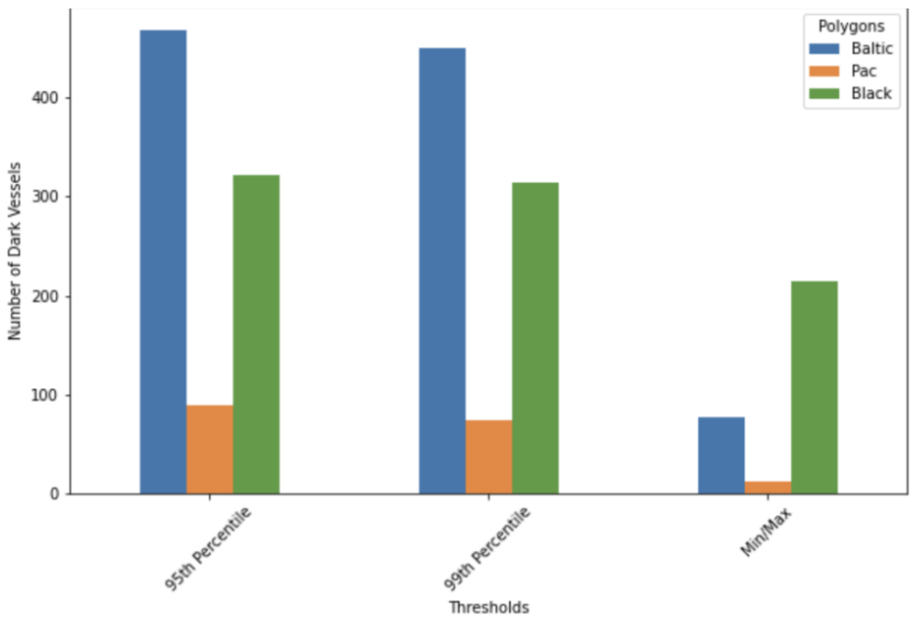


Figure 4.9: Sensitivity Analysis on Time Thresholds

In Figure 4.10 below, we present the same values for minimum percentiles as the above graph but with set maximum values. We set maximum values to analyze whether minimum values alone should be evaluated as a stand-alone measure for assuring sufficient thresholds. Presented by the results, it's visible that establishing a maximum threshold represents a limited effect on the number of suspected dark tankers. The noise from the 99th and 95th percentile minimum thresholds is too large to get a representative result. The effect of adding a maximum 24-hour threshold in the analysis is minimal. We find a total difference of 67 suspected dark vessels in the 99th percentile and a difference of 12 in the 95th percentile, compared to not applying set maximum thresholds. A lot of the noise comes from the Baltic, where we see a high share of suspected dark tankers stemming from this area before implementing a higher minimum threshold. The minimum threshold is set too low using the anomalies, where we see a spike of 466 suspected dark vessels in the Baltic alone using the 95th percentile. Using a minimum/maximum threshold based on average STS transfer time, trims the total suspected dark fleet. This is especially visible within the Baltic polygon, where we previously have seen the most indices. Based on our sensitivity analysis, it has become transparent that finding the best thresholds is pivotal in the search for the dark fleet, removing noise and finding relevant tankers. The matter will be further addressed in our suggestions for further research.

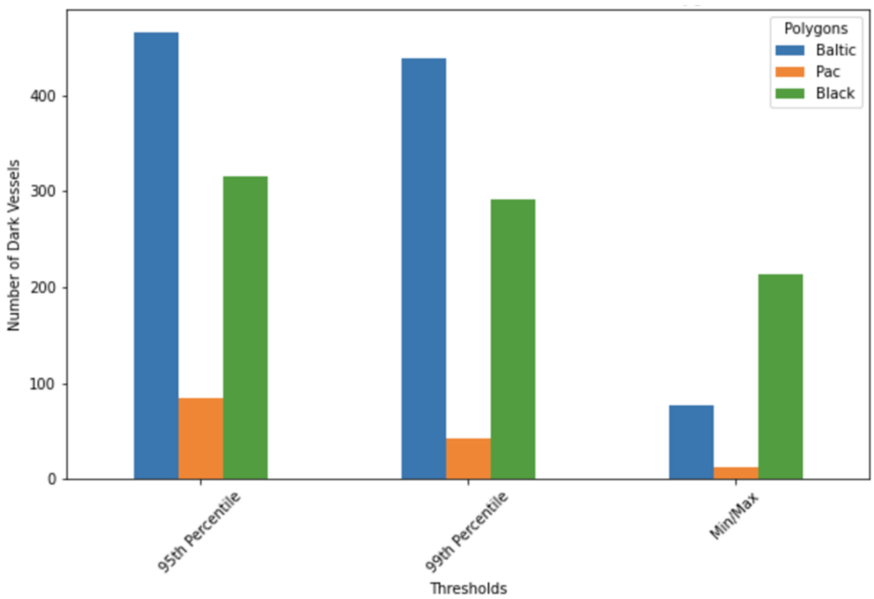


Figure 4.10: Sensitivity Analysis with Max Threshold

5 Empirical Analysis

Chapter 5 presents an empirical study of the December 2022 crude oil embargo's effect on the Russian seaborne trade. Section 5.1 evaluates port visits by relevant tankers, with comparisons to Babina et al.,'s (2023) insights. We delve into the ownership and characteristics of suspected dark tankers in Section 5.2, offering detailed insights into their operations amid geopolitical shifts. This chapter aims to connect theoretical frameworks with observed maritime realities.

5.1 Port Visits

To assess the effect of the crude oil embargo on Russian seaborne trade, we will use port visits by our filtered relevant oil tankers as a starting point.

Its important to examine the trend in Russian port visits both before and after the crude oil embargo on the 5th of December 2022. By doing so, the results are utilized to assess whether there has been an overall rise in the seaborne trade of Russian crude oil, and if there has been a geographical change in export points. These were the expectations earlier referred to as anticipated by Babina et al., (2023), which we will use as a starting point for comparison of our findings.

We decided to analyse on a weekly basis to detect changes quickly, but at a relevant variance interval. Additionally, we can identify the ports through which most vessels transport crude oil and investigate any alterations in these patterns following the imposition of the embargo.

By categorizing all Russian ports engaged in the export of seaborne crude oil, we identified the ports with the highest activity levels based on pre-embargo traffic from the AIS data. Our analysis focused on the most frequently visited ports within each of the four export regions from Russia: the Baltic, the Black, the Arctic, and the Russian-Pacific Sea. The primary ports identified for each region were Primorsk, Novorossiysk, Roslyakovo, and Kozmino Port.

We defined the relevant timeframe from January 2021 to May 31st, 2023, for our analysis of the four port's activity. The inclusion of 2021 was, as mentioned in Chapter 3, to control for potential seasonalities, given the protracted and cyclical nature of tanker shipping (Stopford, 2009). Figure 5.1 presents the four-week rolling average of weekly vessel visits to the previously identified top four ports.

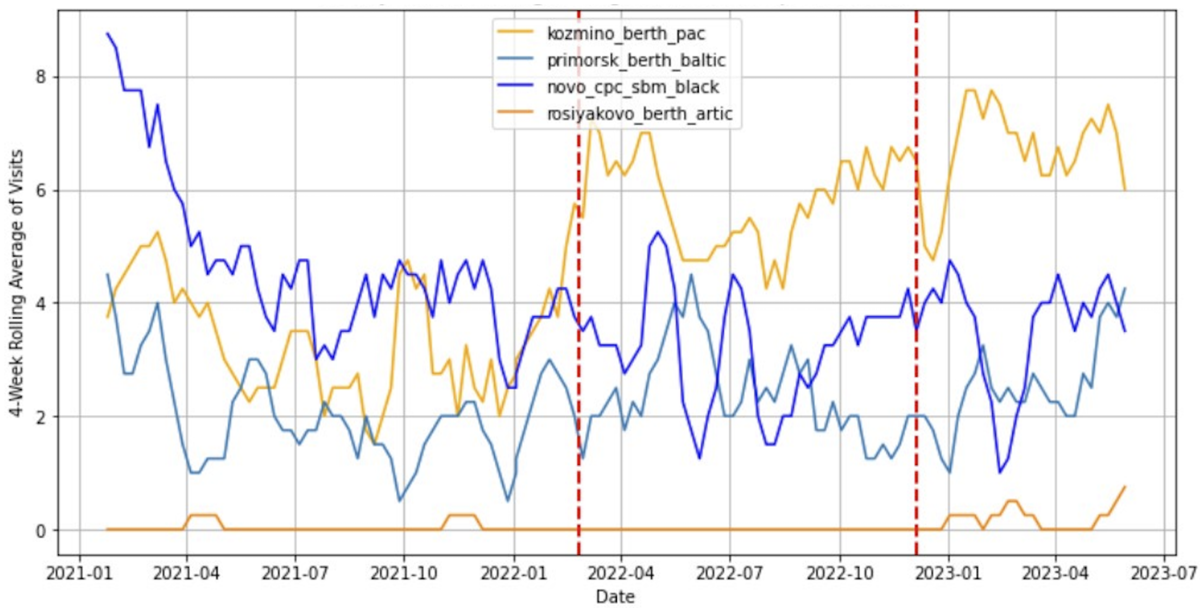


Figure 5.1: 30-Day Rolling Average of Weekly Visits to Top four Ports

From the graph and numerical results we observe that Novoryssisk experienced the highest number of vessel visits in early 2021. Novoryssisk peaked at eight tankers per week in contrast to the other ports, which ranged from two to five weekly visits. The activity normalized in the following months with similar patterns and activity between Kozmino, Primorsk and Novoryssisk. Roslyakovo, as the Arctic region representative, had few to no incidents of traffic from relevant tankers according to AIS signals. In Figure 5.1, Russia's 24th of February 2022 invasion of Ukraine is marked with the first red stapled line. The implementation of the embargo on the 5th of December 2022 is the second red line. We see increased volatility and overall activity from the first red line for the three relevant ports (excluding the Arctic). From the time of the invasion, we observe that a notable shift in behavior became evident, especially for two ports: Kozmino and Novoryssisk.

In Figure 5.2, we present our findings focusing on Kozmino and Novoryssisk at the point in time of Russia's invasion of Ukraine and the implementation of the embargo on Russian sea-borne crude oil exports marked with red lines. We focus on the two ports to examine the geographical shift the two ports represents and the change in export levels between them. The chart and computations reveal some distinct effects. Following

Russia's invasion of Ukraine on the 24th of February 2022, there is a noticeable increase in volatility, accompanied by a shift in the geographical location of exports favoring Kozmino over Novorossiysk. In addition, we see that the total number of vessels exporting crude oil from major ports is increasing. These effects continue for the remainder of our data timeframe.

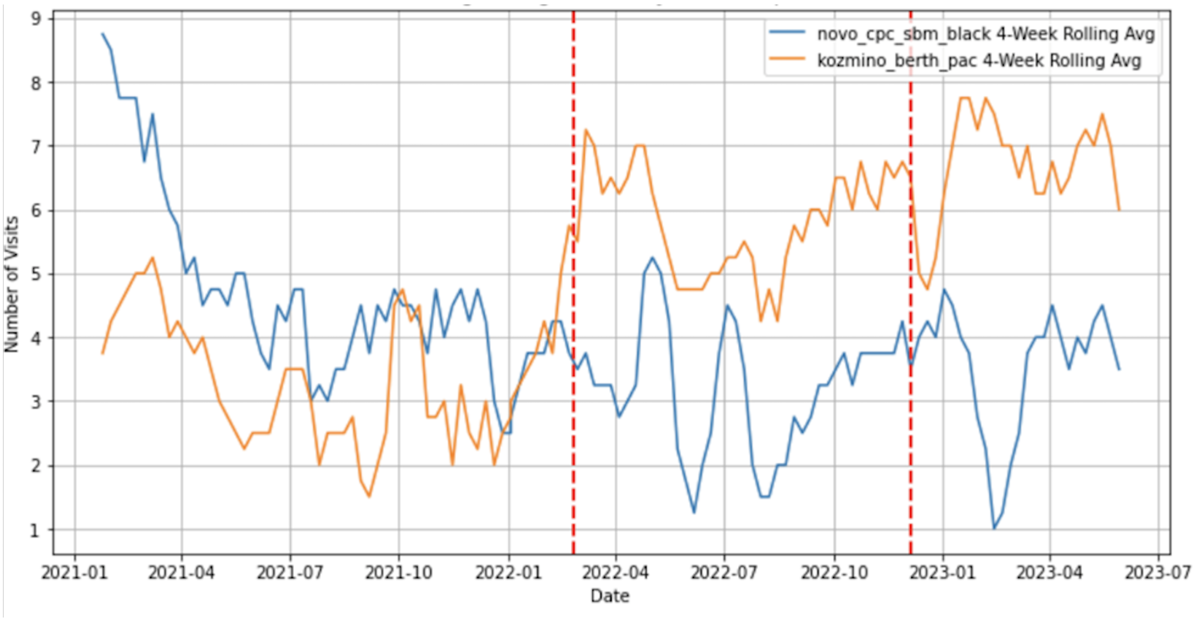


Figure 5.2: 30-Day Rolling Average of Weekly Visits to Specific Ports

Export destinations now gravitate towards Kozimno port, away from the Novoryssisk port in the Black Sea. This movement of export ports and possibly production is an essential geographical shift towards new markets for Russian crude oil destinations. Closer to countries previously identified as potential importers of Russian crude oil post-sanctions. Notably, India and China were suspects, as indicated by Babina et al., (2023). The effect started at the time of the invasion and varied continuously with high volatility and decreasing correlation throughout the following months.

Kozmino averaged 3,53 tanker vessel visits weekly before the invasion, increasing to 6.86 in our 2023 dataframe. Novoryssisk declined from 4,72 to 3,36 weekly visits. The total number of weekly visits increased from 10,56 to 13 combined. Table 5.1 displays our computations for January 2021 to February 2022 for pre-invasion comparison, March 2022 to December 2022, and January 2023 to May 2023 as our post-Babina et al., (2023) estimation window.

	Vessel Visits Combined		
	Jan. 2021 - Feb. 2022	Mar. 2022 - Dec. 2022	Jan. 2023 - May 2023
Kozmino	3.53	5.77	6.86
Novoryssisk	4.72	3.32	3.36
Primorsk	2.31	2.68	3.77
Total	10.56	11.78	13.00

Table 5.1: Average Weekly Vessel Visits Kozmino, Novorossiysk and Primorsk

The correlation between the Kozmino and Novoryssisk before the invasion was positive and significant, with a fit of 0,39. However, after the invasion, we found an insignificant correlation of 0,19. Of course, our findings of statistical significance are more important than the coefficient values. The change in correlation could be closely related to the possibility that exports are moving closer to new export markets for Russian crude. If operations were ordinary and all markets were open, the two would have higher correlation and similar trading patterns, as was the case before the invasion. Table 5.2 displays the change in correlation and significance from before and after the invasion of Ukraine.

Period	**Correlation**	**t-stat**	**P-value**
Jan. 2021 - Feb. 2022	0.39	2.38	0.02
Mar. 2022 - May. 2023	0.19	1.35	0.18

Table 5.2: Correlation and Significance Levels Kozmino and Novoryssisk

When the G7 price cap embargo was implemented on Russian Crude oil on the 5th of December 2023, the two ports had close to the same amount of tanker vessel activity weekly. As seen in table 5.2, they both had approximately five visits in the first week of January. In the following weeks, we saw several changes, underlining the possibility of the sanctions' effect on a geographical shift. Kozmino continued with many weekly visits, having several weeks with eight registered tanker visits. Novoryssisk had significantly lower volumes in intervals one to five.

These findings of change in geographic export and production locations align with the expectations of Babina et al., (2023). In addition, they are supported by newer data retrieved from Bloomberg and computed by Bruegel (Heussaff et al., 2023). They registered monthly Russian crude imports to India of 0 to 0,4 million tonnes per month until February 2022. It then increased every month until May 2023, when the monthly exports were reportedly close to seven million tonnes of imported Russian crude oil. These findings makes India the single largest importer of Russian crude oil. In addition, China has increased its imports From an average of 1,422 million tonnes monthly to 3,98 million tonnes (Heussaff et al., 2023). Table 5.3 tabulates the findings by Bruegel for average monthly Russian crude oil imports for India, China, and the EU North West.

Period	**India**	**China**	**EU North West**
Jan. 2021 - Feb. 2022	0.21	1.42	3.36
Mar. 2022 - Nov. 2022	2.96	3.31	2.29
Dec. 2022 - May 2023	5.67	3.98	0,15

Table 5.3: Monthly Import of Russian Crude Oil in Millions of Tonnes (Heussaff et al., 2023)

To summarize our main findings in regards to Babina et al.,'s (2023) expectations, we found a total increase in tanker exports from the four ports. As illustrated in Figure 5.2, we see a substantial increase in Kozmino and a sudden drop in Novoryssisk in 2023, implying a geographical shift. Including 2021 for seasonal changes, we observe the average total vessel visit activity for the three active ports were 10,55 for Babina et al.,'s (2023) data period. The estimation window from 1st of January 2023, until the 31st of May 2023, had 13 combined weekly visits for the three ports. This implies an increase in tanker activity. Table 5.1 portrayed the computations.

5.2 Suspected Vessel Register/Orbis

After the assessment of detecting suspected dark tankers in Chapter 4, Section 2, we now possess a complete list of all suspected tankers from our defined area and timeperiod. This list contains Vessel IDs such as IMO or MMSI, timestamps before turning dark, and exact locations with coordinates.

We intend to use Orbis to cross-reference our data with their database to examine global ultimate ownership and other relevant information. Our findings reveal a high degree of dominant ownership by Greece, China, the Marshall Islands, and Russia. Further in this subsection, we will uncover some of the characteristics of already suspected vessels from Orbis.

From our total list of suspected vessels, we extracted every unique vessel ID (IMO/MMSI) that our models suspect of doing illegal activities. These suspected vessels have been run through the Orbis database to check for ownership, global ownership, if it have been flagged for previous sanctions, and if it has changed ownership after 2020.

As elaborated in the introduction and Chapter 3, tanker vessels tend to have complicated ownership structures. This list with vessel and ownership information from Orbis can, therefore, be of value if Western countries or other groups were to oppose further sanctions on Russian sea-borne crude oil exports and the vessel owners/ownership. However, the vessels would need to be confirmed with satellite technology.

Our examination revealed 297 suspected vessels that our model detected as going dark. 48,8 percent of these vessels had global ownership in Greece. China had 9,8 percent, which could be an important takeaway from our results if analysed beyond the scope of this thesis. The top five results for ultimate global ownership are presented in Table 5.4

Ownership country	**Quantity**	**Percent**
Greece	145	48.82%
China	29	9.76%
Marshall Islands	19	6.40%
Russia	15	5.05%
Panama	12	4.04%

Table 5.4: Top five Global Ownership Suspected Dark Tankers

We examined the flags of the detected dark vessels. Liberia accounted for 28,28 percent of all findings, the Marshall Islands 18,86 percent and Malta 13,47 percent. Russian flags were only detected on approximately one percent (1,01%) of the dark vessels. Table 5.5 displays the top results for registered flag of countries by the suspected vessels.

Country Flag	**Quantity**	**Percent**
Liberia	84	28,28%
Marshall Islands	56	18,56%
Malta	40	13,47%
Greece	36	12,12%
Panama	30	10,10%
Gabon	10	3,37%
Bahamas	7	2,36%
Palau	6	2,02%
Turkey	5	1,68%
Avitau	4	1,35%
Vietnam	4	1,35%
Russia	3	1,01%

Table 5.5: Registered Flag of Suspected Dark Tankers

Because of the complexity of shipowner structures, one key metric for assessing whether a vessel is trying to stay off the grid is if ownership, vessel name, or vessel flag has recently changed (Scholaert & Jacobs, 2023). From Orbis, we gathered the past information of all vessels to check for name changes after 2020. We found that 35,98 percent of the suspected dark tankers found in the Black Sea, 48,05 percent of the dark tankers in the Baltic and 50,00 percent in the Russian-Pacific had changed vessel names post 2020. Note that these exact computations include six vessels overlapping, as addressed in Table 4.5. Our total computations for country ownership and flag ownership accounted for overlapping.

Orbis also contains information about whether the indicated vessels have earlier been flagged as suspicious or previously sanctioned. We found that for the Black Sea, Baltic and Russian-Pacific, 12,62 percent, 23,38 percent and 41,67 percent were earlier flagged or had names similar to previously sanctioned vessels.

A notable observation from our research is that the Black Sea exhibits the highest concentration of suspected dark activity and vessels and has the lowest percentages of both name changes and previous sanctions. Conversely, in the Russian-Pacific, where we observe minimal activity and fewer instances of suspected dark activities, there is a higher frequency of vessels being flagged as suspicious or previously sanctioned. In addition, it had a greater number of name changes occurring after 2020. These findings suggest that there may be a lower degree of control over vessels in dense, and highly trafficked areas, such as the Black Sea.

6 Discussion

Based on AIS data, our current model has shown promising results in detecting anomalous maritime activities and signs of changes in Russian activity. However, there are limitations that we need to acknowledge. Basing our results primarily on time thresholds can be an effective method to flag vessels for further research. Still, due to AIS's limitations, we recognise the need for additional assessments to conclude the operational purposes of our detected suspected vessels.

As highlighted by our sensitivity analysis, the time threshold set for detecting dark activity is a critical factor. The effectiveness of the model varies significantly depending on the threshold set. This variability can lead to either missed detection's or false positives. Finding the ideal time threshold for detecting dark activities is complex. It involves analyzing various factors, such as the type of vessels, their usual routes, and the nature of their operations. Seasonal changes can influence vessel patterns, making it necessary to re-calibrate the time thresholds to preserve the accuracy of maritime behavior analyses. These adjustments are essential to accommodate the variations in navigation and operational activities with changing seasons. A shorter threshold might be crucial to detect anomalies quickly in high-traffic areas, whereas an extended threshold might be more effective in less trafficked areas. Setting a threshold based on STS transfers gives the most plausible results based on our base assumptions, as seen in the analysis.

Another limitation of our thesis is the fact that it‘s set to specific geographic polygons that constrain our model's effectiveness. Activities outside these predefined areas will go undetected, limiting our monitoring scope for further investigation. However, within these polygons, we get the exact positions of vessels with the timestamp of where they were detected. Our model for detection is designed to be implemented where there is suspected dark activity within certain geographical frames, and where it is natural to conduct dark activity because of sanctions, etc. Our chosen constraints of geographical areas were to get a better fit for our research objectives. It could be expanded to search in other areas. Examples could include Venezuela, China, and North Korea, for places where it might be interesting to utilise the model and examine if there are geopolitical events that attract dark activity.

Integrating satellite data presents a promising opportunity to address these shortcomings. For instance, platforms like Vake.AI offer real-time tracking capabilities, providing a more comprehensive and timely overview of maritime movements (Vake.AI, n.d.). This would allow us to detect activities that AIS data might miss, offering a more robust monitoring system. One of the advantages of satellite monitoring is its ability to see vessels that are not transmitting AIS signals, as is often associated with illegal activities. Satellites can spot these dark vessels, offering a layer of surveillance to complement AIS data.

Another possible approach to flag dark activities is incorporating historical data analysis and monitoring flag-hopping activities. These activities are crucial aspects that can significantly enhance the effectiveness of maritime monitoring models.

6.1 The Limitations of AIS Data

To refer back to the research on AIS limitations in the literature review, we assess this through our thesis's scope and the detection of dark tankers. The shortcomings noted in previous research became transparent throughout the thesis, trying to answer our research question based on AIS data.

Our methodology, detailed in Section 3.1, includes strict data collection and preparation to mitigate coverage issues inherent in AIS data, especially in remote areas and dense port environments. Despite advancements from implementing AIS in the early 2000s', challenges such as signal blockage and message collision persist. Here, the potential for AIS signal loss must be factored into analysis to avoid false positives in identifying dark activities.

The intentional deactivation of AIS transponders is a core focus of our study, as described in Section 3.3.3 and further analyzed in Section 4.3. Human error presents a unique challenge, differentiating between innocent signal loss and deliberate manipulation. As a limitation of AIS, we cannot see them while dark, so we cannot be 100 percent certain that the tankers are partitioning into illegal activities. Satellite manipulation and spoofing are undetectable for us using AIS data - at least in real-time. Sudden changes in position and emerging in another location, far away from the last given signal, can signify these types of manipulation.

AIS data's voluminous nature necessitates extensive cleaning to ensure our analysis's integrity, a process elaborated in Section 3.1. Redundancies and noise, which can obscure accurate vessel movements, are addressed through tailored filtering to extract the most relevant information for our study.

The intricate web of global vessel ownership complicates detecting dark tankers, as detailed in Section 3.3.4. More than AIS data alone is required to unravel these complexities; hence, our methodology incorporates the Orbis database to gain insights into vessel ownership. This approach is critical, particularly when considering the potential for sanctions evasion, and is further examined in the context of our results in Section 4.5.

To flag and account for further sanctions, it's important to examine the global ownership of the vessels to understand who is responsible for the their operations. From using AIS data alone, we need help to grasp the complexity of tanker ownership fully and who conducts the illegal STS transfers. It has been crucial for our thesis to use separate programs to get a hold of information and produce further analysis.

The ability of our model to create a complete list of all the suspected tanker vessels could be inherent for further assessments of Russian sanctions. Suppose the USA, NATO, or Western countries were to impose additional sanctions and target vessel owners, etc. In that case, our model can be a fundamental first step in the investigation to find the responsible owners. As a finishing note on the matter, as found by Oppenheim in a paper regarding the 1976 Arabic oil embargo: An embargo is anticipated to have a greater effect when the sanctioning nation has greater control over the tanker fleet (Oppenheim, 1976).

6.2 Embargo Effect on Russian Crude Oil Tanker Exports

To assess the economic effects of the Russian oil embargo and price cap, we used our models parts regarding port polygons and AIS detection methods. For the ports, we instrumented that the port visits, or AIS signals inside the ports, are without our suspected dark tankers as they have turned the AIS transmissions off before entering the port. We intended to answer some of Babina et al.,‘s (2023) expectations and can now respond with our tanker export observations.

Our port analysis, which deploys specified time series analysis, has identified a notable uptick in tanker activities, suggesting a potential reallocation of production zones and an increase in total production. The absence of corroborative quantitative data, specifically production figures and export documentation from the ports, presents a notable gap in our framework. While we see an apparent increase in ship movements, a valuable sign, we can't say the change is significant based on AIS data as a stand-alone measure. Using large-tanker frequency alone to measure Russian oil exports is insufficient. However, our models contain enough info to build a new model and add our suspected dark tanker findings and the port visits. However, building such a model with good precision would need complementary satellite data to avoid too many assumptions and delegate suspected dark vessels to specific ports, such as in the Black Sea.

So, while ship activity is a helpful clue and a good pointer, we should be careful about using it as the only sign of changes in production as it is unsuccessful in providing a comprehensive view.

7 Conclusion & Further Research

7.1 Conclusion

The continuous rise of dark tankers will still serve as a safety and economic risk in the future. Our model has the capability to serve as a fundamental first step to detect these specific vessels and the areas they operate.

We have contributed to research and existing literature by successfully identifying 77, 214, and 12 suspected dark tankers within the Baltic, Black, and Russian-Pacific Sea. By doing this, we trimmed the total relevant tanker fleet down to 14,29 percent with exact locations and timestamps, ready for further assessment by satellite technology. Our visualized heatmaps serve as a potential search grid for previous and future illicit activity areas. Our methodology can, in an appropriate way, with corrections from our discussion, be a good stepping stone in the path to identifying dark tanker for further sanctions. Without the integration and use of satellite data, it still suffers from uncertainty in the conclusion of whether the vessels are truly dark or not. Through our empirical analysis, we took a deep dive into the complicated ownership of vessels. The results concluded that a high percentage of the suspected dark fleet is under the control of Greek (48,8%) and Chinese (9,8%) ownerships, with most vessels sailing under Liberian (28,28%) and Marshall Island (18,56%) flags.

In the empirical analysis, we have found, as Babina et al., (2023) have suggested, a rise in tanker activity, and we see a shift toward a new market. The geographical turnover, backed by data from Bruegel, would be a natural cause, with India and China buying more Russian sanctioned oil. We found significant positive correlation in exports between Kozmino and Novoryssisk before the invasion and insignificance after. Implying changes in the Russian crude oil export market dynamics. Despite the activity, considering the rise and dark activity as well, we can reasonably conclude that the total tanker and export activity has seen an increase since the outbreak of heated conflict between Russia and Ukraine in February 2022.

7.2 Further Research

Based on the knowledge we have gained throughout this thesis and due to the limitations of AIS discussed in Chapter 5, we propose a set of further research subjects that we believe should be accounted for and researched.

Our model builds on a closed geographical area described as a polygon. We make the polygons around suspected areas and Russian ports. The polygons must be built around specific suspected areas for the model to be used elsewhere. Suppose the thresholds and other detection criteria are improved, and the model is improved for better detection abilities. In that case, one might not need to limit geographical area to the same extent and can use much larger areas for detection. However, our geographical limitation substantially reduces noise and computer's required capacity for computations. Several of our coding computations needed approximately six hours to run and would increase with larger polygons and fewer restrictions for tanker filtering.

For the tanker filtering, essential notes for further research are to use appropriate classifications of SOG or possibly find other ways to measure if vessels are in movement. We also rely heavily on transmissions' ability to provide the correct DWT of vessels, and our model relies on the assumption that vessels below 80.000 DWT do not substantially impact our assessment of suspected dark tankers. For further research, it is also important to note that our model can be applied to other types of ships, but note that the cargo type shipped should be homogenous as AIS can't differentiate different kinds of cargo on a vessel, for example, if containerized (Adland et al., 2017).

Time thresholds are crucial to accurately estimate. Our sensitivity analysis displays the importance of choosing relevant thresholds, both minimum and maximum. Our 99th/95th percentile approach also tried to differentiate geographical differences, as it could be the case that dark vessels need more time to perform STS or other illegalities based on offshore conditions. Further assessment should investigate different types of dynamics that can improve the threshold functions beyond set max/min limits—for example, differentiating by ship size and cargo haul.

The effect of controlling a more significant part of the darker fleet should also be investigated. Further research should elaborate on these statements and analyze whether sanctions should be tighter, more specific, distributed or handled differently.

Our analysis of ownership structures has also made us aware of the complex stakeholder systems that can be behind a vessel. The tactics of changing flags, vessel ID and name should be examined further, and it can be used as a way of filtering for suspected tankers if patterns are found.

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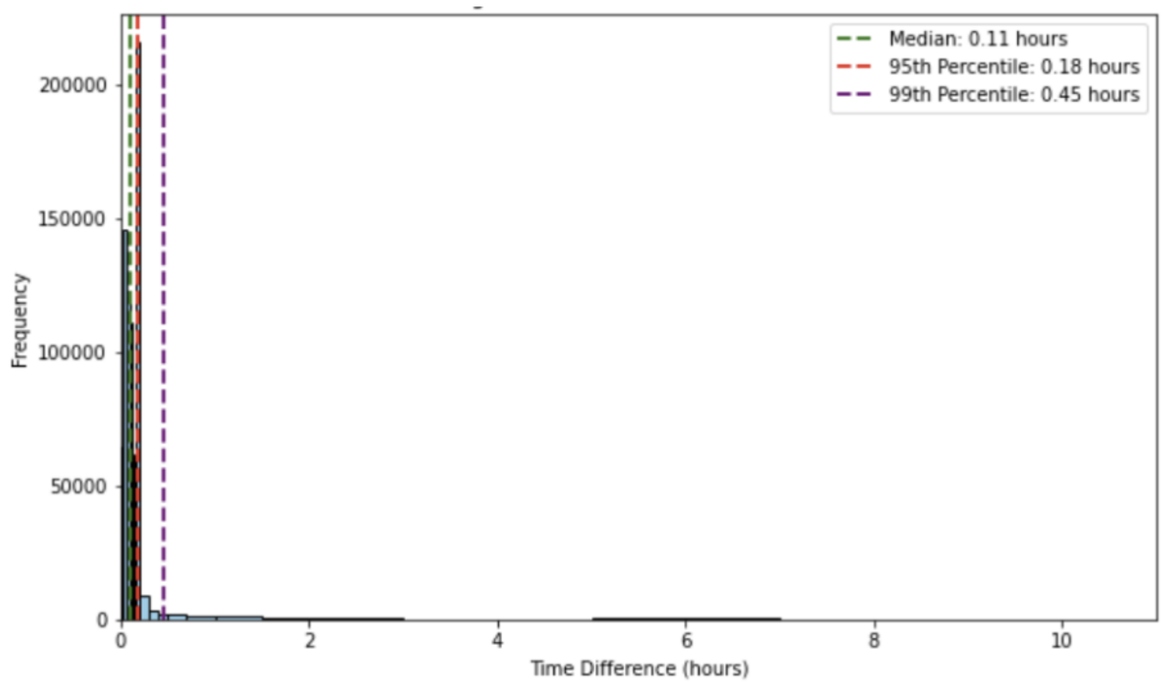
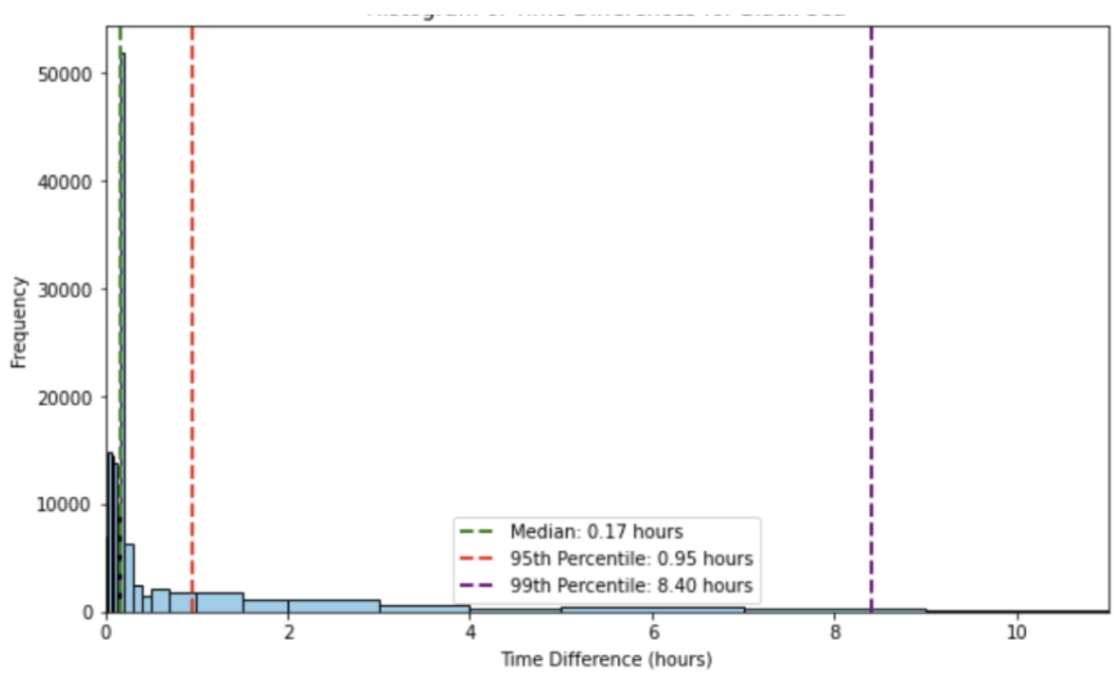
Appendices

Appendix A - Post-Embargo Histogram Analysis

Post-Embargo Histogram Analysis Baltic Sea



Post-Embargo Histogram Analysis Black Sea



Post-Embargo Histogram Analysis Russian-Pacific Sea