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A new methodological approach to assess the effort and spatiotemporal dynamics of a fishery

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RESUMO

Um dos principais desafios para uma gestão eficaz do ambiente marinho é compreender e quantificar com precisão as atividades humanas que nele ocorrem. A pesca, sendo uma das atividades mais importantes e impactantes neste ambiente, é também das mais difíceis de monitorizar e regulamentar, o que torna imperativo melhorar o conhecimento atual sobre estas práticas.

Ao longo da história da investigação e gestão pesqueira, têm surgido várias metodologias e ferramentas com o intuito de melhorar o conhecimento de base sobre estas atividades. Com a implementação de dispositivos de rastreamento de embarcações, como o VMS (*Vessel Monitoring System*) e AIS (*Automatic Identification System*), em algumas embarcações de pesca, os dados daí resultantes revelaram-se uma fonte de informação extremamente útil e importante para aprofundar o conhecimento sobre as atividades de pesca, conhecimento esse que, até então, era muito difícil ou dispendioso de obter. Além disso, quando este tipo de dados é combinado com outros dados, como dados ambientais ou dados da pesca como os de desembarques em lota ou informação de diários de bordo, o conhecimento que pode ser obtido através desta abordagem aumenta tanto em quantidade e qualidade como em diversidade. Os dados de rastreamento de embarcações, e a sua combinação com dados dependentes da pesca, têm sido particularmente úteis para mapear e quantificar o esforço de pesca com resoluções sem precedentes. No entanto, e até ao início desta tese, a grande maioria das abordagens que utilizam estes dados tem-se focado principalmente em atividades de pesca com artes ativas, como o arrasto e o cerco. Por outro lado, as atividades de pesca com artes passivas, especialmente num contexto polivalente, têm recebido consideravelmente menos atenção por parte destas novas metodologias.

O objetivo desta tese foi colmatar a falta de metodologias que permitam abordar importantes lacunas de conhecimento relacionadas com as atividades de pesca polivalente com artes passivas. Para isso, foram desenvolvidas novas metodologias baseadas em dados de rastreamento de embarcações e dados dependentes da pesca, que permitem mapear e quantificar o esforço de pesca com elevada resolução e a uma escala alargada. Foram também explorados os benefícios da combinação destes dois tipos de dados para melhorar o controlo, monitorização e vigilância das atividades de pesca, bem como foi analisada criticamente a qualidade dos dados dependentes da pesca quando utilizados para estimar o esforço de pesca.

Esta tese focou-se nas embarcações de pesca costeira polivalente a operar ao longo da costa continental portuguesa, com um comprimento de fora-a-fora superior a 15m. Estas embarcações, sendo elas polivalentes, podem operar diversas artes de pesca, incluindo durante a mesma viagem de pesca. Apesar de estarem aptas e autorizadas a operar diversas artes, as artes mais utilizadas por esta frota são as redes estáticas (emalhar e tresmalho), armadilhas e covos e palangre.

Numa primeira fase, foi desenvolvida uma metodologia de classificação de dados de rastreamento de embarcações para mapear e quantificar o esforço de pesca, em termos de tempo de imersão, de artes estáticas em contexto polivalente. Esta metodologia permite identificar os quatro principais comportamentos de uma embarcação esperados numa viagem de pesca com artes passivas: navegação, largada da arte, deriva/navegação lenta e recolha/alagem da arte. Os resultados da aplicação desta abordagem a embarcações costeiras que utilizam redes e covos/armadilhas permitiram perceber que os eventos de pesca com redes e com covos/armadilhas diferem bastante em

termos de tempo de imersão. Os eventos de pesca com redes decorrem durante períodos mais curtos, com tempos de imersão geralmente até 24 horas, enquanto os eventos com covos e armadilhas apresentam uma distribuição de tempo de imersão mais ampla. Dada a natureza demersal destes tipos de pesca, a distribuição da atividade desta frota concentrou-se essencialmente na plataforma continental portuguesa e na parte superior do talude continental. A distribuição do esforço de pesca, por outro lado, revelou-se heterogénea, sendo mais prevalente na zona norte do país.

Para obter estes resultados, a metodologia de classificação de dados desenvolvida exige dados de rastreamento de embarcações altamente consistentes e completos, o que nem sempre acontece quando se utilizam dados AIS para esse fim, apesar de serem os melhores atualmente disponíveis. Devido à inconsistência dos dados AIS utilizados, apenas 12,1% do esforço de pesca total da frota analisada pôde ser estimado. Assim, para obter uma estimativa mais completa do esforço total de pesca, foi desenvolvida uma abordagem complementar.

Os dados classificados de rastreamento de embarcações foram combinados com dados oficiais de desembarques para extrapolar o esforço de pesca da frota estudada durante operações com redes. Esta abordagem baseou-se no comprimento médio das redes utilizadas por viagem, informação obtida a partir dos dados de AIS classificados na primeira abordagem, e no número total de viagens de pesca inferido a partir dos dados oficiais de desembarques. Com esta abordagem, foi possível estimar o esforço de pesca com redes, em quilómetros de redes, para toda a frota ao longo de todo o território nacional continental. Corroborando com os resultados do estudo inicial, a zona norte do país é a região que sofre maior pressão de pesca por parte desta frota. A abordagem também forneceu informações sobre a variação sazonal do esforço de pesca, que parece ser maior durante a primavera e o verão. Os valores estimados indicam que o comprimento total de redes utilizadas por esta frota equivale a quatro vezes o comprimento da linha do equador.

Esta extrapolação do esforço depende, naturalmente, da exatidão e do quão completos são os dados dependentes de pesca utilizados. Por essa razão, foi desenvolvida uma abordagem que permite identificar quando as embarcações não reportam os seus desembarques. Esta metodologia, além de permitir avaliar a fiabilidade das estimativas de esforço de pesca baseadas em dados de desembarques, permite também perceber de que forma os pescadores cumprem com a obrigação legal de desembarcar as capturas nos locais apropriados. Os resultados desta análise mostram que nem todos os pescadores se comportam da mesma forma relativamente a esta obrigação. Cerca de um terço das embarcações analisadas são responsáveis por quase 85% dos eventos de desembarque não reportados identificados e, no total, 16% das viagens de pesca registadas com dados AIS não tinham qualquer registo de desembarque associado. Isto significa que estas viagens não teriam sido consideradas na estimativa do esforço de pesca caso se utilizassem apenas os registos de desembarque. Verificou-se ainda uma variação sazonal na proporção de viagens sem registos de desembarque: durante o final da primavera e o verão, o cumprimento dos requisitos legais de descarga parece aumentar, sendo menor no restante período do ano.

Embora esta análise não permita, nem pretenda, comprovar a existência de infrações legais, constitui uma ferramenta valiosa no âmbito da avaliação de risco. Ao identificar embarcações com maiores taxas de viagens não reportadas e os períodos temporais em que tal ocorre, é possível otimizar a alocação dos recursos de fiscalização, orientando-os para os operadores com maior propensão para o incumprimento destas obrigações.

Na parte final desta tese, foram comparados os dois tipos de dados de pesca utilizados (desembarques oficiais e dados de diários de bordo) em termos da sua fiabilidade quando utilizados para estimar o esforço de pesca em número de viagens. De facto, a natureza autodeclarada dos dados de diário de bordo tem sido uma preocupação relevante quanto à sua qualidade e exatidão. Os resultados desta análise confirmam essas preocupações. Quando comparados com o número de viagens inferido a partir dos dados oficiais de desembarque, que são registados e reportados por uma entidade oficial designada para esse fim (DOCAPESCA Portos e Lotas, SA), os dados de diário de bordo registaram menos 23% de viagens. Esta é uma diferença significativa, especialmente considerando que também os dados de desembarque se revelaram incompletos para estimar a totalidade do esforço de pesca da frota analisada.

Em suma, nesta tese foram desenvolvidas novas metodologias capazes de fornecer informação nova e valiosa sobre a quantidade e distribuição espacial e temporal do esforço de pesca. Estas permitem estudar o esforço de pesca em termos de tempo de imersão e comprimento das artes utilizadas, duas métricas com resoluções superiores às tradicionalmente usadas. A combinação de dados de rastreamento de embarcações com dados dependentes da pesca mostrou também ser uma abordagem útil para identificar operadores que não cumprem com as obrigações de desembarque, e para apoiar os esforços de monitorização, controlo e vigilância. Não obstante o seu potencial, a eficácia destas metodologias está fortemente condicionada pela qualidade e completude dos dados utilizados. De facto, essa qualidade revelou ser um dos principais obstáculos à obtenção de estimativas completas e robustas do esforço total de pesca da frota estudada.

No entanto, é importante realçar que a continua inovação tecnológica da coleta e análise de dados de pesca são fundamentais para uma gestão das pescas mais eficiente e sustentável. Foi com sobre esta premissa e com o objectivo de inovar a análise de dados de pesca que esta tese foi desenvolvida. É importante referir que o desenvolvimento tecnológico deve, não só servir a gestão pesqueira, mas também o próprio sector. De forma que este se torne mais eficiente, ambiental e economicamente sustentável e mais seguro para quem anda no mar.

Palavras-chave: dados de rastreamento de embarcações, dados de pesca, esforço de pesca, pesca polivalente, desembarques não reportados

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ABSTRACT

One of the main challenges to effectively manage the marine environment is to fully understand and quantify the human activities happening in this realm. Fishing, as one of the most important and impactful activities happening in this environment, is also one of the most difficult to manage and control, which makes it imperative to improve the current knowledge on these practices.

Throughout the history of fisheries research and management, different methodologies and tools have emerged with the purpose of increasing the baseline knowledge on fishing activities. With the implementation of vessel tracking devices in some fishing vessels, vessel tracking data has proved to be a highly useful and important source of information to increase the knowledge on fishing activities that, until their usage, were either very costly or very difficult to obtain. Moreover, when this type of data is combined with other types of data, such as environmental or fisheries-dependent data, the knowledge that is possible to get increases in terms of quantity and diversity. Vessel tracking data, and its combination with fisheries-dependent data has been particularly useful to map and quantify the fishing effort with unprecedented resolution. However, and until the start of this thesis, the vast majority of approaches relying on such data and approaches have mainly focused on fishing activities using active fishing gears, such as trawls and seiners, whereas fishing activities relying on passive fishing gears, and especially within a polyvalent (multi-gear) context, have received substantially less attention from these new methodologies.

The aim of this thesis was to address this lack of methodologies that allow addressing important knowledge gaps related to polyvalent and passive fishing activities. This was achieved by developing new methodologies relying on vessel tracking data and fisheries-dependent data that allow to map and quantify the fishing effort with high resolution and at a broad scale. The benefits of combining these two types of data to improve monitoring, control and surveillance of fishing activities was also explored, and the quality of fisheries-dependent data when used to estimate the fishing effort was critically analysed.

This thesis focused on a polyvalent coastal fishing fleet operating along the Portuguese mainland coast, with a length overall larger than 15m. These vessels can used different fishing gears, including during the same fishing trip. Despite being capable and authorized to use a wide range of gears, the most commonly used by this fleet are static nets (gillnets and trammel nets), pots and traps, and longlines.

Initially, a vessel tracking data classification methodology was developed to map and quantify the fishing effort, as soak time, of static fishing gears within a polyvalent context. This methodology allows identification of the four main behaviours expected within fishing trips using passive fishing gears: steaming, gear deployment, drifting/slow navigation and gear hauling. The results of applying this approach to coastal fishing vessels using nets, pots, and traps showed that net fishing events and fishing events using pots and traps are quite distinctive in terms of soak time. Net fishing events are carried out for shorter periods, with soak times usually of up to 24h, whilst pots and traps has a much wider distribution of soak time. Given the demersal nature of these fishing techniques, the fishing footprint was essentially distributed within the Portuguese continental shelf and upper part of the continental slope. The distribution of the fishing effort, on the other hand, showed patchy distributions, being more prevalent in the northern part of the country.

To be able to provide such results, the developed data classification methodology requires highly consistent and complete vessel tracking data, which is not always the case when AIS data is used in such estimates. Because of the inconsistency of the used AIS data, the total fishing effort was estimated for only 12.1% of the analysed fleet. Therefore, to have a more complete estimate of the total fishing effort, another approach to estimate the fishing effort was developed.

The classified vessel tracking data was combined with official landings data to extrapolate the fishing effort of the studied fleet when operating nets. It relied on the average length of nets used per trip, information that was obtained from the classified AIS data, and the total number of fishing trips that was possible to infer from official landings data. This approach allowed to estimate the net fishing effort, in km of nets used, for the entire fleet throughout the entire country. Corroborating with the results from the initial study, the northern part of the country is the region that is subjected to higher fishing pressure from this fleet. It also provides information of the seasonal variation of fishing effort which appears to be higher during the spring and summer months, and the estimated values of effort concluded that the total length of nets used by this fleet in each year suffices to encircle the equator 4 times.

This extrapolation of effort is, of course, dependent on the accuracy and completeness of the fishery-dependent data that was used as extrapolation source. This is why, in the following part of this thesis, an approach that allowed to identify when vessels missed reporting their landings was developed. This methodology, besides allowing to understand to which extend fishing effort estimates relying on landings data are accurate, allows understanding how fishers comply with the obligation of landing their catches where they are legally required to do so. The results from this analysis enables to understand that not all fishers behave equally regarding such regulations. Approximately one third of the analysed vessels are responsible for nearly 85% of the identified unreported landing events and, overall, 16% of the fishing trips tracked with AIS data did not have any landing record associated to them. This means that these trips would not have been considered for the estimation of fishing effort if landings records were used to that end. Moreover, a seasonal variation in the proportion of trips without unreported landing events was also identified: during the late spring and during the summer, the compliancy with landing requirements seems to increase, whereas it is lower during the remaining part of the year.

This analysis, although not being able to prove if fishers are committing any illegality, which it was not intended to do, provides very valuable information within a risk assessment framework. By knowing which vessels have higher rates of fishing trips without landing records, and during which months, allows enforcement entities to better allocate their control efforts towards such actors with higher tendency of not following with such regulations.

The last part of this thesis compares the two types of fishery-dependent data used in this thesis (official landings and logbook data) in terms of their accuracy when used to estimate the fishing effort as number of fishing trips. Indeed, the self-reported nature of logbook data has been a relevant concern affecting the quality and accuracy of this form of data. The results of this analysis corroborate such concerns. When compared with the number of fishing trips inferred from official landings data, which is logged and reported by an official third party especially designated to that end, logbook data had nearly 23% fewer fishing trips logged than landings data. This is a significant difference from a dataset, which, as we have seen, is also incomplete for the purpose of fully estimating the total fishing effort of the analysed fleet.

In summary, in this thesis new methodologies capable of providing new and valuable information on the quantity and distribution of fishing effort were developed. They allow the study of fishing effort in terms of soak time and length of used gears, which are two metrics with higher resolution than what has been commonly used. The combination of vessel tracking data with fisheries-dependent data has also proved to be a valuable approach to identify actors that fail to comply with landing and reporting regulations and to assist in monitoring, control and surveillance efforts. Despite the novelty and powerful insights from the developed methodologies, they are deeply dependent on the quality and accuracy of the used data. Indeed, the quality of the data proved to be an important bottleneck when such methodologies are used to provide complete and comprehensive estimates of fishing effort.

However, it is important to emphasize that the continuous technological innovation in the collection and analysis of fisheries data is fundamental for a more efficient and sustainable management of fishing activities. It was upon this premise and with the objective of innovating fishing data analysis that this thesis was developed. It is also important to state that technological developments should not only serve fisheries management but also the sector itself, making it more efficient, environmentally and economically sustainable, and safer for those at sea.

Keywords: vessel tracking data, fishery-dependent data, fishing effort, polyvalent passive fisheries, unreported landing events.

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"No one is someone without anyone"
Henrique de Almeida Sales Henriques

I dedicate this thesis to you, Maria Francisca, my daughter.

Table of Contents

RESUMO III
ABSTRACT VII
ACKNOWLEDGMENTS XI
LIST OF FIGURES XVII
LIST OF TABLES XXI
LIST OF PUBLICATIONS RELATED WITH THE THESIS XXIII
LIST OF ACRONYMS AND ABBREVIATIONS XXVII
1. GENERAL INTRODUCTION 1
1.1. Literature review - Vessel tracking and fishery dependent data: their role in improving fishing effort estimates and detecting uncompliant behaviours 6
1.1.1. Classification of vessel tracking data to detect and map fishing activities 6
1.1.2. High resolution estimates of fishing effort - Passive gears effort metrics: soak time and km of used gears. 8
1.1.3. IUU - Estimate unreported landing events.. 11
1.1.4. Quality assessment of Fishery dependent data 13
1.2. Brief overview of the Portuguese Polyvalent Coastal fishing fleet. 14
1.3. Coastal polyvalent fishing fleet in Portugal and relevant legislation for the thesis.. 15
1.4. Research gaps and significance for this study 17
1.5. General Objectives 18
1.6. Chapters Outline 19
2. CHAPTER II: AN APPROACH TO MAP AND QUANTIFY THE FISHING EFFORT OF POLYVALENT PASSIVE GEAR FISHING FLEETS USING GEOSPATIAL DATA. 23
2.1. Abstract 23
2.2. INTRODUCTION 25
2.3. METHODS 28
2.3.1. Data 28
2.3.2. Data pre-processing... 30
2.3.3. Set up the Classification Variables 31
2.3.4. Data classification.. 34
2.3.5. Footprint and Effort assessment 35
2.4. RESULTS 36

2.4.1. Model validation 36
2.4.2. Soak time 37
2.4.3. Footprint and Effort 38
2.5. DISCUSSION 41
3. CHAPTER III: LET'S MEASURE IT: AN APPROACH OF HIGH-RESOLUTION ESTIMATES OF BOTTOM FIXED NET FISHING EFFORT AT NATIONAL LEVEL. 47
3.1. ABSTRACT 47
3.2. INTRODUCTION 48
3.3. Methods 52
3.3.1. Rationale and required data 52
3.3.2. Match of fishing effort with landings and logbook data 53
3.3.3. Selection of trips that only used static nets, based on info from logbooks 55
3.3.4. Calculation of the average length of nets used per trip, by LOA class ($AvgNet_c$) 56
3.3.5. Effort calculation: AvgNet x N fishing trips 57
3.3.6. Effort validation 58
3.4. RESULTS 59
3.5. DISCUSSION 64
4. CHAPTER IV: IMPROVING MONITORING, CONTROL AND SURVEILLANCE EFFORTS THROUGH VESSEL TRACKING AND FISHERY DEPENDENT DATA. 71
4.1. ABSTRACT 71
4.2. INTRODUCTION 73
4.3. METHODS 75
4.3.1. Study region and fleet description 75
4.3.2. Data description 77
4.3.3. Assumptions and rational of the approach 77
4.3.4. Data fusion 78
4.3.5. Risk assessment at vessel level – unreported landing events 79
4.3.6. Seasonal variation of unreported landing events 79
4.4. RESULTS 81
4.4.1. Summary of the combined data 81
4.4.2. Risk assessment at vessel level – unreported landing events 81
4.4.3. Seasonal variation of unreported landing events 82
4.5. DISCUSSION 84
4.6. CONCLUSION 87

5. CHAPTER V: ON THE ACCURACY OF SELF-REPORTED DATA FOR FISHING EFFORT ESTIMATES - A CASE STUDY. **89**
5.1. INTRODUCTION **91**
5.2. RATIONAL OF THE APPROACH **93**
5.3. RESULTS **95**
5.4. DISCUSSION AND CONCLUSIONS **96**
6. GENERAL DISCUSSION **101**
6.1. Summary of the Results **101**
6.1.1. Chapter II - Development of a Vessel Tracking Data classification approach to map and quantify the fishing effort of polyvalent fisheries 101
6.1.2. Chapter III – Estimation of the national fishing effort with high resolution 103
6.1.3. Chapter IV – Risk assessment and estimation of unreported landing events 105
6.1.4. Chapter V – assessment of the data quality of self-reported data (i.e., logbook data, when used to estimate fishing effort) 106
6.2. Relevance of this work - Implications and perspectives for management **107**
6.3. Research potential of the developed approaches and further research **114**
7. REFERENCES **117**
8. APPENDICES **147**
8.1. Chapter II – Appendix **147**
8.2. Chapter III – Appendix **164**
8.3. Chapter IV - Appendix **166**

LIST OF FIGURES

Figure 2.1 The current approach focuses on the Portuguese polyvalent fishing fleet operating within the Portuguese Economic Exclusive Zone (EEZ). 28

Figure 2.2 Schematic representation of the major steps carried out throughout our procedure. For a more detailed description of the data and the data selection procedure, check the Supplementary material. 30

Figure 2.3 AIS tracks with three different fishing events. Fishing events are represented by the deployment datapoints (in yellow) that are displayed underneath the hauling datapoints (green) when they overlap in space, meaning that a fishing event, as expected, starts with the deployment of a gear, at a fast navigation speed and terminates with its hauling, which is carried at low speed. The tracking data was interpolated at a 1 minute rate, meaning that the larger the distance between consecutive datapoints, the faster the vessel navigates and vice-versa. The behavioural diversity and complexity of this fishery is evident from this figure: A) vessels can deploy two sets of fishing gears in a single event and haul them within the same trip; B) deploy just one gear and after the deployment the vessel waits some hours, while slowly navigating/ drifting, and then collect the gear within that same trip; or C) a vessel can go out to sea to deploy a gear and then return on a following day to haul the gear. The soak time will depend on the type of gear and target specie. 33

Figure 2.4 Confusion matrices and Cohen's coefficient values from the validation data classified by the procedure. Confusion matrices plot the number of datapoints, of each state, classified by the model (Predicted) against the actual number, of each state, of the validated data (Reference). The validation procedure was carried for the overall validation dataset, i.e. for all fishing trips regardless of the gear used (Nets & Pots and traps) and for fishing trips using the same type of gear: Nets or Pots and traps. 36

Figure 2.5 Distribution of the average soak time, in days, of each fishing event of one vessel using only nets (A), one vessel using only pots and traps (B) and of one vessel both types of gears (C). The average soak time of each fishing event was calculated as the average difference of timestamp between pairing deployment and hauling datapoints of a given fishing event. Vessels using nets tend to fish during short periods of time, usually up to one or two days, while vessels using pots and traps tend to leave the gears fishing for longer periods. The distribution of soak time of vessels using both types of gear is expected to resemble the combination of the distributions of nets (high number of fishing event with short periods of soak time) with the distribution of soak time values of pots and traps (a wider distribution of fishing events that can range for several days). The average values of soak time for each fishing event were calculated

to the resolution of one decimal place. Meaning that a fishing event that lasts 0.5 days (12 hours) it is represented on a different bar that of a 24 hours (1 day) fishing event, for example. 38
Figure 2.6 Map of fishing effort (soak time) of fishing events using nets, pots and traps, during the period from 2014 to 2020. The resulting effort map represents 24353 fishing events, from 13224 fishing trips carried by 84 fishing vessels. The majority of the fishing activity is distributed within the 500m depth, and the fishing effort presents a patchy distribution appearing to be more relevant in the northern part of the study area. 40
Figure 3.1 Example of AIS data classified into the four most common behaviours within fishing trips using passive gears, under the approach developed by Sales Henriques et al. (2023). The classified AIS data was used as sample effort data to extrapolate the total fishing effort, in km of nets used, for vessels with LOA >14m, operating within mainland Portuguese waters, during the period of 2014-2020. 52
Figure 3.2 Map of the Portuguese mainland, which represents the study region of the present work. The 15 landing ports present on the landings and logbook records are shown. The 500m bathymetric line is displayed, as it represents a good proxy of the region where demersal net fishing occurs (Leitão et al. 2022; Sales Henriques et al. 2023). 53
Figure 3.3 Representation of the workflow to match the effort spatial data (AIS) with the fishery dependent data (Landing and Logbook data) and an example of the output. The process relies on the match through the ID of the vessel and the date of arrival to port (vessel tracking data) and the landing date (Landing and logbook data). 55
Figure 3.4 Scatterplot representing the correlation between the calculated monthly effort as per the presented approach (*f*) and the estimated monthly effort (*f'*) through the k-fold cross validation process. The Peason's correlation and corresponding *p*-value are shown. B – Distribution of the residuals between the calculated monthly effort (*f*) and the predicted monthly effort (*f'*) for each LOA class. The highest density of the residuals is centred around 0 with an even distribution for both sides of the mean value (0). 60
Figure 3.5 Time series showing the evolution of the total monthly fishing effort from vessels with LOA > 14m, as km of nets, along the Portuguese mainland waters. The shaded grey area along the black line represents the 95% Confidence Interval and the vertical shaded bars represent the warmer months (April to September). 61
Figure 3.6 Contribution of each vessel LOA class to the overall fishing effort allocated to each port and the total effort with the 95% Confidence Interval. The amount of effort and the effort contribution from each LOA class varies distinctly among ports. Yet, it is observed that the proportion of effort contribution from each LOA class, within each port, remains relatively stable during the study period. 62

Figure 3.7 Annual values of effort, in km of nets, calculated for the 15 landing ports, during the study period. Landing ports were assumed as a proxy for the region where fishing vessels operated before landing their catches since the majority of these vessels perform daily fishing trips, and when performing longer trips, landing events occur in the port nearest to the fishing ground. 63

Figure 4.1 Map of the study region, the landing ports and the fishing footprint of the analysed fleet. The footprint was mapped using the methodology developed by Sales Henriques *et al.,* (2023). 76

Figure 4.2 Seasonal variation of the percentage of trips with unreported landing events (shaded CI) and the variation of the price per kg throughout the year (dashed CI lines). The four seasons are highlighted. The description of the models, with formulas, variables, R^2 and Deviance Explained can be found in Appendix section, Table A2. The plots and histograms from the resulting residuals can also be found in Appendix section Figure A1 – Unreported landing events and Figure A2 – Price of landed species. 83

Figure 5.1 A - Number of fishing trips inferred from landing data and logbook data, during the period of 2014-2020, for each of the 157 analysed vessels. Only one vessel showed the same number of fishing trips from both datasets, whereas 132 vessels had lower numbers of fishing trips logged on logbooks than those registered in landings data. The remaining 24 vessels had more landing events logged on logbook data than on landing data. The fitted linear regression model (light grey line) and the R value are shown. To compare the slope of the linear regression model with the expected slope = 1, a x = y line (dashed black line) is also displayed; B – Histogram showing the distribution of the difference of fishing trips estimated from both datasets for each of the analysed vessels. 96

LIST OF TABLES

Table 2-1 Results of the accuracy assessment for the deployment and hauling states for both types of gear. The performance of the model was assessed through the Sensitivity (true positive rate), the Specificity (true negative rate) and the Balanced Accuracy which is the arithmetic average of the Sensitivity and the Specificity of the model. 37

Table 2-2 Data composition from application of the vessel selection criteria until the final steps of the procedure. Overall number of vessels, trips and fishing events that were kept and identified from the AIS data, during the period 2014 to 2020, throughout the three main steps of our procedure. 39

Table 3-1 Summary of the calculation of the average length of hauled nets per trip, for the four LOA classes of vessels present in the AIS effort dataset, for which we were able to match trips with landing and logbook data. Due to the fact that the distributions of the length of nets used by trip did not follow any known distribution, bootstrapping procedure was performed with the purpose to: 1) assess if the sample mean would resemble the population mean derived from bootstrapping and 2) to calculate the 95% Confidence Intervals (CI) of the length of nets being used per trip. 59

Table 3-2 Overall number of vessels and landing trips for the coastal polyvalent fishing fleet operating nets bottom nets during the period 2014-2020. The number of landing events were used as proxies for the number of fishing trips, under the assumption that each landing event corresponds to a fishing trip. The total effort of this fleet was calculated using the number of fishing trips (landing events) and the average km of nets used by each vessel LOA class. 60

Table 4-1 Summary table from the data used in the current work. Unreported landing events were identified when there was no landing record from fishing trips (recorded with AIS) that had gear-hauling events. 81

Table 4-2 Summary table regarding the unreported landing events. The overall mean percentage of trips with unreported landing events was 14% which was the threshold % value defined to classify fishing vessels as risk units. The number of vessels with more than 14% of unreported landing events was 23 out of 66 and were responsible for nearly 85% of the detected unreported landing events. 82

Table 4-3 Table with the first 20 vessels and the number of fishing trips recorded with AIS data. Fishing vessels with more than 14% of unreported landing events are highlighted. The IDs of the vessels are anonymized due to confidentiality agreements. The complete table of all 66 vessels can be found in the Appendix section, table A1. 82

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Chapter II - Sales Henriques N, Russo T, Bentes L, Monteiro P, Parisi A, Magno R, Oliveira F, Erzini K, Gonçalves JMS, (2023) An approach to map and quantify the fishing effort of polyvalent passive gear fishing fleets using geospatial data. ICES Journal of Marine Science 80:1658–1669. https://doi.org/10.1093/icesjms/fsad092

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LIST OF ACRONYMS AND ABBREVIATIONS

AIS – Automatic Identification System

CFP – Common Fisheries Policy

DGRM – Directorate General of the Maritime Resources

DL – Decree Law

IUU – Illegal, Unreported and Unregulated

EFCA – European Fisheries Control Agency

FAO – Food and Agriculture Organization

GPS – Global Positioning System

HMM – Hidden Markov Model

ICES – International Council for the Exploration of the Sea

INE – Instituto Nacional de Estatistica

LOA – Length Over All

MCS – Monitoring, Control and Surveillance

MMSI - Maritime Mobile Service Identity

SSF – Small-Scale Fishing

VMS – Vessel Monitoring System

1. GENERAL INTRODUCTION

To effectively manage human activities, it is vital to understand the operational, economic, environmental, and social attributes of those activities (Fischer *et al.*, 2024; Kupika *et al.*, 2024; Murphy *et al.*, 2024). Fisheries, as any other human activity are no exception. An effective and comprehensive fisheries management plan requires well established goals and a very wide range of information to meet them.

Fisheries management approaches have common benchmark goals which are: to maintain target species at a level that ensures their continued productivity, to minimize the impacts of fishing activities on non-target species and on the physical environment, to maximize the net incomes of fishers, and to maximize employment opportunities (FAO, 2009). To meet such management objectives, fisheries management should rely on science-based approaches (Constable, 2011; Hilborn and Ovando, 2014; Hilborn *et al.*, 2020), which requires solid information about a broad range of factors related with fishing activities (Munro and Scott, 1985; Cochrane, 1999; Jentoft, 2000; Weijerman *et al.*, 2021). Among these, fishing effort is a crucial component that needs to be taken in consideration to plan and implement effective fisheries management (Pauly *et al.*, 2002; Anticamara *et al.*, 2011; Pascoe *et al.*, 2024).

Fishing effort, which is usually defined as the amount of fishing activity exerted on a fish population or fishing ground during a given time period (FAO, 1997), has a critical relevance for achieving sustainable fishing practices that takes in consideration the conservation of the marine environment and targeted species whilst also considering the socio-economic wellbeing of those relying on fisheries (FAO, 1997; Rees *et al.*, 2021). Through an effective monitoring, control and regulation of fishing effort it is possible to protect vulnerable habitats and species, to establish effective marine protected areas and implement comprehensive marine spatial plans (McCluskey and Lewison, 2008, Miller et al., 2013; FAO, 2018; Castrejón and Defeo, 2024). Moreover, with accurate estimates of fishing effort, it is possible to make more reliable stock assessments, to study the performance of management measures through the analysis of fishing efforts trends, and to study market trends and fishers' profitability (McCluskey and Lewison, 2008a). Yet, accurate measures and inferences derived from fishing effort are only possible with precise fishing effort estimates (Bordalo-Machado, 2006; Stewart *et al.*, 2010; Campbell *et al.*, 2014; Barua and Liu, 2024; Yang *et al.*, 2024).

The fact that fishing activities occur in a remote environment poses a big challenge to comprehensively collect all the data necessary to fully understand and monitor this activity. To overcome these challenges, different data collection methods have been used to study the fishing effort since the early days of fisheries research and management. These include questionnaire surveys (Veiga *et al.*, 2013; Diogo *et al.*, 2020; Alexandre *et al.*, 2022), surveys (Kimura and Somerton, 2006; Dennis *et al.*, 2015; Currie *et al.*, 2019), onboard observers (Tamsett *et al.*, 1999; Oliveira *et al.*, 2015; Ewell *et al.*, 2020; Marçalo *et al.*, 2024) and through fishery dependent data, like landings and logbook data (Cotter and Pilling, 2007; Grilli *et al.*, 2021; Raup *et al.*, 2021; Reis-Filho *et al.*, 2021).

All the aforementioned data collection approaches have their advantages and disadvantages. Inquiries or questionnaires allow to harness fishers' knowledge and experiences, to understand fishers perspectives on management issues, to be able to identify the ecological knowledge of fishers and to study the temporal trends of a fishery condition (Johnson and van Densen, 2007; Diogo *et al.*, 2020; Bernos *et al.*, 2021; de Boois *et al.*, 2021). However, they are subject to potential sampling and response bias. Indeed, enquiries are time-consuming, subject to bias from the respondents, as fishers may not want to participate and/or disclose all their knowledge. Another issue with questionnaires relates with the quantitative data that is possible to get and use in statistical analysis and inferences, which is usually limited (Silver and Campbell, 2005; Bernos *et al.*, 2021; de Boois *et al.*, 2021).

Fisheries surveys have the advantages that they allow a comprehensive data collection, which includes catch rates, effort levels and species compositions and distribution; it is a methodology that can be standardized across different areas or countries, which then allows to make comparisons. They also allow to monitor and detect changes over time, like changes in fishing effort (Parker-Stetter *et al.*, 2009; Caldwell *et al.*, 2016; Currie *et al.*, 2019). On the other hand, fisheries surveys also present disadvantages: sampling can be biased when ensuring representative samples is challenging, such as in areas of limited/difficult access. Moreover, It is a methodology that is not ideal for obtaining accurate estimates of fishing effort (Petitgas, 2001; Dennis *et al.*, 2015).

Data collected from onboard observers poses great advantages when studying fisheries. Data collected onboard is usually quite accurate, and some of the information that is possible to extract from this sampling methodology is hard, if not impossible, to collect with other sampling methodologies, like accidental catches or biological samples (Dias *et al.*, 2020; Marçalo *et al.*, 2024). However, onboard observers' programs are very costly, which limits vessel sampling coverage. Moreover, the presence of onboard observers may also influence fishers' behaviours, like making their operations more compliant with regulations, which could add bias to the sampled data (Duarte and Cadrin, 2024; Morrell *et al.*, 2024).

Fishery dependent data like logbook data and landing data have been one of the main sources of information within fisheries research and management (Holmes *et al.*, 2011; Lordan *et al.*, 2011; Eayrs *et al.*, 2015). These types of data have many advantages, such as their extensive, broad and continuous collection as the record of landings and fishing operations is mandatory for a vast array of fishing fleets (EU Council Regulation 1224/2009). From such data sources it is possible to obtain information on catches and species composition, as well as the fishing effort. It is a form of data collection that is very cost-effective, as much of it is either self-reported or logged in established and harmonized formats, which makes it possible to standardise such data across regions and fleets (Maunder and Punt, 2004; Ochwada-Doyle *et al.*, 2016; Cheng *et al.*, 2023). However, the reporting of these types of data may be biased or there may even be underreporting, since the quality and existence of such data is dependent on fishers' willingness to accurately log and report the information regarding their trips and catches (Verdoit *et al.*, 2003; Maunder and Piner, 2015).

Despite the importance of such data collection approaches and the increasing efforts to improve the knowledge on fishing activities, it is agreed that our understanding on fishing effort, including its distribution and precise quantification, is still far from ideal, which is why the improvement of data collection and fishing effort estimates is still needed (Kroodsma *et al.*, 2018; Leblond *et al.*, 2019; Barua and Liu, 2024; Yang *et al.*, 2024).

Thanks to recent technological developments in data collection, storage and analysis, new types of fishery data have emerged. These include satellite imagery (Marsaglia *et al.*, 2024; Paolo *et al.*, 2024), CCTV footage (Emery *et al.*, 2019b) and vessel tracking data (Jennings and Lee, 2012; Russo *et al.*, 2016c). These new types of data have been revolutionizing fisheries research and monitoring (Witt and Godley, 2007a; Metcalfe *et al.*, 2018; Kumar *et al.*, 2022) as the information that is possible to obtain from them was otherwise impossible to get from the classical data collection approaches.

Vessel tracking devices were initially used for maritime safety reasons, especially to avoid collisions between vessels, in the 80's (www.imo.org). These devices, which are installed onboard the vessels, automatically transmit information about the vessel and its movement, such as the vessel ID, current position, speed and heading. In Europe, fishing vessels started to be monitored with vessel tracking devices in 2004. Under the EU Counsil Regulation 2244/2003, fishing vessels with a Length Over All (LOA) equal or above 18m are required to be equipped with Vessel Monitoring System (VMS) so their activities could be monitored and controlled. Presently, fishing vessels with LOA equal or above 12m are also required to have VMS onboard (EU Council Regulation 1224/2009) with some exceptions. AIS (Automatic Identification System) which is another vessel tracking system, was developed with the primary purpose of increasing maritime safety by avoiding collision, mainly when entering and leaving ports. The legal requirement for European fishing vessels to be equipped with AIS started in 2014. According with the EU Council Regulation 1224/2009, vessels with a LOA above 15m must be fitted with AIS and must be continuously transmitting.

Conceptually, both systems provide similar information about the vessel, its movement and location, meaning that both provide the ID of the vessel, its exact location, current speed and heading. They do differ, though, in terms of their technical aspects, mainly in terms of data transmission frequency, where VMS have a lower transmission frequency (30 minutes to 2 hours) than AIS (30 seconds to 5 minutes). The transmission signal from VMS is exclusively based on satellite transmission, whereas AIS signal relies on VHF radio signal but also on satellite transmission. Another important difference between these two types of tracking data, has to do with how they are broadcasted: AIS is publicly broadcasted, which means that it is of easy access, whereas VMS data, since it was developed for monitoring and control purposes, is exclusively for fisheries monitoring and enforcement entities, which means that they are not publicly available (Hinz *et al.*, 2013; Shepperson *et al.*, 2018).

Thanks to vessel tracking data, estimates of fishing effort have seen a dramatic improvement, especially in the accuracy of estimations of the total fishing effort by a given fleet and its spatial distribution (Vermard *et al.*, 2010; de Souza *et al.*, 2016; Russo *et al.*, 2016c; Vespe *et al.*, 2016; Le Guyader *et al.*, 2017). For example, Vespe et al., (2016), mapped the fishing activity of EU trawlers across EU waters using AIS data; Gerritsen et al., (2013), estimated how much of the seabed is impacted by trawling gears within the Irish Celtic Sea, using VMS and AIS data. The results obtained from the mentioned works are of extreme importance to improve the sustainable use of the marine environment. However, they were not feasible to get without the data provided by these devices.

Like for any other type of data, the usage of vessel tracking data alone falls short in their potential for providing useful information for fisheries management (Robards *et al.*, 2016; Wang *et al.*, 2024; Anastasi *et al.*, 2025). Indeed, the combination of different types of data is a much more reliable, comprehensive and accurate approach to improve our knowledge on fishing activities (Methot and Wetzel, 2013; Hilborn *et al.*, 2020, 2025; Tracy *et al.*, 2025).

The combination of vessel tracking data with other types of data, like fishery dependent data, such as logbook or landing data, or environmental data, for example, has proven to be able to provide very valuable information for fisheries management which could not be realistically obtained otherwise (Bastardie *et al.*, 2010; Stewart *et al.*, 2010; Dunn *et al.*, 2018). For example, such approaches allow to estimate the productivity of fishing grounds, to map the distribution of fished species or to estimate the fishing footprint and effort in cases when tracking data has poor or unavailable coverage (Pedersen *et al.*, 2009; Gerritsen and Lordan, 2011; Russo *et al.*, 2018, 2019b). Moreover, vessel tracking data when combined with other types of data, has also proven to be useful to identify and monitor illegal fishing activities (Iacarella *et al.*, 2022; Zuzanna *et al.*, 2022; Orofino *et al.*, 2023).

Regardless of the potential and reliability of the approach used to study and monitor fishing activities, they all depend on the quality and consistency of the data which they rely on. This is why it is important to understand the accuracy and completeness of such data (Pauly and Zeller, 2016).

As mentioned above, logbook and landings data are a very important source of data for fisheries management and research (Grilli *et al.*, 2021; Jones *et al.*, 2022; Thatcher *et al.*, 2024). To ensure the consistent and accurate provision of such data, many countries mandated the legal requirement of logging fishing activities in logbooks and that catches to be recorded and officially landed (EU Regulation CE 1224/2009). Both types of data have been used to quantify and monitor the fishing effort (Fahy *et al.*, 1992; Punt *et al.*, 2000; Punt, 2019), to estimate stock sizes and trends (Maunder and Punt, 2004; McCluskey and Lewison, 2008a), to study species distributions (Karp *et al.*, 2023) and to estimate by-catch and accidental catches of protected species (Walsh *et al.*, 2002; Figus and Criddle, 2019). However, given that these types of data are inherently dependent on fishers' willingness to accurately and consistently log their activity and officially land and/or declare their catches, there is the risk of bias or incompleteness (Verdoit *et al.*, 2003; Walsh *et al.*, 2005; Jiorle *et al.*, 2016; Noleto-Filho *et al.*, 2022; Howard *et al.*, 2023). Such inaccuracies will inevitably contribute to the underlying uncertainty from the inferences derived from such data (Bishop *et al.*, 2008; Maunder and Piner, 2015), which is why it is important to understand if the recording and reporting of such information is being followed and to detect and quantify when it is not (Bishop, 2006; Fuster-Alonso *et al.*, 2024; Kim *et al.*, 2024).

Until the start of this PhD, the great majority of fishery research relying on vessel tracking data and the combination of track data with other types of data, had been mainly focused on fishing fleets using single and mobile gears, such as trawlers, dredgers and seiners (e.g. Natale *et al.*, 2015; Vespe *et al.*, 2016; Russo *et al.*, 2019b). Fishing fleets operating passive and static gears, especially within a polyvalent (multi-gear) context, had received less attention.

Polyvalent fisheries span a wide range from traditional and small-scale to large and industrial fisheries, which makes this class of fishing the world's biggest fishing sector. Whilst its proportion varies depending on the region and country, its significance as a source of food for human consumption, employment, socio-economic and cultural foundation of coastal communities is undoubtably of extreme importance (Kelleher *et al.*, 2012). In Portugal, polyvalent fisheries employ more than 72% of licenced fishers, land 38.2% of the total national catches in weight, and 83% of all fishing gear licences belong to fishing gears used within polyvalent fishing (INE, 2024), making it one of the most important fishing segments at national level.

This thesis aims to contribute to close the gap in fisheries research using vessel tracking data and the combination of such data with other types of data to improve the knowledge of fishing activities of polyvalent passive fishing fleets. Besides developing approaches to contribute to a better knowledge of polyvalent and passive fishing activities, it also contributes to a deeper understanding of the fishing effort of the Portuguese polyvalent coastal fishing fleet, the quality of its fishery-dependent data and how fishers comply with reporting and landing legal requirements.

1.1. Literature review - Vessel tracking and fishery dependent data: their role in improving fishing effort estimates and detecting uncompliant behaviours

Vessel tracking data and their combination with other types of data have been playing a crucial role in improving the necessary information to manage fisheries (Robards *et al.*, 2016). Given that vessel tracking data can prove that vessels performed some sort of activity, such as a fishing trip or performing a fishing event (Natale *et al.*, 2015; Vespe *et al.*, 2016), such data has also been valuable to detect uncompliant and illegal behaviours, which would not be detected through other types of fishery data (Zuzanna *et al.*, 2022).

1.1.1. Classification of vessel tracking data to detect and map fishing activities

The usage of vessel tracking data has been increasing since they were initially implemented in the 90's. To use such data in fisheries research and management, the first vital step is to detect, within the data, when a vessel is fishing or not (Vermard *et al.*, 2010; Poos *et al.*, 2013). This means that vessel tracking data needs to be classified into the different phases of a fishing trip before it can be used for fisheries research and management approaches.

Given that vessel tracking datasets are usually very large, the classification of such data has been performed through different methodologies that vary in complexity. The simplest and most common approaches to identify fishing activities has been based on speed filtering. They rely on the assumption that when a vessel is engaged in a fishing activity it navigates at a much slower speed than steaming (Campos *et al.*, 2023). However, even though advantageous given their simplicity and low computational requirements, these approaches can only be used for fishing practices that follow such assumption. In case a vessel performs a fishing event, or part of that fishing event, at a higher speed, like purse seiners when deploying their nets for example, a simple speed filtering approach might not be suitable to identify the full duration of such fishing activities. Moreover, if a vessel is slowly navigating it does not necessarily means it is fishing. For example, this can happen when a vessel is arriving to port, waiting to start fishing or some unpredictable events are reasons for a vessel to slowly navigate. Classifying vessel tracking data based only on speed profiles would identify such moments as fishing events.

However, and to account for the behavioural complexity of fishing activities, more complex classification methodologies have been developed (Kroodsma *et al.*, 2018; Marsaglia *et al.*, 2024; Samarão *et al.*, 2024). They usually rely not only on speed, but also on trajectory metrics such as turning angles, acceleration, and correlation with external factors, such as environmental variables, like depth and distance to shore, to infer the different behaviours within a fishing trip (Lee *et al.*, 2010; Russo *et al.*, 2014a; Leblond *et al.*, 2019; Mendo *et al.*, 2019a). Given the higher number of variables used to classify the track data, these methodologies often rely on different models and/or Machine Learning approaches to classify the data, such as Hidden Markov Models (Vermard *et al.*, 2010; de Souza *et al.*, 2016; Whoriskey *et al.*, 2017; Mendo *et al.*, 2019a), Neural Networks (Kroodsma *et al.*, 2018; Russo *et al.*, 2019b; Kontopoulos *et al.*, 2021, 2024; Cheng *et al.*, 2025), Support Vector Machines (Russo *et al.*, 2016b), and Random Forrest (Mendo *et al.*, 2023b; Rufino *et al.*, 2023; Samarão *et al.*, 2025), among others.

Since the start of this PhD, the majority of studies and development of vessel data classification methodologies had been mainly focused on fleets operating active gears, such as trawls and seiners (Lee *et al.*, 2010; Natale *et al.*, 2015; de Souza *et al.*, 2016). Vessel tracking data classification methodologies on fleets operating passive gears, such as nets and traps, albeit their importance in terms of their overall fleet proportion, fishing effort and impact on the marine environment (Kelleher *et al.*, 2012; Cashion *et al.*, 2018), had received less attention from the scientific community.

The existing studies on mapping the fishing effort of static fishing gears had relied on the identification of fishing events through the identification of the moments when vessels hauls their gears, which are carried out at a very low speed (Marzuki *et al.*, 2018; Mendo *et al.*, 2019a; Leitão *et al.*, 2022; Campos *et al.*, 2023). Although this approach allows the fishing effort of this type of gears to be mapped and quantified, it does not allow an important effort metric of static gears, the soak time, to be quantified.

Soak time, which is the period which a fishing gear is submerged whilst fishing, plays an important role in this type of fishery (Erzini *et al.*, 2008; Alexandre *et al.*, 2022). Depending on the period of time a given gear stays fishing, the catch rate of these gears may change, as do captures in terms of composition and quantity (Boutillier and Sloan, 1987; Erzini *et al.*, 1997a; Ward *et al.*, 2004; Li *et al.*, 2011). This is why accurate estimates of soak time are of extreme importance for stock assessments. Furthermore, given that the longer the time a gear is fishing, the higher will be the impacts on the marine environment (Erzini *et al.*, 1997a), some gears are not allowed to stay fishing for more than certain periods of time (EU regulation No. 227/2013), which makes the calculation of gear soak time also important within a fisheries monitoring and controlling context. Regardless of the importance of soak time in static gear fishing, effort assessments in terms of soak time have rarely been addressed.

One of the probable reasons for the absence of studies relying on vessel tracking data to address the soak time of static gears is the difficulty of identifying when a vessel is deploying a gear. Indeed, if the navigation pattern of a vessel when deploying a gear is different from when it is steaming, the start of these fishing events have been identified (Charles *et al.*, 2014). However, when the behaviour of gear deployments is too similar to steaming, this poses some challenges to identifying gear deployments based on vessel behaviours (Mendo *et al.*, 2019a) and therefore to calculate the soak time for static gears with vessel tracking data for fishing fleets.

1.1.2. High resolution estimates of fishing effort - Passive gears effort metrics: soak time and km of used gears.

The precise understanding of fishing effort is a vital component for the proper management of marine resources and their environment (Bordalo-Machado, 2006; Behivoke *et al.*, 2021). Information on fishing effort has been used with different aims, such as in fish stock assessments (Punt *et al.*, 2000; Dichmont *et al.*, 2016; Cheng *et al.*, 2023), in marine spatial plans (Branch *et al.*, 2006; Russo *et al.*, 2019a; Kneebone *et al.*, 2025; Xia *et al.*, 2025), and to evaluate the impacts caused by fishing activities (Tasker *et al.*, 2000; Oliveira *et al.*, 2015; Mendo *et al.*, 2023a) for example. This is why it is critical to have a good understanding of the different attributes of fishing effort, like its distribution, seasonal variation and extent (Anticamara *et al.*, 2011).

Different effort estimates and metrics have been used and published throughout the scientific literature. Some of the most common and oldest approaches to quantify the fishing effort have relied on fleet capacity metrics, such as the number of active vessels (Pauly and Christensen, 1995; Jennings and Kaiser, 1998), and the fishing power, such as the fleets' total engine power, tonnage, vessels' length or total crew number (le Pape and Vigneau, 2001; Parente, 2004; Rijnsdorp *et al.*, 2006).

However, and although larger vessels tend to catch more than smaller vessels, it is also known that vessels with similar attributes, such as LOA, engine power or used gear for example, do differ in terms of catches (Hilborn, 1985; Thorson and Ward, 2014). Which is why it is important to increase the resolution of effort estimates (Stewart *et al.*, 2010; Anticamara *et al.*, 2011; van Poorten and Brydle, 2018).

Another common, and more recent approach to study and quantify the fishing effort has relied on fisheries dependent data (Punt *et al.*, 2000; Fuster-Alonso *et al.*, 2024; Xu *et al.*, 2024), mainly using logbook data and landings/sales notes records (Bishop, 2006; Cotter and Pilling, 2007; Su *et al.*, 2008; Prchalová *et al.*, 2011). Effort assessments through logbook data rely on the information logged by skippers (Grilli *et al.*, 2021; Sari *et al.*, 2021; Karp *et al.*, 2023), whereas effort studies relying on landing or sales notes data need to follow some assumptions, such as that a landing event corresponds to a fishing trip (McCluskey and Lewison, 2008a; Greenstreet *et al.*, 2009; Trudeau *et al.*, 2021). Such approaches allow a better understanding of the actual effort when compared to effort estimates based only of fleet attributes (Stewart *et al.*, 2010; Gibson-Reinemer *et al.*, 2017). However, the quantification of the number of fishing days, days at sea, or fishing trips, for example, do not provide the whole picture of the fishing effort. For example, as some vessels are larger than others, they will have higher effort per trip, or some might perform more fishing events per trip than others (Piet *et al.*, 2007; Jackson *et al.*, 2024). Moreover, the spatial distribution of the effort is also a very important attribute, which also affects the catch rates, quantity and composition (Russo *et al.*, 2018, 2019a; Leitão *et al.*, 2022). Although the location of fishing activities can be inferred from logbooks, this information is known to be highly unprecise (Thomas-Smyth, 2013; Jones *et al.*, 2022) and it cannot be studied with other types of data that do not explicitly disclose the exact location of the fishing activities, such as landing data.

Despite the shortcoming of these effort metrics, they have been quite useful in broad-scale effort assessments, such as at regional or national level. However, low-resolution of effort metrics can represent a problem as they could lead to false conclusions, such as wrong estimates of abundance and actual areas with higher fishing effort (Gillis and Peterman, 1998; Mendo *et al.*, 2023a). This is why there have been efforts to improve the resolution of effort estimates in recent years (Chinacalle-Martínez *et al.*, 2024; Wang *et al.*, 2024; Lazaris *et al.*, 2025; Samarão *et al.*, 2025).

Ideally, the resolution of effort estimates should be based on the attributes and dimensions of the fishing gears (Marcaccio *et al.*, 2025; Taylor *et al.*, 2025). For example, the total number of hooks used by a given vessel or fleet, the total swept area of trawling or the total length of nets used within an area or per unit of time provides a much more precise estimate of effort. Indeed, such precise effort estimates are possible and have been done on a broad scale through very costly and specific monitoring or sampling programs (Punt *et al.*, 2000; Mandelman *et al.*, 2008; Coelho *et al.*, 2012). Other studies have estimated fishing effort with such resolutions (Lauridsen *et al.*, 2008; Akyol and Ceyhan, 2009; Gönener and Bilgin, 2009; Batista *et al.*, 2015; Sara *et al.*, 2017). However, they focused on particular subjects, such as by-catch (Gönener and Bilgin, 2009) or estimated the effort within a narrow area. Indeed, fishing effort estimates with higher resolution and at broad scales, such as at country level, albeit their importance, still remain a big challenge and, despite the increasing number of studies addressing this knowledge gap, they are still underrepresented in the scientific literature.

With the introduction of vessel tracking data, the estimation of fishing effort has seen a major revolution (Tetreault, 2005; Russo *et al.*, 2018; Yang *et al.*, 2019; Thoya *et al.*, 2021; Samarão *et al.*, 2024). For example, Jennings and Lee (2012) identified fishing grounds around the UK for different fishing vessels, using VMS data; Natale et al., (2015) using AIS were able to map and estimate, at high resolution, the fishing effort of trawlers in Swedish waters, and Russo et al., (2011) were even able to assign fishing effort to specific metiers at a resolution of single fishing trips.

Besides the usage of vessel tracking data for effort estimates, the combination of such data with fishery dependent data has proven to be an even more advantageous approach (Lee *et al.*, 2010; Gerritsen and Lordan, 2011; Yuniarta *et al.*, 2024). Especially because it allows to overcome some of the shortcoming of effort estimates based only on vessel tracking data related with the incomplete fleet´s coverage of tracking data (Russo *et al.*, 2018).

1.1.3. IUU - Estimate unreported landing events

Illegal, Unreported and Unregulated (IUU) fishing activities are amongst the most threatening activities affecting the marine environment and those depending on it (Agnew *et al.*, 2009). Amongst these, Unreported activities are within the most common practices of IUU fishing and it refers to unrecorded fishing activities and fishing-related activities that have not been reported, or wrongly reported, to authorities (Pauly and Zeller, 2015; EFCA, 2022).

Given the difficulties in Monitoring, Controlling and Surveying (MCS) fishing activities, it is commonly agreed that in order to prevent, deter and eliminate IUU fishing practices, it is important to quantify such activities so their impacts can be estimated and to understand, among other things, how these activities are performed and what are the main drivers behind them (Agnew *et al.*, 2009; Fajardo, 2022; Auld *et al.*, 2023; Widjaja *et al.*, 2023). Such information is vital to make risk assessments on IUU activities, which are acknowledged as a necessary step to improve the efficacy of MCS efforts (Macfadyen *et al.*, 2016).

Depending on the objective(s) of each study, different methods have been developed and applied to study IUU activities. Indeed, throughout the scientific literature, it is rarely the case that two studies use the same method, which reflects the availability of different types of data available to study IUU fishing activities (Macfadyen *et al.*, 2016; Hosch and Macfadyen, 2022).

Throughout the published studies focused on IUU fishing, one of the most common goals has been to estimate the total unreported catches, with the primary aim of estimating the total fisheries removal, beyond what is officially recorded (Ainsworth and Pitcher, 2005; Zeller *et al.*, 2007, 2011; Coll *et al.*, 2014; Leitão *et al.*, 2014; Swartz and Ishimura, 2014; Pauly and Zeller, 2016). Other studies have focused on IUU fishing for some particular species like salmon (Clarke *et al.*, 2009), sharks and rays (Clarke *et al.*, 2006; Harris and Stevens, 2024). Some studies have made estimates of IUU fishing with the purpose of making recommendations on management actions, where hotspots of IUU activities were identified to improve the MCS actions (Funge-Smith *et al.*, 2015; Ford *et al.*, 2018a), or through risk assessments with the purpose of identifying risk units with higher risk of practicing IUU activities (MRAG, 2015; Petrossian, 2015; Temple *et al.*, 2022).

An important objective also addressed in many of the published studies on IUU fishing has been to identify the main drivers of such practices. Overall, the main drivers contributing to IUU practices have been the economic advantage of IUU practices, political and social factors and the weak and ineffective fisheries MCS efforts (Schmidt, 2005; Song *et al.*, 2020; Fujii *et al.*, 2021; Mozumder *et al.*, 2023).

Different methods and types of data have been used to study IUU activities. For example, MCS inspection data have been used to estimate the total retained catches of certain species (Aanes *et al.*, 2011). Ainsworth and Pitcher (2005) and Belhabib et al. (2014) used records of infringements to estimate illegal and unreported catches in British Columbia and Senegal, respectively, while records of inspections have also been used to estimate unreported bycatches (Bremner *et al.*, 2009) and MRAG (2016) used the same type of records, amongst other types of data, to quantify the volume, species composition and value of IUU fishing in the Pacific tuna fishery.

Trade, catch and official landing data have been used to estimate unreported and illegal catches either for particular species or at country level. For example, Clarke et al., (2009) estimated illegal and legal catches of sockeye salmon from trade and market data and Planányi et al., (2011) estimated illegal catches of abalone based on trade and catch data. Pramod et al., (2014) estimated seafood imports to the USA from illegal and unreported fishing using catch and trade data, and Donlan et al., (2020) used enforcement and trade data to estimate the proportion landed catches provided from illegal and unreported fishing in Chile.

With the introduction of remote sensing data, such as satellite imagery, vessel tracking data or air surveys data, IUU studies could also focus on IUU fishing related with the estimation of illegal fishing effort, like the number of vessel fishing without licence (Agnew *et al.*, 2009) or to study the spatial component of IUU fishing, like fishing in prohibited areas (Iacarella *et al.*, 2022) for example. Within this context, the use of vessel tracking data, such as VMS or AIS, has been one of the most recent approaches to study IUU fishing activities. This type of data has been used to identify illegal fishing activities, such as transhipment and fishing in protected areas (Chuaysi and Kiattisin, 2020; Iacarella *et al.*, 2022; Kumar *et al.*, 2022). AIS data has been used to study and label fishing vessels according to their likelihood of engaging in loitering behaviours (Ford *et al.*, 2018a). Hosch et al. (2019) combined AIS data to infer vessel activity and their visit to major landing ports to make a risk assessment, at port level, to identify ports with higher risk of IUU-caught seafood passing through them.

Regardless of the objectives of IUU studies and the methodologies used, it is commonly agreed that to improve the MCS efforts, so they can be more effective in identifying and, consequently penalizing non-compliant practices, IUU risk assessments need to be made (Petrossian, 2015; EFCA, 2022; Temple *et al.*, 2022). If MCS effort are adapted and focused to target units with higher risk of practicing IUU activities, then the probability of detecting and penalizing such actions will increase (EFCA, 2022; Temple *et al.*, 2022). However, it is important that such rick assessments are made at the highest resolution possible, like at vessel level, so MCS efforts can be better allocated (Macfadyen *et al.*, 2016; Ford *et al.*, 2018b; Temple *et al.*, 2022).

1.1.4. Quality assessment of Fishery dependent data

The regular data collection and analysis of fishery dependent data has been one of the main sources of information used to estimate, control and monitor fishing effort (Bordalo-Machado, 2006; Maunder and Punt, 2013).

Logbook data, which is a form of self-reported data, is a practical and inexpensive source of a wide range of valuable information about fishing activities. Indeed it is one of the most used sources of information to estimate and map fishing effort (Grilli *et al.*, 2021; Raup *et al.*, 2021; Reis-Filho *et al.*, 2021). However, a common concern regarding self-reported data is that its consistency and accuracy is highly dependent on those responsible for reporting it (Granberg and Holmberg, 1991; Klebanoff *et al.*, 2001; Murray *et al.*, 2013; Mion *et al.*, 2015).

There have been different studies addressing the data quality and consistency of logbooks. Whilst it is commonly agreed that the information provided by this data source is of great importance, and in some cases it corroborates with observers data when used to describe the spatiotemporal patters of target species (Mion *et al.*, 2015), or it showed congruence with electronic monitoring regarding catch data (Emery *et al.*, 2019b), the majority of these studies found that logbook data showed significant inaccuracies and imprecisions. For example, Sampson (2011) when compared logbook data with official landing data, observed discrepancies regarding retained catches, and that information on location and depth of fishing activities logged on logbooks were inconsistent. Bishop et al. (2008) found logbook data systematically incomplete and occasionally unreliable when used to standardize catch rates. Another common concern regarding logbook data relates with the logged information being purposefully biased (Walter *et al.*, 2014; Smallwood *et al.*, 2024). For example, it has been shown that fishers underreport catch quantities when Total Allowable Catches (TACs) are in place (Domínguez-Bustos *et al.*, 2025). Such inaccuracies, inconsistencies and biased information can influence estimates based on logbook data, and this is why it is important to understand the accuracy of the information that can be inferred from such data sources (Cotter and Pilling, 2007; Sampson, 2011).

1.2. Brief overview of the Portuguese Polyvalent Coastal fishing fleet.

According to the UN's Food and Agriculture Organization (FAO), polyvalent fishing vessels are all vessels that use more than one fishing gear. These vessels range from small-scale fishing vessels (below 12m LOA) to vessel larger than 24m LOA (FAO, 2025). Given that the majority of small-scale fishing vessels operate more than one type of fishing gear and target different species, polyvalent fishing vessels play a vital role in terms of the world's global catches, accounting for up to 40% of all catches. Moreover, it represents the majority of fisheries workforce, which reaches 90% of employed fishers globally (FAO, 2024).

According with the EU fleet registry database, in 2025, the European fishing fleet is composed of 68922 registered fishing vessels, where 69% are polyvalent fishing vessels. This polyvalent fishing fleet is composed mainly (96.4%) by small-scale fishing vessels (LOA < 12m) and the remaining 3.6% correspond to coastal and large-scale fishing vessels (LOA ≥ 12m).

In Portugal, just as it happens in Europe and throughout the world, polyvalent fishing vessels correspond to the majority of the national fleet. In Portuguese mainland waters, polyvalent fishing vessels use mainly three types of fishing gears: pots and traps, static nets (gillnets and trammel nets) and longlines. Although the first two types of fishing gears are the most widely used, the usage of the latter is less frequent and has been declining (Leitão *et al.*, 2025).

According with the Directorate General of the Marine Resources (DGRM) and during the period 2014 to 2020, the analysed period of this thesis, 94.3% of all active fishing vessels landing in the Portuguese mainland ports belonged to the polyvalent fishing sector. Within the polyvalent sector, 90.9% of fishing vessels belong to the small-scale fishing (SFF) fleet, whereas the remaining 9.1% of all active fishing vessels belong to the coastal polyvalent fishing fleet. During the same period, polyvalent vessels were responsible for 36.8% of all the landed catches, of which 17.9% of total landings corresponded to landing from polyvalent small-scale fleet (SSF) fleet and 18.9% were landed by the polyvalent coastal fleet. In terms of landed value, polyvalent fishing vessels contributed to 62.4% of the total transaction value at first-sale auctions in mainland ports, with 28.8% and 33.6% accounted for by the coastal polyvalent fishing vessels and the polyvalent SSF vessels, respectively.

According to the DGRM landing records, polyvalent fishing vessels captured nearly 380 different species from 2014 to 2020. Of these, the most captured species were the common octopus (*Octopus vulgaris*), the pout (*Trisopterus luscus*), the hake (*Merluccius merluccius*), the jack mackerel (*Trachurus trachurus*), the thornback ray

(*Raja clavata*), the conger (*Conger conger*), the monkfish (*Lophius piscatorius*), the common sole (*Solea solea*) and the john dory (*Zeus faber*).

Besides its relevance in terms of fleet size, total catches and first sale at auction value, polyvalent fisheries are the most important segment in terms of workforce, employing 72.3% of licensed fishers, and 83% of licenced fishing gears are used by this fleet segment (INE, 2024).

1.3. Coastal polyvalent fishing fleet in Portugal and relevant legislation for the thesis

The primary goal of the Common Fisheries Policy (CFP) is to ensure that fishing activities are carried out in the most sustainable way whist safeguarding the economic and social provisioning of fishing activities. Portuguese Polyvalent Coastal fishing vessels, as any other Portuguese and European fishing vessel, are subject to different European and national laws and regulations that aim to ensure the sustainability and economic viability of fishing activities.

As far as this thesis is concerned, there are some important European and national regulations that should be highlighted:

The first set of regulations are related to the requirements of vessels being equipped with tracking devices. The EU Fisheries Control Regulation (Regulation (EC) No 1224/2009), which provides the legal framework for enforcing the rules of the CFP, mandates, under Article 9, that fishing vessels with a LOA equal or above 12m, must be equipped with VMS devices. These devices must provide the vessel's position, speed and course at regular time intervals to the flag state authority where the vessel is registered. The purpose of VMS data is to ensure the effective monitoring and control of compliance with fisheries and conservation regulations. Another regulation within the CFP that mandates the usage of another type of vessel tracking device is Regulation (EU) 404/2011. Under Article 10, fishing vessels with a LOA equal or larger than 15m must be equipped with AIS transponders. The AIS must be operational and continuously transmitting at all times, except under exceptional and safety related circumstances.

Another CFP regulation that is relevant to this thesis relates with the requirements of fishing vessels recording their activity on logbooks. Fisheries Control Regulation (Regulation (EC) No 1224/2009), Article 14 requires that fishing vessels with a LOA equal or above 10m to have and record their activity on logbooks. It also defines the mandatory information to be logged, such as caught species, their quantity, the capture date and location, used gear and fishing effort as number of fishing operations. A relevant aspect regarding the logging requirement of captured species is that it is only mandatory for species for which catches surpass 50kg of live weight.

Article 15 from the same regulation, requires that fishing vessels with a LOA equal or above 12m, must record their activity on electronic logbooks and transmit that information to authorities after the last fishing operation and before arriving to port. However, there are important exemptions within this article that allow member states to exempt fishing vessels with LOA above 12m and under 15m, to report and transmit their activity through electronic logbooks. If a fishing vessel within this range of LOA operates exclusively within national waters and does not carry out fishing trips that last longer than 24 hours, then it may be exempted from electronically logging and transmitting logbook data.

In Portugal, to renew the licences that allow fishing vessels to continue using the fishing gears they have been using, they must comply with the requirements stated on Article 47 of the Regulatory Decree (Decreto Regulamentar nº 7/2000). As far as this thesis is concerned, this decree states that in order to renew fishing gears' licences, the fishing vessel must prove that it has a regular fishing activity. To do so, vessels need to have a yearly income, proved by official landing/sales notes records, that allows them to pay the wage of its crew during the entire year. Another important aspect is that the deadline for submitting the request for renewal of fishing gear licences is the last day of August.

The Law Decree (Decreto-Lei 81/2005) provides the legal framework for the first sale of catches within the Portuguese mainland. According with this legislation, all catches must be officially landed in the port where the vessel arrives after a fishing trip. The first sale of all catches must be carried out through auction at the same landing port. There are some exemptions regarding the first sale of fresh catches that relates with pre-established contracts between fishers and buyers. Notwithstanding, all catches still need to be landed and recorded at the port of arrival.

As any other fishing activity, fishing with nets is subject to certain regulations imposed be the Portuguese government through the Portaria nº 1102-H/2000 which provides the legal regulation of net fishing. Article 6 establishes the maximum length of nets allowed to be used by each vessel, which depends on the size of the vessel. These values are given in Appendix II of the same regulation. Although not relevant for this thesis, the total length of trammel nets allowed to be used by each vessel were updated in 2023, with a very relevant increase which more than doubles the allowed sizes of trammel nets for vessels larger than 14 m LOA. Article 8 is also relevant for this thesis, as it establishes the maximum soak time of nets. Under normal circumstances, nets are not allowed to be consecutively fishing for more than 24 hours. However, there are exceptions when nets are used at depths below 300 m and their mesh size is equal or larger than 100 mm. In this case, nets may be continuously fishing for up to 72 hours.

1.4. Research gaps and significance for this study

Research dedicated to study and quantify the fishing effort, though the means of vessel tracking data, throughout Portuguese mainland waters has been rather unbalanced towards the study of trawling (Fonseca *et al.*, 2008; Pilar-Fonseca *et al.*, 2014a, 2014b; Bueno-Pardo *et al.*, 2017) when compared with purse seine and polyvalent fishing. As stated above, the polyvalent coastal fishing fleet plays an important role in terms of total catch and first sale at auction value throughout the Portuguese mainland. Despite its importance, research focused on the quantification and mapping of its fishing effort has been rather scarce. Until the start of this PhD, there were no published studies addressing fishing activity of this fleet using vessel tracking data. However, whilst this thesis was being conducted, new research was published. Leitão et al. (2022) predicted landings per unit of effort, for some species targeted by the Portuguese coastal fishing fleet using VMS and official landing data. Campos et al., (2023) used VMS and AIS data, combined with logbook data to map the distribution of longline fishing in the Gorringe bank. However, both studies rely on the approach of filtering the vessel tracking data based on speed values, under the assumption that if a vessel is slowly navigating, then it is most likely fishing. Such an approach does not allow to estimate important effort metrics inherent to passive fishing gears, such as the soak time and the total length of gears deployed. As far as we are aware, until the start of this PhD, no methodology had been developed that was able of classifying vessel tracking data that allows estimating and mapping the passive gears' fishing effort at such effort metrics.

In terms of research dedicated to study unreported catches throughout Portuguese fisheries, only Leitão et al. (2014) addressed the estimation of Illegal, Unreported and Unregulated catches throughout Portuguese mainland waters. In their work, they focused on estimating and reconstructing total catches besides the ones that were officially landed. To improve the fight against IUU fishing it is important to understand what are the drivers that influence such activities, which may very well depend on the country, regulations and enforcement where fishing activities occur (Agnew *et al.*, 2009; Petrossian and Clarke, 2014; Petrossian *et al.*, 2015a). Hence the importance to understand how such practices are performed throughout Portuguese fisheries. Moreover, development of methodologies to assist in IUU risk assessments are still lacking globally and most certainly for the Portuguese fishing fleet.

Fishery dependent data, such as self-reported data, is one of the pilar-stones of fisheries research and management (Magnusson and Hilborn, 2007). However, such type of data is known to be biased, lacking consistency and accuracy, as different studies throughout the world have shown (Walsh *et al.*, 2002; Bishop *et al.*, 2008; Howard *et al.*, 2023). This is why it is important to understand how their quality may affect the estimation of different fishing metrics, such as the quantification of fishing effort. Despite the importance of such understanding, there is still no assessment on the quality and consistency of the Portuguese fishery dependent data when used to estimate fishing effort, for example.

1.5. General Objectives

Given the global underdevelopment of methodologies relying on vessel tracking data and fishery dependent data to improve the information about polyvalent and passive fisheries, this study primarily aims to develop new methodologies that allow to better understand the spatiotemporal dynamics of the fishing effort of such fishing fleets. It also aims to explore how the combination of vessel tracking data with fishery dependent data can be useful to understand unreported catches and to improve the Monitoring, Control and Surveillance efforts of fishing activities. Such methodologies were developed and applied to study the Portuguese polyvalent coastal fishing fleet, for which this type of information is still scarce. To address these broader goals, four different studies were conducted in this thesis with the aim of addressing one or more specific objectives:

1. To develop a vessel tracking data classification methodology that is able to detect and classify the start (gear deployment) and the end (hauling of the gears) of passive fishing events within a polyvalent fishing context (Chapter II)
2. To map and estimate the fishing effort, as soaktime, of passive fishing gears from the polyvalent coastal fishing fleet operating in Portuguese mainland waters (Chapter II)

3. To estimate at national level, the fishing effort of net fishing at a resolution of the total length of nets used by the studied fleet (Chapter II and III)
4. To study the seasonal variation of the total fishing effort, as km of nets, from the Portuguese coastal polyvalent fishing fleet operating in Portuguese mainland waters (Chapter III)
5. To explore how combining vessel tracking data with fishery dependent data can be useful within a risk assessment framework to improve MCS efforts. (Chapter IV)
6. To understand the seasonal variation of unreported catches and some of the possible drivers responsible for such fluctuations (Chapter IV)
7. To understand how reliable self-reported data, in this case, logbook data, is as a source of information when used to make inferences and estimates of fishing effort (Chapter V)
8. To link and analyse the results and conclusions of the aforementioned objectives and provide recommendations to improve the management, data collection and monitoring of fishing activities in Portugal and in Europe under the new regulations from the Common Fisheries Policy.

1.6. Chapters Outline

Except for the General Introduction (Chapter I) and the General Discussion (Chapter VI) each chapter is structured in paper-style format and suitable for peer-reviewed publication. Each of these four chapters can be read independently as each has its own Introduction, Methods, Results and Discussion sections.

Chapter II (*An approach to map and quantify the fishing effort of polyvalent passive gear fishing fleets using geospatial data*.): this chapter aims to address an important gap in terms of vessels tracking data classification of fishing vessels operating static fishing gears. The aim was to develop a data classification algorithm that is able to estimate the soak time of passive fishing events in a multi-gear fishing fleet context. It relies on its innovative capability of identifying the start of fishing events (gear deployments), and by merging the timestamp of the start of the fishing event with the timestamp of the end of that same event, it is able to calculate how long given passive fishing events lasted. This approach was then applied to the available AIS data from the analysed fleet to map the distribution, i.e., the footprint of this fishing fleet and to assess which areas are more targeted by these vessels. This work developed an innovative approach that can be used in other fleets operating passive fishing gears. It also allowed to identify the areas, within Portuguese mainland waters, that are more important for this fleet, which is a vital information in fisheries management and to future marine spatial plans.

Chapter III *(Let's measure it: an approach of high-resolution estimates of bottom fixed net fishing effort at national level.*): Starting from the classified AIS data from the previous chapter, this study aims to improve the fishing effort resolution of the analysed fleet using nets. It estimates the fishing effort through the combination of trip-based effort estimates from the classified data in chapter II and the number of fishing trips estimated from official landing records. It then extrapolates the total fishing effort, as km of nets, of this fleet. Given that the AIS data used in this study did not show a consistent quality to have a full coverage of the fishing fleet, in this chapter the aim was to overcome that gap and to provide estimates of fishing effort based on the characteristics of the used fishing gear. Moreover, it also aimed to analyse the seasonal variation of the fishing effort and to assess which regions have higher presence of such fishing activities. Besides developing an approach that is able to estimate the fishing effort at an unprecedented resolution and at national level, it provides important new information about how many km of these gear are used during a given period and provides insights on the variation of their usage throughout the year.

Chapter IV (*Improving Monitoring, Control and Surveillance efforts through Vessel Tracking and Fishery Dependent Data.*): The third study of this thesis explores the usefulness of the combination of vessel tracking data with fishery-dependent data to improve Monitoring, Control and Surveillance (MCS) efforts. This approach combines fishing trips' classified AIS data, from chapter II, with official landing data of each vessel, and identifies, for each vessel, each of the fishing trips tracked with AIS data that did not return an official landing record. This approach aims to identify vessels that have higher tendency of not reporting their landing events and to identify in which seasons there is a higher probability of misreported landing events. The lack of effective MCS efforts is one of the main reasons for the continued existence of IUU activities, and a commonly agreed approach to improve such efforts is through risk assessment approaches. This study identifies which risk units, vessels and season, have higher tendency to incur unreported landing events. Such information is vital so that MCS efforts can be allocated to those high-risk units, which should improve the probability of detecting and consequently penalizing such actions.

Chapter V (*On the accuracy of self-reported data for fishing effort estimates – a case study.*): This chapter briefly analyses the quality of self-reported data, i.e., logbook data when used to estimate fishing effort. It compares the number of fishing trips of each vessel that can be drawn from logbook records versus the number of fishing trips that can be inferred from official landing records. The results indicate that self-reported data has a significantly lower number of recorded fishing trips when compared with the number of fishing trips that can be gathered from official landing data. These findings support the general concern regarding self-reported data, and in particular when used to estimate fishing effort. This study supports the idea that, if possible, fishing effort estimates based on fishery dependent data should preferably rely on data recorded by a 3rd party, such as officially logged landing data, instead of relying on self-reported data, like logbook data.

Chapter VI (*General Discussion*): the last chapter of this thesis starts by providing a summary of the main results from each study and discusses their implications in terms of management purposes and provides a general discussion and main conclusions of this thesis. It also goes back to the initial goals of this thesis, discuss if they were met and the main limitations of this study. It finally ends by providing recommendations for management and future research.

2. **CHAPTER II:** AN APPROACH TO MAP AND QUANTIFY THE FISHING EFFORT OF POLYVALENT PASSIVE GEAR FISHING FLEETS USING GEOSPATIAL DATA.

2.1. Abstract

The use of tracking devices, such as Vessel Monitoring Systems (VMS) or Automatic Identification System (AIS), enabled us to expand our knowledge on the distribution and quantification of fishing activities. However, methods and models based on vessel tracking data are mostly devised to be applied to towed gears, whereas applications to multi-gear and passive fisheries have been underrepresented.

Here, we propose a methodology to deal with geospatial data to map and quantify the fishing effort, as soak time, of passive fishing gears used by a multi-gear fishing fleet. This approach can be adapted to other passive multi or single-gear fisheries, since it requires only three variables that can be extracted from a pre-classified dataset, to identify the beginning (gear deployment) and the end (hauling) of passive fishing events.

As far as we are aware, this is the first time a methodology that allows quantifying the soak time of static passive fishing events, within a polyvalent fishery context, is presented. We argue that the information that can be extracted from such approaches could contribute to improved management of multi-gear and static gear fisheries and the ecosystem-based approach.

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2.2. INTRODUCTION

To ensure appropriate management and conservation of the marine environment it is important to understand the distribution and impact of human activities at sea. Fisheries, as one of the most important sources of food for human consumption, are also one of the most impactful extractive activities occurring in this environment (Pauly *et al.*, 1998; Swartz *et al.*, 2010). To ensure the proper management of the marine environment, by establishing comprehensive marine spatial plans, design effective marine protected areas and protect vulnerable habitats and species it is vital to understand how this activity is performed and where it occurs (Halpern *et al.*, 2008; Campbell *et al.*, 2014; McCauley *et al.*, 2016; Vespe *et al.*, 2016). Despite the efforts to increase knowledge on fisheries, the distribution and quantification of fishing effort are far from being fully understood (Kroodsma *et al.*, 2018; Leblond *et al.*, 2019).

Accurate estimates of fishing effort is critical for ensuring sustainable fisheries, being essential for improving stock assessment, tracking market trends, and studying fishers' profitability (McCluskey and Lewison, 2008b; Peterson *et al.*, 2017). Direct control of fishing effort could be a possible alternative to other traditional forms of fisheries management, such as the use of Total Allowable Catches (TACs) and quotas. But, due to the difficulty of precisely estimating and comparing fishing effort of different vessels, gears and locations, this management approach has seldomly been implemented (Shepherd, 2003).

With the introduction of tracking devices in fishing vessels, such as VMS (Vessel Monitoring System) and AIS (Automatic Identification System), the possibility to study the spatial and temporal distribution of fishing activities and the quantification of fishing effort has improved dramatically (Witt and Godley, 2007b). A growing number of studies have used data from tracking devices to identify fishing grounds (Gerritsen and Lordan, 2011; Jennings and Lee, 2012; Le Guyader *et al.*, 2017) and to estimate and map fishing effort (Natale *et al.*, 2015; Russo *et al.*, 2019) with an accuracy that was not previously possible. The underlying approaches when dealing with this data are generally to identify and classify different states of fishing trips (e.g. steaming, resting, fishing), and to determine whether a vessel is fishing or not (Vermard *et al.*, 2010; Poos *et al.*, 2013). These approaches often rely on a simple statistical speed filter to detect fishing activities, under the assumption that fishing occurs at a speed much lower than steaming. In other cases they use more complex models that rely on trajectory metrics, such as step length, turning angle, and correlation with environmental cues to infer the different phases of fishing trips (Lee *et al.*, 2010; Russo *et al.*, 2014b; Leblond *et al.*, 2019; Mendo *et al.*, 2019a). Hidden Markov Models (HMM) have been widely used to classify vessel tracking data using these metrics (Vermard *et al.*, 2010; de Souza *et al.*, 2016; Whoriskey *et al.*, 2017; Mendo *et al.*, 2019a).

The majority of studies using geospatial data derived from AIS or VMS have focused on active gears such as trawls (Lee *et al.*, 2010; Natale *et al.*, 2015), with few studies on static or passive gears that represent an important proportion of fishing effort and impact (Kelleher *et al.*, 2012). One of the main reasons is that passive gear fishing events are more complex to model than active ones. Fishing with active gears generally involves continuous movement, with the vessel being connected to the gear throughout the entire fishing event, which usually lasts up to some hours. Meanwhile, a passive fishing event is composed of two phases: the first is the start of the fishing event, which is the gear deployment, then it ends with the second phase of the fishing event, which is when the gear is retrieved onboard, i.e., the hauling of the gear. The period between these two phases is called soak time, and it can take hours to days or even weeks. During this period the vessel is detached and away from the gear.

The existing studies on static gears have mainly focused on mapping fishing activities by identifying the moments when vessels hauled their gears. Hauling events are characterized by low vessel speed, usually in an approximately linear direction. These events are quite distinctive from other states of a fishing trip, like navigation or gear deployment (Marzuki *et al.*, 2018; Mendo *et al.*, 2019a). Yet, to estimate the fishing effort of passive gears in terms of soak time, the beginning of the fishing event, i.e., the deployment of the gear, needs to be identified. It is critical to identify deployment, soaking of gears, and hauling in the correct sequence. In fact, let’s imagine the case in which one of the deployment or hauling phase occurring during a fishing day is absent within the spatial data: the corresponding estimation of soak time would be dramatically biased.

When the behaviour of vessels deploying a static gear is different from steaming, the identification of the deployments was shown to be possible (Charles *et al.*, 2014). But, in cases where the behaviour of the vessel when deploying is too similar to when it is steaming, this poses an additional challenge to identify gear deployments using only the behaviour variables of the vessel (Mendo *et al.*, 2019a), and therefore to calculate the soak time of that particular gear.

The quantification of soak time allows identification of illegal fishing behaviours, as some gears are not allowed to fish for more than a certain period of time (EU regulation No. 227/2013). It is also important in a stock assessment context, not only because captures vary, in quantity and variety, depending on the time a gear is fishing, but also because soak time affects catch rates of fishing gears (Boutillier and Sloan, 1987; Erzini *et al.*, 1997b; Ward *et al.*, 2004; Morgan and Carlson, 2010; Li *et al.*, 2011).

In the present study we propose an approach to deal with high resolution geospatial data from a polyvalent (multi-gear) passive gear fishing fleet. We used AIS data from the Portuguese mainland coastal fishing fleet operating two main fishing gears: bottom nets (gillnets and trammel nets), and pots and traps. The methodology is primarily devised to be applied to single vessels to identify and classify the different behaviours within a trip: steaming, gear deployment, hauling of gears and slow navigation. With the presented methodology, we aim to assess the distribution of this type of fishery and to provide insights on its effort, as soak time, by identifying the start (deployment) and the end (hauling) of a passive gear fishing event.

As far as the authors are aware, this is the first study to present a methodology to address the distribution and quantification of fishing effort, in terms of soak time, for a polyvalent passive gear fishing fleet using geospatial data.

2.3. METHODS

2.3.1. Data

Fishery dependent and spatial data from the Portuguese coastal polyvalent fishing fleet (Length Overall - LOA > 12m) using nets and pots and traps, from 2014 to 2020, was used. This fleet operated within the continental Portuguese EEZ (Economic Exclusive Zone) (Figure 2.1).

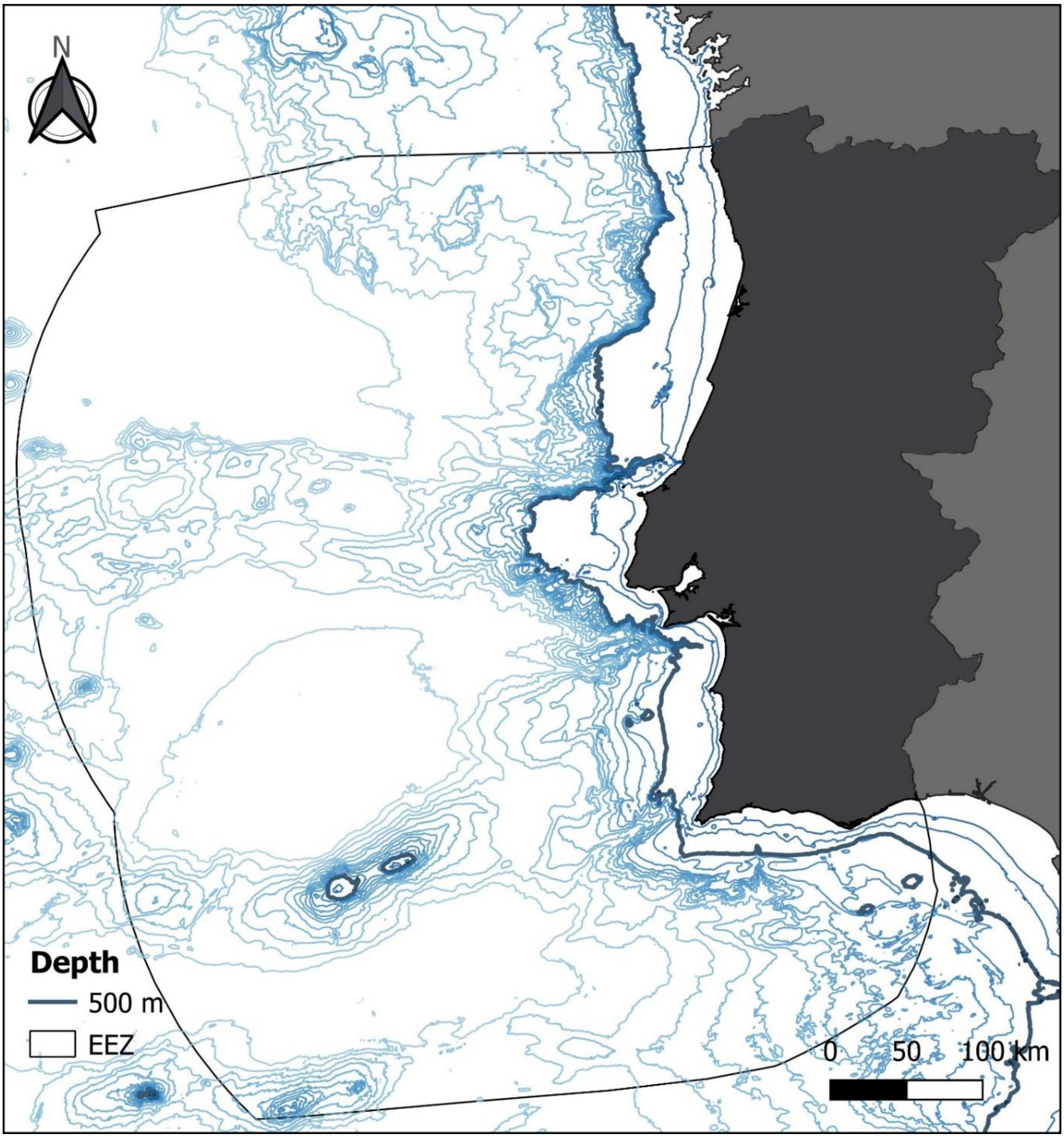

Figure 2.1 The current approach focuses on the Portuguese polyvalent fishing fleet operating within the Portuguese Economic Exclusive Zone (EEZ).

The Directorate-General for Natural Resources, Safety and Maritime Services (DGRM) provided fishery dependent data in the form of daily landings and logbook data. For spatial data, we used land-based AIS data collected from the AIS repository AIShub (www.aishub.net) and from MarineTraffic (www.marinetraffic.com).

To train and validate the classification models, two sources of data were used: 1. onboard GPS collected data and 2. manually labelled AIS data. The onboard GPS data was collected from 32 fishing trips, from 9 different fishing vessels, of which 5 used nets (gill nets and trammel nets) and the remaining 4 vessels operated pots and traps. Fishing trips were classified into four different phases: Steaming, Deployment, Hauling and Slow navigation. The latter corresponds to when a vessel is either drifting or slowly navigating, usually waiting for a gear to fish before starting the hauling process. The classified GPS and AIS data were then split into training and validation data.

For a summary on the raw AIS data, details of the process on selecting the AIS data from the desired vessels, and a description of the data used to train and validate the classification models check the Supplementary material, Section 1.

A schematic representation of the entire workflow is represented in Figure 2.2.

Figure 2.2 Schematic representation of the major steps carried out throughout our procedure. For a more detailed description of the data and the data selection procedure, check the Supplementary material.

2.3.2. Data pre-processing

Pre-processing of the data included: cleaning erroneous data points; split the AIS data into singular fishing trips; remove inadequate/ incomplete fishing trips and interpolating the track data to a consistent frequency.

To reconstruct fishing tracks to have a timely consistence of datapoints, the tracks were interpolated using the algorithm developed by Russo et.al., (2011a, 2014a) that relies on the Catmull-Rom approach, a modification of the hermit cubic spline algorithm (Tremblay *et al.*, 2006; Hintzen *et al.*, 2010). The interpolation was set to generate data points at one minute intervals, as this frequency has shown to be best suited to identify passive fishing events (Mendo *et al.*, 2019b). For a more detailed description of these steps, check the Supplementary material, Section 2.

2.3.3. Set up the Classification Variables

The approach intends to classify the AIS data into four different phases of a fishing trip: Steaming, Deploying, Hauling, and Slow navigation. To do so, we defined 3 classification variables: 1 – vessel speed; 2 – Future Overlap (FO) and 3 – Past Overlap (PO). Vessel speed aided classification in states by observing that steaming and deployment were carried out at high navigation speeds, while slow navigation and hauling of gears were carried out at lower speeds (Figure 2.3 and S8.1.1).

The FO and PO aided in distinguishing 1) deployment events from steaming and 2) hauling events from slow navigation or drifting, respectively. We relied on the fact that if a gear is deployed, it must be hauled with vessels running the same path when deploying and hauling a gear. To identify a gear deployment, there must be overlap with a hauling track (carried out at a slow speed), happening in the future in relation to the deployment track. Likewise, to identify the hauling of a gear, there must be an overlap with a deployment track (carried at fast speed), happening in the past in relation to the hauling track (Figure 2.3).

Given the previous rationale, we determined a distance to establish if two datapoints overlapped. To do so, we calculated the distance of 3620 deployment datapoints to the closest hauling datapoint, within the same fishing event and conversely, 14690 distances from the hauling datapoints to their closest deployment datapoints of the same fishing event (Figure S8.1.2). With the calculated distances we defined two threshold distances: 1- Future Overlap Distance (FOD), being the threshold distance from a deployment datapoint to a hauling datapoint occurring in the future in relation to the deployment datapoint; and 2- Past Overlap Distance (POD), being the threshold distance from a hauling datapoint to deployment datapoint that occurred in the past in relation to the hauling datapoint. These threshold distances were then defined using the Normal distribution to model the distance value at which $P (X \leq x) = 0.99$, using the mean and standard deviation obtained from the calculated distances. The established distance values for FOD and POD were 150m and 235m, respectively (Figure S8.1.3).

When calculating the minimum distances between datapoints, an important aspect to consider was the maximum soak time. The range of the soak time of the two gear types is very wide, and to identify the overlapping deployment and hauling datapoints, we precautionarily selected a time window that spanned from 90 minutes to 20 days. This window assumed that after a deployment, the gear is fishing for at least 90 minutes (in the case of nets) and that it can be soaking/fishing for up to 20 days (pots/traps).

Considering the parameters and assumptions previously described, for each datapoint with speed values corresponding to possible deployment or steaming events (≥ 3.6 knots), we assigned a value equal to one to the binary variable Future Overlap (FO). The assigned value of one means that for that given datapoint, there is an overlapping datapoint within the established threshold distance, at a low speed (< 3.6 knots), 90 minutes to 20 days ahead in time to the referred datapoint. For high speed datapoints without overlapping datapoints and all low speed datapoints were assigned zero for the FO variable. Conversely, for low speed datapoints (possible hauling or slow navigation/drifting datapoints) we assigned the Past Overlap (PO) binary variable, where value 1 means the existence of an overlapping datapoint, with speed of a deployment datapoint (≥ 3.6 knots) that was generated 90 minutes to 20 days in the past, in relation to the low speed datapoint. Low speed datapoints without overlapping datapoint and all datapoints with speed values ≥ 3.6 knots were assigned zero for the PO variable.

We are aware that in the case of pots and traps, fishers do not always haul the entire gear on deck and then deploy it elsewhere. Instead, fishers may run slowly along the line checking if there is any catch in each trap/pot whilst leaving the entire set in the water, and this behaviour can be repeated indefinitely for a given gear. This means that the overlapping tracks are all performed at a low speed. At the present, the identification of this particular fishing behaviour is beyond the scope of our approach.

For a complete description on the process of setting up the classification variables, check the Supplementary material, Section 3.

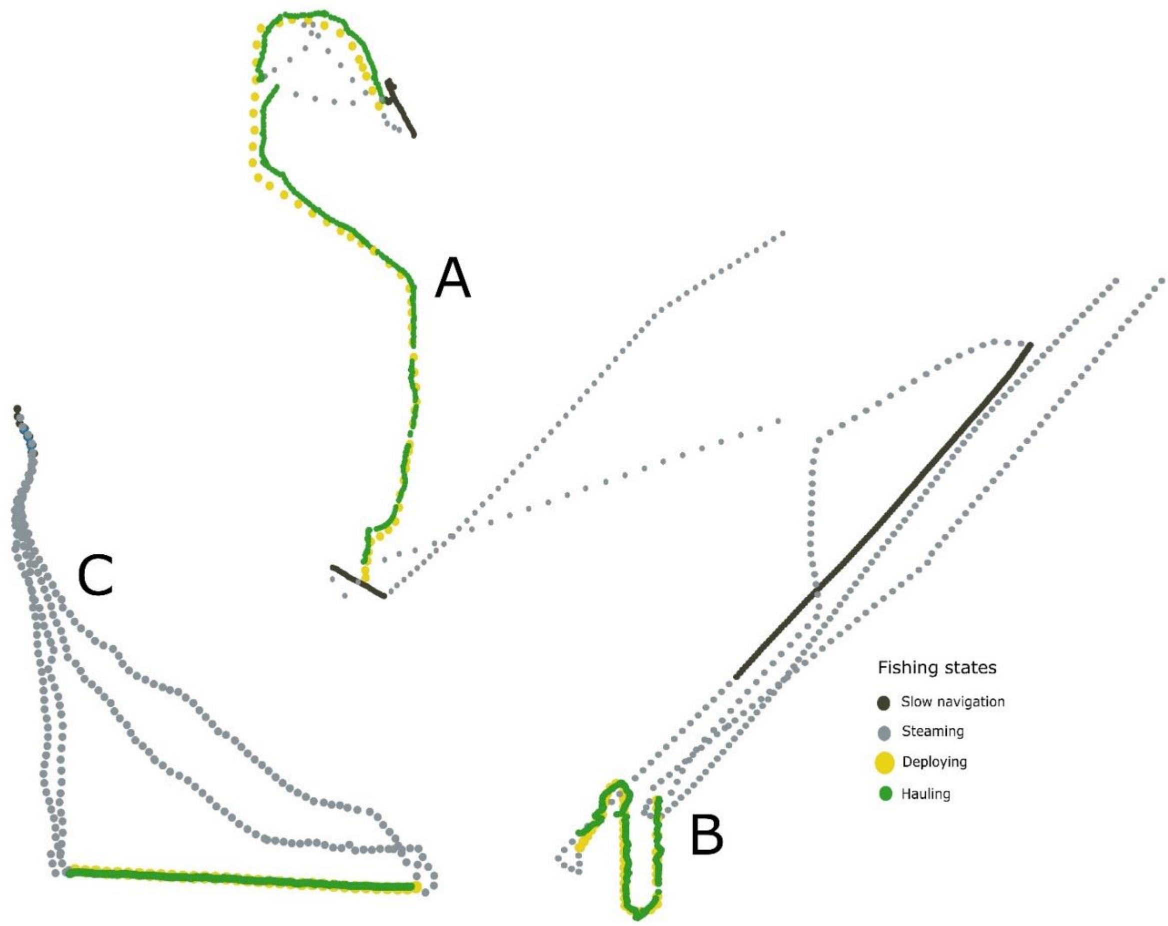

Figure 2.3 AIS tracks with three different fishing events. Fishing events are represented by the deployment datapoints (in yellow) that are displayed underneath the hauling datapoints (green) when they overlap in space, meaning that a fishing event, as expected, starts with the deployment of a gear, at a fast navigation speed and terminates with its hauling, which is carried at low speed. The tracking data was interpolated at a 1 minute rate, meaning that the larger the distance between consecutive datapoints, the faster the vessel navigates and vice-versa. The behavioural diversity and complexity of this fishery is evident from this figure: A) vessels can deploy two sets of fishing gears in a single event and haul them within the same trip; B) deploy just one gear and after the deployment the vessel waits some hours, while slowly navigating/ drifting, and then collect the gear within that same trip; or C) a vessel can go out to sea to deploy a gear and then return on a following day to haul the gear. The soak time will depend on the type of gear and target specie.

2.3.4. Data classification

The R package MomentuHMM (McClintock and Michelot, 2018) was used to classify each of the data points into one of the four different underlying hidden states of a fishing trip: steaming, deploying, hauling, and slow navigation.

We used three different variables in the HMM analysis: 1- Speed, 2- Future Overlap (FO) and 3- Past Overlap (PO). To model speed values, we used the positive gamma distribution and given that datapoints were interpolated into regular time intervals of 1 minute, we used the standard approach of MomentuHMM and converted speed values into distance values between datapoints (step length) as a proxy for speed. The distribution parameters of each fishing state, calculated from the training data, were used as the initial distribution parameters of the HMM model. Since the FO and PO were established as binary, we used the Bernoulli distribution to model these two variables. After assigning the Overlap variables to the training data, we assessed the probability of FO = 1 and PO = 1 for each of the four states. Just like for the step parameters, these probability values, directly calculated from the training data were used as initial parameters for the HMM model. For a further description of the data classification with the HMM, check the Supplementary material, section 4.1.

Because the HMM classification alone yielded an undesirable number of false positives for both states of the fishing event (deployment and hauling), the next step was to clean the miss labelled fishing datapoints. A description on the cleaning of false positives is described in section 4.2 of the Supplementary material.

After establishing the distribution parameter for the three variables considered in the HMM analysis, and developing the procedure to clean false positives, we ran the entire classification analysis on the validation dataset. The rational of the assessment of the performance of the classification procedure is based on the comparison of the accuracy of the procedure's output with the onboard groundtruthed and the manually labelled data, used as test/validation dataset to assess the model performance. For a more detailed description on the model validation, see the section 4.3 on the Supplementary material.

2.3.5. Footprint and Effort assessment

After the classification of datapoints into the different states of a fishing trip, the last step was to identify the fishing events by matching the corresponding start (deployment) and the end (hauling) of the fishing events. This is a critical step as both moments of a passive fishing event need to be correctly matched to calculate the soak time of a gear. The approach to identify the fishing events was carried for each vessel, by matching each classified deployment datapoint with the most recent hauling datapoint that falls within the pre-established time window (90 minutes to 20 days) ahead of the deployment datapoint timestamp and within the FOD in relation to the deployment datapoint. For the full explanation on the process of identification of the fishing events and calculation of the soak time, check the Supplementary material, Section 5.

To map the fishing footprint of this fleet, we divided the study area into a 1x1 km grid. The footprint was then assessed through the presence/absence of the identified fishing events in each grid cell.

To map and calculate the total effort, as total soak time, we used the same 1x1 km grid. The effort was then calculated as the sum of the averages of soak time of each fishing event's datapoints present within each grid unit. The Effort formula for each grid unit can be represented as such:

$$\text{Effort} = \sum_{f=1}^{n} \frac{\sum_{j=1}^{N} S_{fj}}{N}$$

Where *j* is the fishing vessel, *f* is the fishing event, *S* is the soak time, i.e. the difference between timestamps of the matching deployment and haul datapoints, and *N* is the number of pairs of matched datapoints, of each fishing event, within the grid square unit.

As already stated, AIS data have some limitations in terms of inconsistent spatial and temporal coverage (Metcalfe *et al.*, 2018; Shepperson *et al.*, 2018). For that reason, we studied the proportion of total effort that we were able to quantify and map. To do so, we compared the number of AIS fishing trips that passed all the steps of our approach, with the number of fishing trips of the same vessels, inferred from the landings dataset, under the assumption that each landing event corresponds to a fishing trip.

2.4. RESULTS

2.4.1. Model validation

After setting the parameters that yielded the best accuracy values for the training data, which is the highest value of the average between the rate of true positives (Sensitivity) and the rate of true negatives (Specificity), we ran the classification procedure on the validation data and assessed its accuracy. The accuracy was assessed through confusion matrices for all the fishing trips, regardless of the gear used. To evaluate the classification performance for each type of gear used, we also carried out the validation of the model for trips using only nets and for trips operating only pots and traps (Figure 2.4 and Table 2-1). For a further description on the model validation, check the Supplementary material, section 4.3.

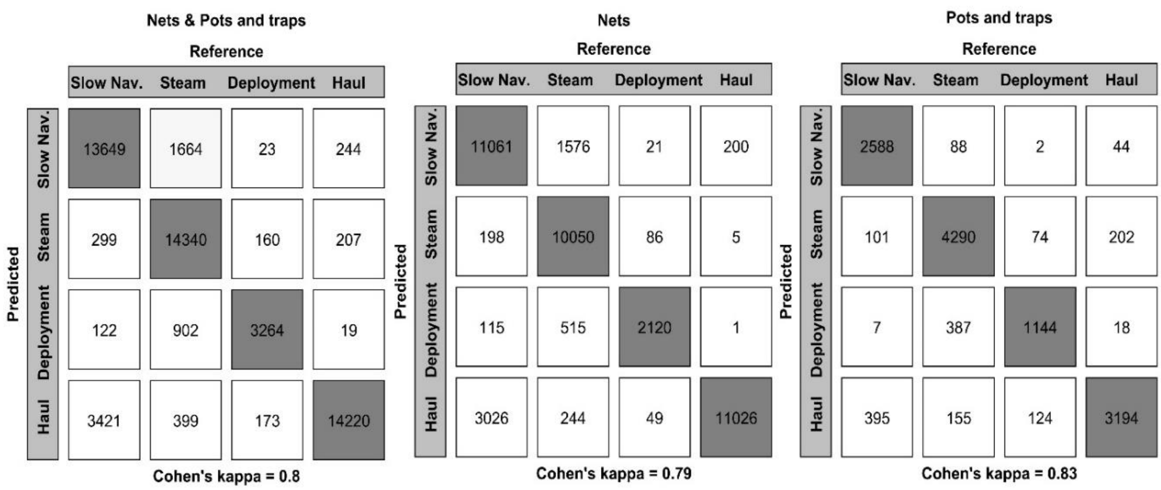

Figure 2.4 Confusion matrices and Cohen's coefficient values from the validation data classified by the procedure. Confusion matrices plot the number of datapoints, of each state, classified by the model (Predicted) against the actual number, of each state, of the validated data (Reference). The validation procedure was carried for the overall validation dataset, i.e. for all fishing trips regardless of the gear used (Nets & Pots and traps) and for fishing trips using the same type of gear: Nets or Pots and traps.

Table 2-1 Results of the accuracy assessment for the deployment and hauling states for both types of gear. The performance of the model was assessed through the Sensitivity (true positive rate), the Specificity (true negative rate) and the Balanced Accuracy which is the arithmetic average of the Sensitivity and the Specificity of the model.

	All gears		Nets		Pots & Traps	
Fishing State	Deployment	Haul	Deployment	Haul	Deployment	Haul
Sensitivity (recall)	0.90	0.97	0.93	0.98	0.85	0.92
Specificity	0.98	0.90	0.98	0.89	0.96	0.93
Balanced Accuracy	**0.94**	**0.93**	**0.96**	**0.93**	**0.91**	**0.93**
Number of vessels	11		7		4	
Number of trips	34		22		12	

Overall, the model performed well in identifying the start and the end of fishing events, with an accuracy of more than 90% for both phases of the fishing events. Comparing the two types of gears, the model, as it was set up, seems to be better suited to identify fishing operations with nets than with pots and traps. The classification accuracy of deployments of pots and traps was the lowest, with only 85% of the deployment datapoints classified as such by the algorithm and because of that, the balanced accuracy for the deployment of pots and traps was the lowest. On the other hand, the model returned a higher rate of false positives for hauling events when classifying fishing events using nets (Specificity = 89%).

Through the analysis of Cohen's coefficient, the results of the classification demonstrate an overall strong agreement between the reference and the predicted data: kappa ≥ 0.8 (McHugh, 2012), especially when classifying fishing trips with pots and traps.

2.4.2. Soak time

The soak time of each fishing event was assessed through the difference between the timestamp of corresponding deployment and hauling datapoints. From the analysis of the gear used in each fishing event recorded in the logbook data, the analysed vessels commonly use both types of gear. Of the 146 vessels, 7 vessels reported using only one type of gear, with 6 vessels using only nets and one using just pots and traps during the period of 2014 to 2020.

To visually assess the distribution of the soak time of fishing events, we calculated the average soak time between matching deployment and haul datapoints of each fishing event (Average soak time). As expected, the distributions of soak time of these two types of gears are different. Pots and traps are known for being left fishing for a long period, ranging from some days to several weeks, while fishing with nets usually takes less time, from hours to a maximum of a few days (see example in Figure 2.5A and 2.5B). For most of the vessels that used both gears, the distribution of soak time, depending on the proportion of use of each type of gear, is expected to resemble, to some extent, the combination of the distributions of both types of gears (Figure 2.5C).

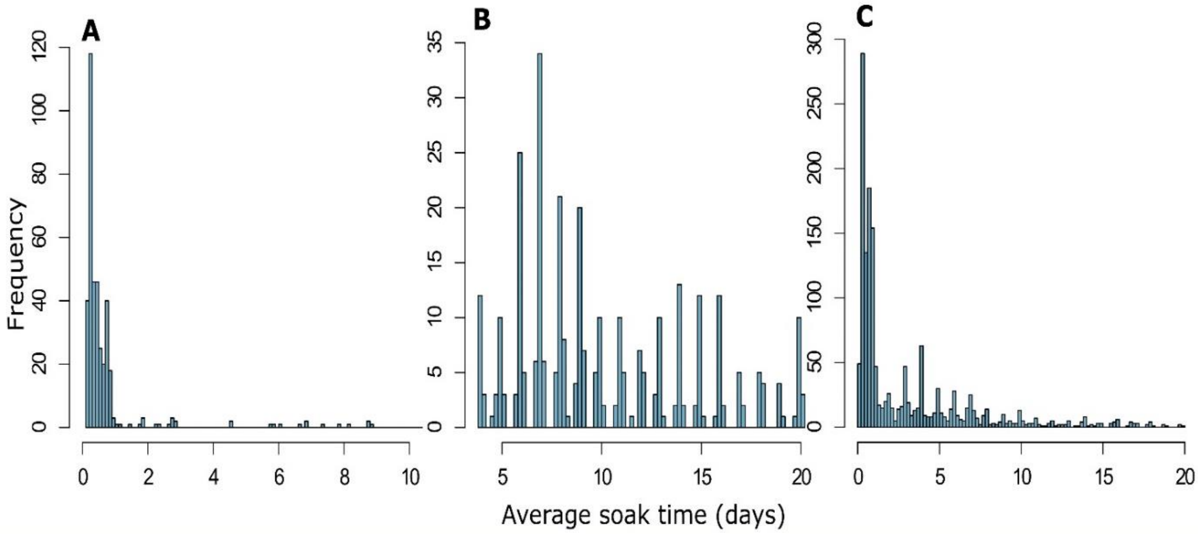

Figure 2.5 Distribution of the average soak time, in days, of each fishing event of one vessel using only nets (A), one vessel using only pots and traps (B) and of one vessel both types of gears (C). The average soak time of each fishing event was calculated as the average difference of timestamp between pairing deployment and hauling datapoints of a given fishing event. Vessels using nets tend to fish during short periods of time, usually up to one or two days, while vessels using pots and traps tend to leave the gears fishing for longer periods. The distribution of soak time of vessels using both types of gear is expected to resemble the combination of the distributions of nets (high number of fishing event with short periods of soak time) with the distribution of soak time values of pots and traps (a wider distribution of fishing events that can range for several days). The average values of soak time for each fishing event were calculated to the resolution of one decimal place. Meaning that a fishing event that lasts 0.5 days (12 hours) it is represented on a different bar that of a 24 hours (1 day) fishing event, for example.

2.4.3. Footprint and Effort

Applying the selection criteria for this study, i.e., fishing vessels of LOA >12m, operating in the waters of mainland Portugal and using only nets and/or pots and traps, from 2014 to 2020, resulted in a list of

301 fishing vessels. When querying the AIS databases from the list of these fishing vessels, and after cleaning the AIS dataset of erroneous datapoints, we started our analysis with approximately 85.4 million AIS datapoints, from 151 vessels.

After the procedure of identification of the fishing trips and removing fishing tracks with gaps, 21950 fishing trips from 146 vessels remained to be interpolated and classified by the HMM procedure. Overall, the data availability, combined with the data requirement of the procedure, enabled us to classify 21.7% of the fishing trips carried out by these 146 vessels, during the period of 2014-2020 (Table 2-2). An example of the classified data is shown on Supplementary material section, Figure S8.1.5.

To map the footprint (Figure S8.1.6) and the effort (Figure 2.6) of this fishery, we selected the classified fishing trips containing matching states of the fishing events (deployments and hauls). This selection criteria, along with the existence and quality of the AIS data, allowed us to keep 13224 out of the 21950 classified fishing trips, from 84 of the 146 vessels from the classification dataset, corresponding to 12.1% of the total number of trips carried out by the number of vessels within the initial AIS dataset. From the remaining fishing trips we were able to quantify 24353 complete fishing events, carried out by 84 vessels (Table 2-2).

Table 2-2 Data composition from application of the vessel selection criteria until the final steps of the procedure. Overall number of vessels, trips and fishing events that were kept and identified from the AIS data, during the period 2014 to 2020, throughout the three main steps of our procedure.

	Initial list of vessels with AIS data	Classification dataset	Footprint & Effort dataset
Number of vessels	151	146	84
Number of trips (from landing data)	109006	101152	49876
Number of trips (from AIS)	NA	21950	13224
Proportion inferred from AIS	NA	21.7%	26.5%
Number of fishing events (from AIS)	NA	NA	24353

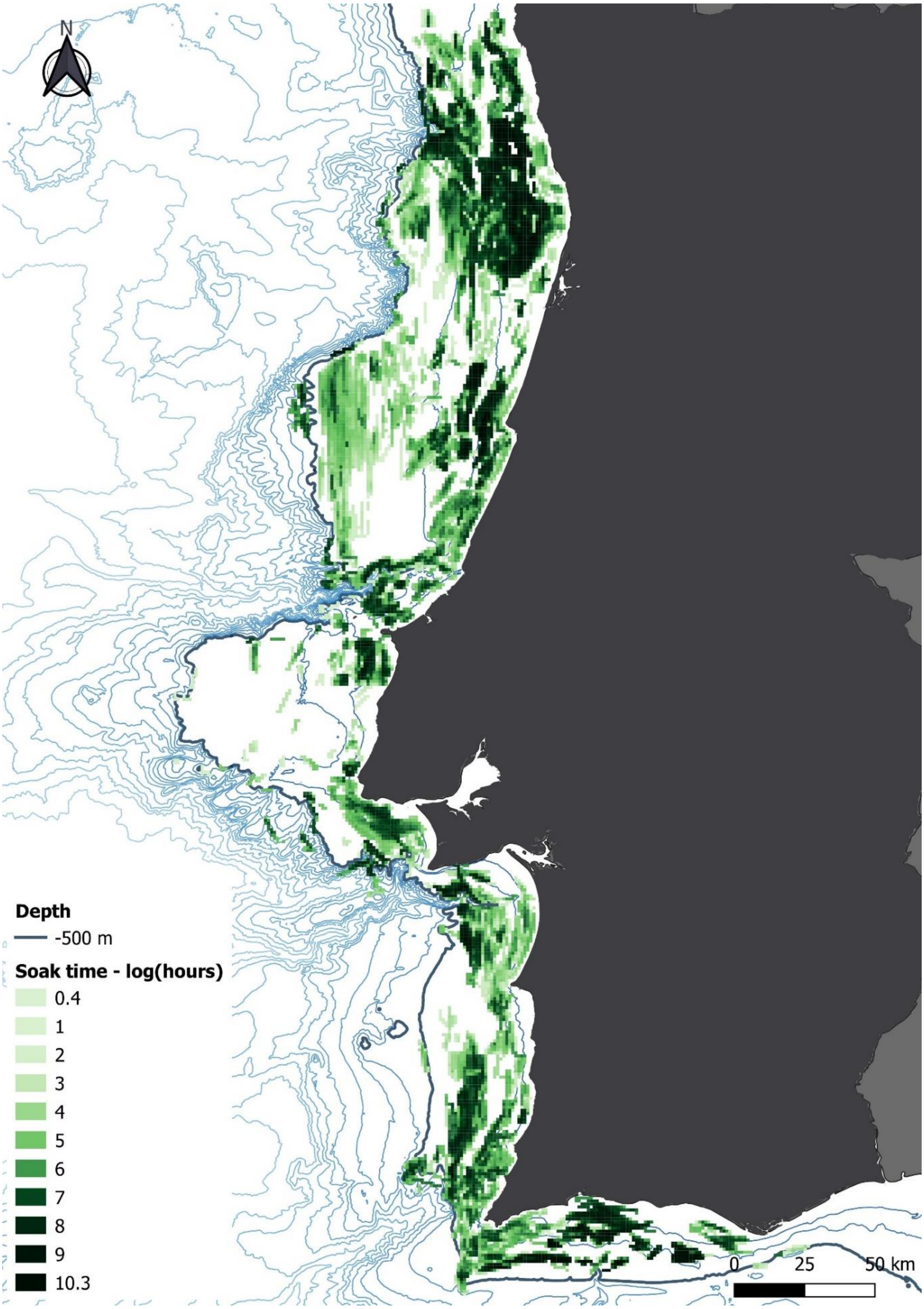

Figure 2.6 Map of fishing effort (soak time) of fishing events using nets, pots and traps, during the period from 2014 to 2020. The resulting effort map represents 24353 fishing events, from 13224 fishing trips carried by 84 fishing vessels. The majority of the fishing activity is distributed within the 500m depth, and the fishing effort presents a patchy distribution appearing to be more relevant in the northern part of the study area.

2.5. DISCUSSION

We introduce a method to *a posteriori* map the fishing effort, in terms of soak time, of passive fishing gears used by a polyvalent fishing fleet, using data from high resolution tracking devices. The method relies on the ability to classify vessel tracking data into a set of *a priori* defined states, and in particular the beginning (deployment) and end (haul) of fishing events. By doing this for all vessels, it allows the footprint of the fishery to be studied and to quantify and explore, with high resolution, the spatial and temporal dynamics of the fishing effort of these polyvalent fishing vessels at an aggregated (e.g. fleet segment) scale.

Previous studies have also addressed the spatial dynamics of passive fishing gears through vessel tracking data. Mendo et al., (2020) and Jennings and Lee, (2012), for example, mapped the footprint of a passive fishery and studied the distribution of the fishing effort. The approach in Mendo et al., (2020) allows assessing the distribution of the footprint of a passive fishery, but it does not calculate the fishing effort. Meanwhile the method used by Jenning and Lee, (2012) defines the fishing effort as the time vessels spent hauling their gears, which is different from the time gears fished (soak time). Campos et al., (2023) took a different approach: the fishing effort was mapped and calculated as the distance carried by the vessels during the period of the fishing event as recorded on the logbook. This approach may overestimate the location and total length of fishing events, as the vessel after deploying a fishing gear can navigate while waiting for the gear to fish or it can even deploy other gears before finishing (hauling) the initial fishing gear.

The proposed methodology brings the possibility of identifying the full duration of passive fishing events which, until now, was only possible by means of onboard observers or from logbook data. Monitoring with onboard observers is very costly and generally only covers a small fraction of the fleet, while logbooks are compiled by fishers and their quality depends on the willingness of fishers to precisely log every important detail of the fishing activity, which is not always the case (Bastardie *et al.*, 2010; Sampson, 2011; Russo *et al.*, 2016a).

The proposed method was developed and set up to be applied to a polyvalent passive fishery, regardless of which gears, with overlapping deployment and hauling tracks. Despite the good performance of the classification algorithm (>90% for deployment and hauling events), when analysing the accuracy for both gears separately, there is indeed a difference depending on gears and events. As the model was set up, the accuracy detecting fishing events using nets outperformed the ones using pots and traps. The deployments of pots and traps had a lower rate of true positives compared to the deployment of nets. The reason for this is probably related to the fact that in some cases, the deployment of pots and traps happens at a lower speed than the defined overall "fast speed threshold" (≥3.6knots). On the other hand, when assessing the specificity (rate of true negatives) of hauling datapoints, fishing events with nets returned a higher number of false positives. This has to do with the behaviour of the vessel after deploying a net. The vessel commonly stays in the vicinity of where the net was deployed, usually slowly navigating or drifting, waiting for the net to fish. This proximity to the deployment or steaming tracks increases the chances of slow navigation datapoints being assigned the Past Overlap variable and consequently being classified as hauling datapoints. Contrary to most fishing events with nets, when fishing with pots and traps the vessel leaves the area after deploying the gear, as these gears are almost never hauled within the same deployment trip. Therefore, the rate of false positives on hauling events using pots and traps was lower.

As anticipated, fishing events of nets, and pots and traps vary distinctly in terms of soak time. Fishing with nets usually means leaving the net fishing for some hours up to a few days, as caught fish tend to die and risk being eaten by scavengers. Also, the legal maximum soak time is 24 hours, except for nets of mesh size larger than 100 mm operating in zones of depth greater than 300 m (Portuguese Ordinance No. 1102-H/2000). This exception is associated with particular fishing metiers targeting, for instance, monkfish (*Lophius* spp.; Szynaka *et al.*, 2021, 2022). In contrast, sheltering or trapping gears like pots and traps, the catches remain alive, allowing these gears to fish for much longer periods. Furthermore, unlike gillnets and trammel nets, maximum catch rates of traps are often a week or more after deployment (Erzini *et al.*, 2008). Still, according to logbook data, one fishing vessel using nets had fishing events reaching up to 9 days of soak time. This either mean that this vessel used a gear such as pots or traps, or that it left nets fishing for longer periods than the maximum soak time permitted by law. In any case, neither the information about use of pots and traps nor net soak times of up to 9 days of fishing were reported in the logbook, making this approach also useful to monitor the compliance of fishers with existing regulations, such as maximum soak time.

Within the analysed fleet, there were only seven vessels that reported using only one type of gear. For this reason, the distribution of soak time of vessels using both gears was studied. As expected, the distribution of the soak times of these vessels resembles the combination of the distribution of vessels that only use one type of gear, with several fishing events lasting around one and two days (nets) and several fishing events lasting up to 14 days, with a few soak times of up to 20 days (pots and traps).

The fishing footprint of this fleet is mainly located within the continental shelf, extending to the upper part of the continental slope, as also shown by Leitão et al. (2022). Fishing effort was patchily distributed and seems to be more relevant in the northern part of the study area and along two submarine canyons. It is important to stress that these maps do not represent the whole reality of this fleet. In fact, they represent the footprint and the fishing effort of 12.1% of the fishing trips carried by the 151 vessels included in the initial AIS dataset.

There are several issues with AIS systems, one of which is potential poor fishing fleet coverage (Russo *et al.*, 2016b, 2019; Shepperson *et al.*, 2018). Also, land-based AIS systems, even though more accurate than satellite-based AIS, have the disadvantage of having a limited range and are dependent of the existence of AIS antennas on land. Moreover, the signal transmission can be affected by external factors, such as weather conditions and it can be deliberately switched off in case the skipper does not want to disclose his vessel's whereabouts (Russo *et al.*, 2016c; Emmens *et al.*, 2021). So, the footprint and distribution of fishing effort presented here mostly depends on the AIS fleet coverage, the signal reception infrastructure (existence of AIS antennas), and on the willingness of the skippers to leave the AIS transponder ON throughout the entire trip. In fact, when sorting the classified data from the 146 vessels to map and quantify the fishing effort, 62 vessels and 8726 fishing trips were discarded, as these trips did not include fishing events. From a GIS based assessment of these incomplete trips, we saw that most of these vessels had the AIS transmitting while leaving the port, probably as a safety measure to avoid collisions with other vessels, but once at sea, the AIS would stop transmitting.

Another specificity of this approach that requires consistent data has to do with the fact that the identification of the start and end of a fishing event are dependent on each other. This means that in case the tracking data of a deployment is missing, the hauling data, even though existent, will not be classified as hauling because of the inexistence of the Past Overlap variable, but instead will be classified as slow navigation. A similar situation happens in case the data for the hauling event is missing and the deployment track is present: the deployment track will be classified as steaming, since the Future Overlap variable is missing. It is also important to stress that the frequency of datapoints generated by the tracking devices is of the upmost importance. This approach is able to identify the full duration of passive fishing events because average frequency of datapoints generated by the AIS system is of 3 minutes (Table S8.1.1). If the data frequency would be lower, the identification of the deployment events would probably not be possible, as these events can take 15 minutes to be completed.

The last process of grouping deployment datapoints into a single fishing event requires prior knowledge about the fishery being studied. By observing the training data, where deployments always took more than 17 minutes to be carried out and given that these vessels deploy gears with several kilometres in length, we set a conservative threshold of 15 minutes, as the minimum time a deployment would need to be carried out. This value was set based on the specificity of this type of fishery, and indeed, if a vessel deploys a smaller gear, or takes less than 15minutes to deploy it, then the fishing event would be discarded.

The development and tailoring of this methodology cannot ignore the specificities of the different fisheries it is intended to be applied to. The fact that this procedure allows the study of more than one type of gear or fishery is one of its major advantages. But, at the same time, because nets, pots and traps are not handled exactly the same way, nor have the same distribution of soak time, there is the compromise of setting up parameters suitable to model different gears which may be less suitable from those to model single-gear fisheries. For example, choosing a time window from 90 minutes to 20 days to calculate the overlapping distances between datapoints, does not make much sense from a pots and traps standpoint, as the soak time of these gears is longer than one or two days, and net presumably do not fish for up to 20 days. But because we are dealing with two types of gears that do differ considerably in terms of soak time, we needed to choose a time window that could accommodate the soak times of both gears. This is a trade-off that must be considered when dealing with a polyvalent fishery. But in case this method is used in fisheries with just one type of gear, or a particular fishery, then the parameters, such as speed and time window, can be set according to the peculiarities of the studied fishery or gear.

The comprehensive knowledge about fisheries distribution and the quantification of fishing effort is fundamental to improve ocean governance as well as to improve fisheries management and marine conservation (Halpern *et al.*, 2008; Campbell *et al.*, 2014; McCauley *et al.*, 2016; Vespe *et al.*, 2016). Yet, the precise and complete understanding of this sort of information is still lacking (Kroodsma *et al.*, 2018; Leblond *et al.*, 2019), especially regarding polyvalent fisheries, which comprise the majority of the fishing fleets worldwide (Kelleher et al., 2012). Improving the resolution of fishing effort through the knowledge of where and for how long a gear is fishing will allow us not only to map the distribution of the fishing effort, but will also provide us with better estimates for stock assessment, better monitor fishing activities and assess the relationships between soak time and landing composition or bycatch. By increasing the coverage of the different fishing fleets with high resolution and high frequency datapoint generation tracking devices, it will be possible to apply approaches such as the one described in this paper to a whole fleet segment, contributing to ecosystem-based approaches and improve management and conservation of the marine realm.

3. CHAPTER III: LET'S MEASURE IT: AN APPROACH OF HIGH-RESOLUTION ESTIMATES OF BOTTOM FIXED NET FISHING EFFORT AT NATIONAL LEVEL.

3.1. ABSTRACT

Fisheries are one of the most important food sources for human consumption whilst being amongst the most impacting and extractive activities happening within the marine environment, which makes it imperative to properly manage this activity. To improve fisheries management, the precise quantification of fishing effort is of the outmost importance. Yet, present methods for effort estimation, especially at broad scales, are hampered by difficulties in data access and usually rely on coarse effort metrics or on costly data collection for quantifying fishing effort with higher resolution.

In the present work, we propose an approach of high-resolution fishing effort estimates of net fishing, as length of nets operated by a given fleet, at the national level. It relies on sampling of effort, derived from classified and easy to access vessel tracking data – AIS, and fishery dependent data – logbook and landings data. The proposed methodology combines trip-based effort estimates, derived from AIS data, as a foundation to extrapolate the total fishing effort, through the number of fishing trips linked to official landings and logbook data.

It is estimated that in the years from 2014 to 2020 an average of 180 200 km of static nets (gillnets and trammel nets), which corresponds to approximately 4.5 and 210 times the lengths of the equator and the Portuguese Atlantic coastline respectively, are used in Portuguese mainland waters each year, by a fleet of slightly more than 100 vessels. The presented methodology allows to quantify and study the variation of the nominal fishing effort, at country level, with a higher resolution than what is usually used and at very low cost. We argue that such methodologies need to be developed and explored in order to have better and more comprehensive estimates of fishing effort which will contribute and improve the sustainable management of fisheries and the marine environment.

Published in Fisheries Research

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3.2. INTRODUCTION

As the human population grows, so does the need for food production. Fisheries, as one of the most relevant sources of protein for human consumption, have been increasing since the 1970s (Anticamara *et al.*, 2011). Besides its importance as a food source, it is also one of the most impactful and extractive activities happening in the marine realm (Pauly *et al.*, 1998; Swartz *et al.*, 2010), meaning that it needs to be properly managed in order to keep on contributing for human food security (Pauly *et al.*, 2002).

One of the most relevant aspects for the sustainable management of fish stocks and the marine environment is to accurately know how much fishing pressure is being exerted, as it allows to understand the trends of catch rates and better estimate the impacts, such as bycatch and discards caused by a given fishery. This means that the precise estimate of the fishing effort is paramount to manage fisheries effectively and sustainably. Yet, for many countries and fisheries, data on fishing effort is still very unprecise and unreliable, making it imperative to improve the global fishing effort estimates, including at country level (Kieran, 2009; Anticamara *et al.*, 2011).

Bottom contacting fishing gears are known to be the most impactful and most damaging forms of fishing (Glover and Smith, 2003; Hourigan, 2009). Bottom contacting nets such as gillnets and trammel nets are among the most commonly used fishing gear worldwide (Cashion *et al.*, 2018) and are known for their impacts on the marine environment, such as ghost fishing (Erzini *et al.*, 1997b; Richardson *et al.*, 2019) and habitat damage (Gonçalves *et al.*, 2008; Dias *et al.*, 2020). Therefore, the precise quantification of net fishing effort and the knowledge of its distribution is vital to improve ocean management and conservation. But, despite the improvements in mapping and quantifying of fishing effort, the quantification of the fishing effort at regional, national or even global level is still far from ideal (McCluskey and Lewison, 2008b; Anticamara *et al.*, 2011; Kroodsma *et al.*, 2018; Leblond *et al.*, 2019).

To study the fishing effort, different metrics and quantification approaches have been used throughout the years, such as the engine power (in kilowatts or horsepower) (Rijnsdorp *et al.*, 2000; Eigaard *et al.*, 2011), number of vessels (Rodríguez-Quiroz *et al.*, 2010), size of vessels (Bordalo-

Machado, 2006; Leitão *et al.*, 2022), days at sea or fishing days (Rijnsdorp *et al.*, 2006; Guiet *et al.*, 2019) and the combination of these metrics (Joint Research Centre (European Commission) *et al.*, 2022, 2023). These units of effort have been particularly useful when assessing the fishing effort at a broader scale, such as at national or regional level. Yet, broad units of effort may be problematic as they may lead to misleading conclusions. For example, it has been shown that catch per unit of effort (CPUE) can be a misleading index of abundance if inappropriate units of nominal effort are used (Gillis and Peterman, 1998), or that the spatial distribution of fishing effort based on fishing gear soak time do differ from effort distribution based on the time vessels spend at sea (Mendo *et al.*, 2023b).

To improve the estimates of effort resolution units and metrics, such as those based on the characteristics and dimensions of the fishing gears, like the total swept area for trawl fishing, the number of purse seine hauls, or the total number of hooks and length of nets used per unit of time and/or area, poses a big challenge. In many instances this precise quantification of effort is dependent on and only possible for very specific and usually costly fishery monitoring and sampling programs, such as those relying on onboard observers (Punt *et al.*, 2000; Mandelman *et al.*, 2008; Coelho *et al.*, 2012). Such challenges make it unfeasible to estimate the fishing effort with the desired level of resolution, for all fisheries within wider areas or at a country level. There have been several studies though, that have estimated the fishing effort with higher resolution and with more precise metrics without being involved in large-scale fishery monitoring programs (Lauridsen *et al.*, 2008; Akyol and Ceyhan, 2009; Gönener and Bilgin, 2009; Batista *et al.*, 2015; Sara *et al.*, 2017). But these studies focused on particular subjects, like bycatch (Gönener and Bilgin, 2009), or studied a subset of a fleet or addressed very narrow spatial areas, without the intention to estimate the total effort of an entire fleet or at a broad scale.

The introduction of vessel tracking devices has revolutionised fisheries research (Tetreault, 2005; Russo *et al.*, 2018; Yang *et al.*, 2019; Thoya *et al.*, 2021). Thanks to data derived from Vessel Monitoring Systems (VMS), Automatic Identification Systems (AIS) and other GPS-based tracking devices, and especially when combined with fisheries dependent data, the study or fisheries productivity, the distribution of fished species, and the quantification and distribution of the fishing effort has seen tremendous developments (Russo *et al.*, 2011b; Jennings and Lee, 2012; Eigaard *et al.*, 2016b; Russo *et al.*, 2016c, 2018). Yet, in order to study an entire fleet's effort, either almost complete fleet coverage from vessel tracking data, or some other procedures that rely on a sample of the fishing fleet, is required (Russo *et al.*, 2018).

As it is mandatory for all fishing vessels with Length Overall (LOA) above 12m and it is continuously transmitting, VMS is the most comprehensive vessel tracking device that enables the study of the spatial and temporal effort attributes of an entire fleet (Russo *et al.*, 2016c, 2018). Yet, due to confidentiality regulations, access by researchers to this type of data is very difficult. Moreover, the transmission frequency is usually very low (1 – 2 hours), which poses an additional challenge as some fisheries and fishing techniques such as small-scale fisheries and fisheries using passive gears require much higher data frequency, (Mendo *et al.*, 2019b; Sales Henriques *et al.*, 2023).

AIS, on the other hand, has some relevant advantages compared to VMS data: it is of easy access and the data frequency is much higher (usually 1 - 5 minutes), which is ideal to study fisheries with short duration fishing operations (Mendo *et al.*, 2019b, 2023b). Unfortunately, AIS systems also present some disadvantages that compromise the spatiotemporal coverage of the data. For example, for land-based AIS signals, if a vessel is too far away from a receiving antenna, the AIS transmission can be lost, the AIS signal is very dependent on weather conditions, and the AIS transponder can be manually switched off by the skipper (Russo *et al.*, 2016c; Emmens *et al.*, 2021). These liabilities associated with AIS makes it difficult to have a comprehensive fleet coverage. In fact, the coverage of the fleets was usually low in many of the published works where AIS data was used to study fishing activities, either due to the poor fleet coverage by AIS or due to the high-quality data requirements used in the analysis (Natale *et al.*, 2015; Russo *et al.*, 2016c; Sales Henriques *et al.*, 2023).

In the work by Sales Henriques et al. (2023), the authors developed a methodology to classify vessel tracking data from passive fishing events from a polyvalent coastal fishing fleet operating bottom contacting nets and pots and traps. With the developed methodology, the authors were able to classify

AIS data from 84 polyvalent coastal fishing vessels into the four common behaviours happening within a fishing trip: navigation; gear deployment; gear hauling and slow navigation (Figure 3.1). This work allowed fishing effort of this fleet to be mapped and quantified as soak time, during the period from 2014 to 2020. But, due to the aforementioned disadvantages inherent to the AIS data and data quality requirements of the developed methodology, this work was only able to map and quantify a fraction of the total effort of this fishing fleet: 26.5% of the fishing effort of 56% of the polyvalent fishing vessels equipped with AIS (Sales Henriques *et al.*, 2023).

In the present work, we develop and explore a new methodology to quantify the national fishing effort of static nets, as total length of nets, from a polyvalent coastal fishing fleet. To do so, we combine the sample of the fishing effort, obtained from the work by Sales Henriques et.al. (2023) and fishery dependent data, as the foundation to extrapolate the total fishing effort of this fleet at a national level.

Given the global absence of complete fleet coverage with vessel tracking data (Paolo *et al.*, 2024) to precisely estimate the total fishing effort with better resolution, it is vital to explore and develop methodologies to address this important knowledge gap. We hope that the proposed methodology represents a step forward and contributes to open up the discussion and incite others to develop and apply new methodologies to better estimate the fishing effort at a broader scale than what is currently done.

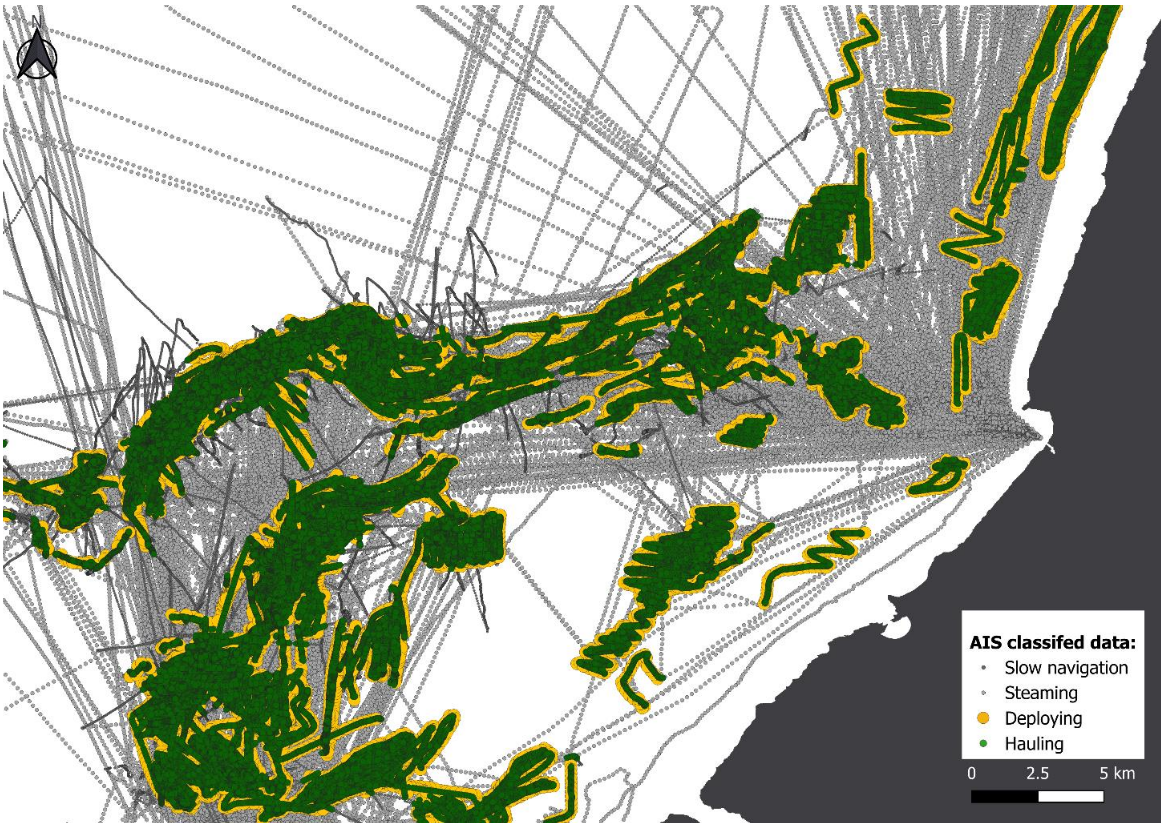


Figure 3.1 Example of AIS data classified into the four most common behaviours within fishing trips using passive gears, under the approach developed by Sales Henriques et al. (2023). The classified AIS data was used as sample effort data to extrapolate the total fishing effort, in km of nets used, for vessels with LOA >14m, operating within mainland Portuguese waters, during the period of 2014-2020.

3.3. Methods

3.3.1. Rationale and required data

This approach relies on two different types of data: classified AIS data from polyvalent coastal fishing vessels and fishery dependent data: logbooks and/or daily landings/sales notes data, from here on referred to as landing data. The fishery dependent data was provided by the Directorate-General for the Natural Resources, Safety and Maritime Services (DGRM). The land-based AIS data was classified in the study by Sales Henriques et al. (2023). The AIS data classification procedure, which was able to map and quantify, as soak time, 26.5% of the fishing effort of 56% of the polyvalent fishing vessels equipped with AIS was able to identify more than 13200 fishing events using nets and pots and traps (Sales Henriques *et al.*, 2023).

For each fishing event, which is composed of two tracks: 1 - gear deployment and 2 - hauling of the gear, we measure the length using tracking data from the deployment events. To measure the length of each fishing event, we summed the distances of consecutive AIS data points belonging to each deployment track from each fishing event.

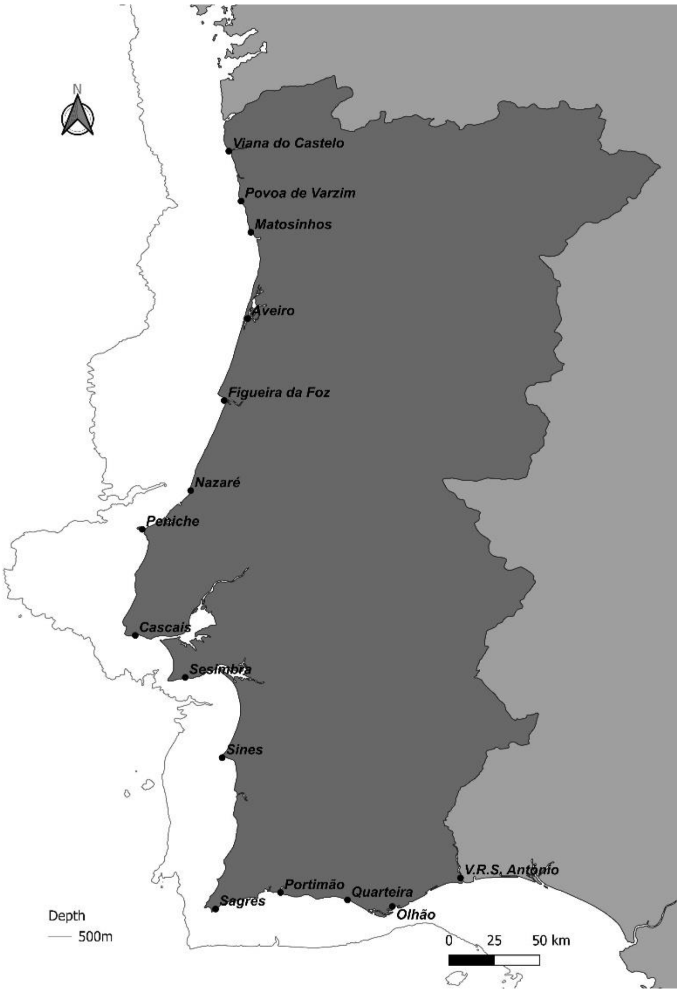
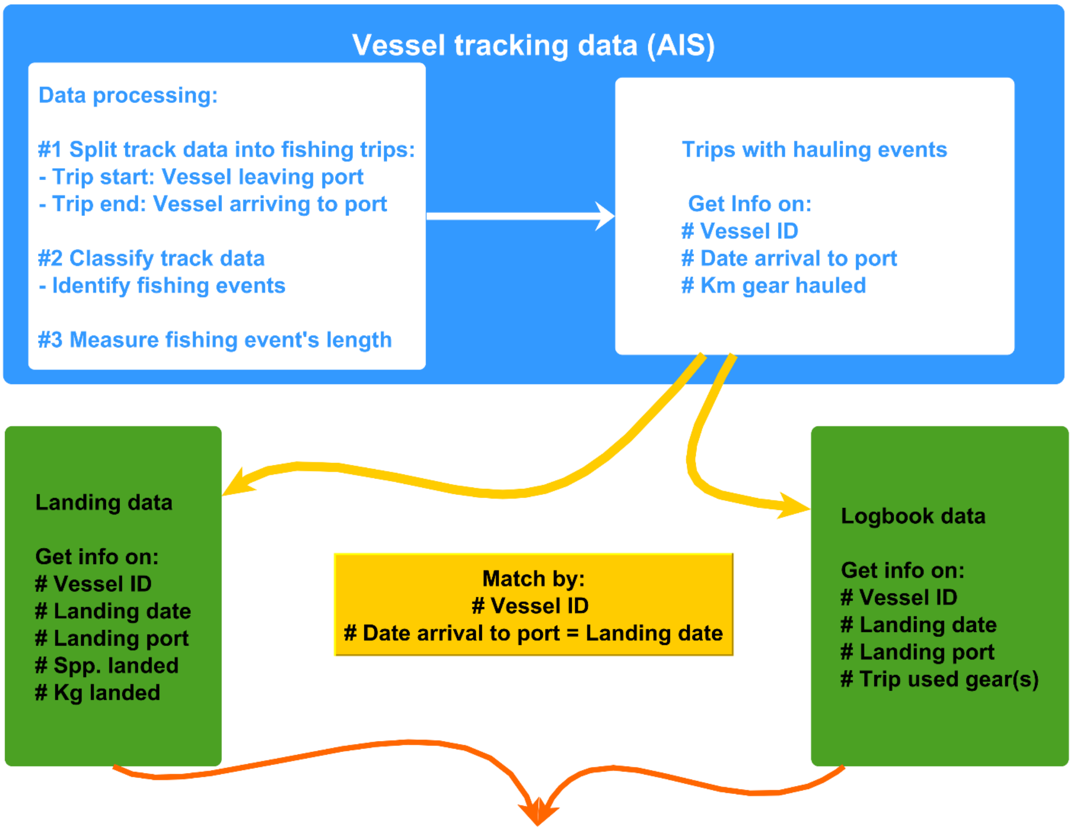


Figure 3.2 Map of the Portuguese mainland, which represents the study region of the present work. The 15 landing ports present on the landings and logbook records are shown. The 500m bathymetric line is displayed, as it represents a good proxy of the region where demersal net fishing occurs (Leitão et al. 2022; Sales Henriques et al. 2023).

3.3.2. Match of fishing effort with landings and logbook data

The next step was to cross the effort data (AIS data) with logbook and landing data. Given that the effort data, for each vessel was split into isolated fishing trips based on the moment of departure (start of fishing trips) and arrival to port (end of fishing trips), we first identified the date and time each vessel arrived in port based on the last AIS datapoint of each trip. Then, for fishing trips with hauling events, we matched the fishing trips effort data with the information provided in landing and logbook data corresponding to that trip. The crossing of effort data (track data) with fishery dependent data (landings and logbook data) was based on vessel's ID and the date of arrival to port within track data and the field "landing date" within logbook and landing data. This procedure allowed us to get a data set where we have the information about the spatiotemporal attributes of the fishing operations, like date and time, location, duration (soak time) and length of the fishing event(s), and the respective information declared by fishers and recorded for landing events, such as the used fishing gear(s), the landing port and the respective yields, such as landed species and how much of each species was landed, in kg (Figure 3.3).



Vessel ID	LOA class	Landing date	Landing port	Used gear	Total hauled gear (m)	Landed species	Landed weight (kg)
AA	VL1416	01/01/2019	Aveiro	GNS	11 000	*Spp1*	152
AA	VL1416	01/01/2019	Aveiro	GNS	11 000	*Spp2*	50
BB	VL1618	01/01/2019	Nazaré	GTR	13 000	*Spp1*	200
BB	VL1618	14/01/2019	Sagres	GNS	15 000	*Spp3*	75
CC	VL1416	05/08/2019	Matosinho	GNS	8 500	*Spp4*	95

Figure 3.3 Representation of the workflow to match the effort spatial data (AIS) with the fishery dependent data (Landing and Logbook data) and an example of the output. The process relies on the match through the ID of the vessel and the date of arrival to port (vessel tracking data) and the landing date (Landing and logbook data).

3.3.3. Selection of trips that only used static nets, based on info from logbooks

Given that the current study aims to estimate the length of static nets used by the coastal fishing fleet, from the dataset resulting from crossing effort and fishery dependent data, we only selected the fishing trips that used static nets (gill nets and trammel nets) and no other gears. This procedure was done using the information within the logbook field “gear type”, and only the landing trips that used these gears were kept.

3.3.4. Calculation of the average length of nets used per trip, by LOA class ($AvgNet_c$)

Because we are using a subset of the total fishing effort that we crossed with fishery dependent data, we needed to develop a methodology that allows to extrapolate the total fishing effort to a reasonable estimate of effort for the entire fishing fleet. Under our methodology, we assume that fishing vessels, on average, use the same length of nets within each fishing trip and that the total length of nets handled by trip is dependent on the size of the vessel. Under these assumptions, we calculated the average length of nets, from the AIS effort data, hauled in each trip and by vessel Length Overall (LOA) class. Therefore, the calculation of the average length of nets hauled in each trip, (from here on: AvgNet) was carried out for groups of vessels that were defined based on the vessel LOA.

According to the Portuguese legislation (Portuguese Ordinance No. 1102-H/2000), the length of nets allowed to be operated by vessel is dependent on the vessel size. Therefore, AvgNet was calculated for each LOA class as defined by the Portuguese legislation. The LOA classes that establish the maximum total length of nets allowed are: ≤ 9m – VL0009; (9-12m] – VL0912; (12-14m] – VL1214; (14-16m] – VL1416; (16-18m] – VL1618; (18-20m] – VL1820 and > 20m – VL20+, where "(" means LOA sizes bigger than the stated LOA value and "]" includes the specified LOA value. Because we are dealing with coastal fishing vessels with AIS devices, the LOA classes that we considered were the ones that include vessels with LOA above 14m. Despite AIS being mandatory only for vessel with LOA bigger than 15m, there were 4 vessels with LOA between 14m and 15m within the classified AIS data. Therefore, to increase the number of vessels for the estimation of effort, we decided to include all vessels longer than 14m (Table 3-1).

As the distribution of sampled values of km of nets used by trip (AvgNet) for each vessel LOA class did not follow any known distribution (Figure s8.2.1), we performed a nonparametric bootstrapping with replacement to the sampled data, with 10 000 resamples to obtain overall effort values with 95% Confidence Intervals (CI). We then assessed the bias between the sampled AvgNet with the same effort unit derived from the bootstrap procedure and checked for significant differences through a t-test. If there was no difference between the sampled and bootstrap average effort values for each trip, we used the 95% CI obtained from the sampling distribution of means from the bootstrapping (Table 3-1).

3.3.5. Effort calculation: AvgNet x N fishing trips

After obtaining values of AvgNet and respective upper and lower limits belonging to the 95% CI used in each trip for the different LOA classes, we calculated the fishing effort for every polyvalent fishing vessel with LOA > 14m, operating nets within Portuguese mainland waters from 2014 to 2020. Strictly speaking, the total net fishing effort of this fleet was calculated as the product of the number of landing events, as a proxy for fishing trips, and the AvgNet. More specifically, the effort (*f*) of vessel (v) during the month (m) for fishing trips ending in port (p) was calculated as the product of the number of fishing trips (Nt) per vessel (v) for month (m) landing in port (p) by the average km of nets used per trip (AvgNet) specific to the vessel's LOA class (c) as calculated from the AIS classified data:

$$f_{v,m,p} = Nt_{v,m,p} \times AvgNet_c \quad (1)$$

As done for the vessels within the AIS classified dataset, from which we calculated the values of AvgNet before calculating the total effort of net fishing, we needed to select the fishing trips that used nets and no other gears. Since fishing vessels with LOA ≥ 12m are required to use electronic logbooks (EU Control Regulation 1224/2009) and log which gears were used in their fishing trips, we selected only fishing trips/landing events that only operated static nets (trammel and gillnets) during the study period and then calculated the effort using Eq. 1 (Table 3-2).

The total fishing effort for landing events happened in port (p) during month (m) was calculated as follows:

$$f_{p,m} = \sum_{v=1}^{V} f_{v,m,p} \quad (2)$$

where *V* is the total number of vessels.

3.3.6. Effort validation

As we used a subset of the total fishing effort to estimate the overall effort of a fleet, to validate the effort values from the AIS data calculation we adapted the model from the work of Russo et al. (2018) and assumed that landings (L), in kg, from a given vessel (v), during the month (m), landed in port (p) is given by:

$$L_{v,m,p} = f_{v,m,p} \times LPUE_{c,m,p} \tag{3}$$

Where $LPUE_{c,m,p}$ is specific to the vessel's LOA class (c), landing in port (p), during month (m). In other words, the monthly landings of a given vessel in a given port during a given month is a result of the product of its effort and the average LPUE of its LOA class, landing in the same port during the same period (month).

To validate our approach, we used k-fold cross validation, with k = 25, where we split our data into 80% as estimation data and 20% validation data. Then, we calculated the $LPUE_{c,m,p}$ from the estimation dataset and for the validation dataset we calculated the predicted effort ($f'_{v,m,p}$) through:

$$f'_{v,m,p} = \frac{L_{v,m,p}}{LPUE_{c,m,p}} \tag{4}$$

Then, to assess the assumptions of effort derived from AIS data, we compared the estimated effort (*f'*) with the calculated effort (*f*) and assessed the distribution of the residuals.

3.4. RESULTS

The crossing of the sample effort spatial data with landings and logbook data from fishing trips using nets, returned a dataset with 5478 fishing trips performed by 73 vessels. Fishing vessels can deploy and haul one or more sets of nets in one trip and in fact 8163 net fishing events were identified and measured within these fishing trips. Given that there was no significant difference ($p > 0.05$) between sampled average km of nets used per trip (AvgNet) and the same effort metric derived from the bootstrapping (Table 3-1), the sampled effort unit was used to calculate the overall fishing effort and the 95% CIs were calculated from the bootstrap results. Table 3-1 provides a summary of the outputs of this initial procedure.

Table 3-1 Summary of the calculation of the average length of hauled nets per trip, for the four LOA classes of vessels present in the AIS effort dataset, for which we were able to match trips with landing and logbook data. Due to the fact that the distributions of the length of nets used by trip did not follow any known distribution, bootstrapping procedure was performed with the purpose to: 1) assess if the sample mean would resemble the population mean derived from bootstrapping and 2) to calculate the 95% Confidence Intervals (CI) of the length of nets being used per trip.

LOA class	Number of vessels	Number of trips	Average km of nets hauled/trip (Sample data)	Average km of nets hauled/trip (Bootstrap)	Bias Sample data VS Bootstrap	Standard Error (km) (Bootstrap)	95% CI in km (Bootstrap)
VL1416	17	886	10.74	10.75	2.5	0.18	10.39 – 11.09
VL1618	31	2814	13.64	13.64	0.54	0.13	13.38 – 13.9
VL1820	22	1670	16.72	16.72	-0.12	0.21	16.31 – 17.13
VL20+	3	108	30.45	30.44	-11	1.73	27.06 – 33.86

According to landings and logbook records, 106 vessels with LOA > 14m, performed 79 573 fishing trips using bottom nets from 2014 to 2020. These trips ended in 15 different fishing ports along the Portuguese mainland coast, with the total number of trips corresponding to the total effort of fishing vessels of the fleet operating bottom nets (Figure 3.2 and Table 3-2).

Table 3-2 Overall number of vessels and landing trips for the coastal polyvalent fishing fleet operating nets bottom nets during the period 2014-2020. The number of landing events were used as proxies for the number of fishing trips, under the assumption that each landing event corresponds to a fishing trip. The total effort of this fleet was calculated using the number of fishing trips (landing events) and the average km of nets used by each vessel LOA class.

LOA class	Number of vessels	Number of trips
VL1416	31	21 370
VL1618	37	30 643
VL1820	23	17 669
VL20+	15	9 891
TOTAL	106	79 573

The model presented in equation (3) and (4) was developed for validation purposes and therefore it was tested as such. The performance of the presented methodology in predicting *f'* for the validation dataset showed to be good (Figure 3.4A), meaning that the calculated values of average length of nets used by trip are reliable for extrapolating the total fishing effort for this fleet. It is note-worthy though, that despite the good overall prediction of *f'* ($R^2=0.9$) some variance is observed especially as the *f* increases. Nonetheless, as we see from the distribution of the residuals (Figure 3.4B), it is clear that the mean value is equal to 0 and that the majority of the residual values are close to 0 and evenly distributed on both sides of the residual mean value.

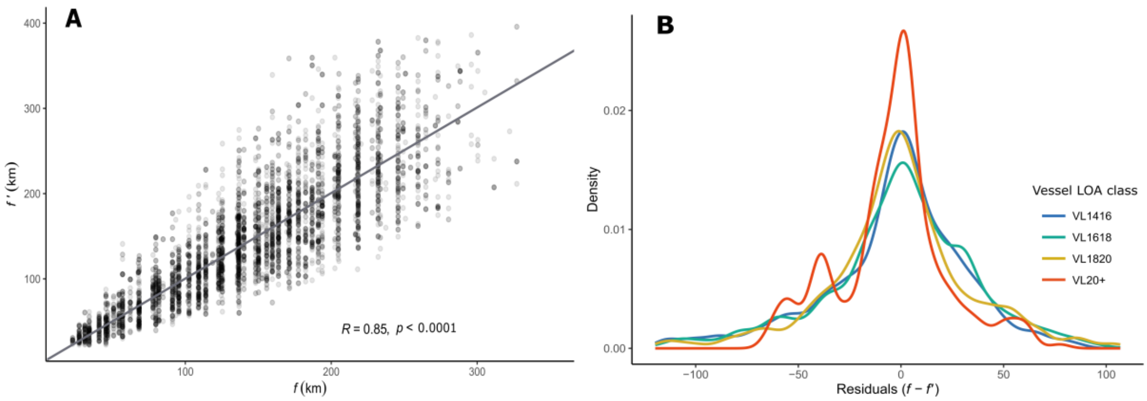


Figure 3.4 Scatterplot representing the correlation between the calculated monthly effort as per the presented approach (*f*) and the estimated monthly effort (*f'*) through the k-fold cross validation process. The Peason's correlation and corresponding *p*-value are shown. B – Distribution of the residuals between the calculated monthly effort (*f*) and the predicted monthly effort (*f'*) for each LOA class. The highest density of the residuals is centred around 0 with an even distribution for both sides of the mean value (0).

Given the prediction and validation results described, the AIS calculated values of trip-based effort were used to estimate the fishing effort through the approach described in Eq. (1) and (2).

We estimate that the total length of nets used during the study period was 1 261 497km (95% CI: 1 203 936 - 1 318 081 km), which corresponds to approximately 180 200 km of nets used per year along the Portuguese mainland coast. The effort intensity showed accentuated fluctuations along the study period without a conspicuous pattern. Yet, it seems that the effort was generally higher during most of the spring/summer months than the autumn/winter period (Figure 3.5).

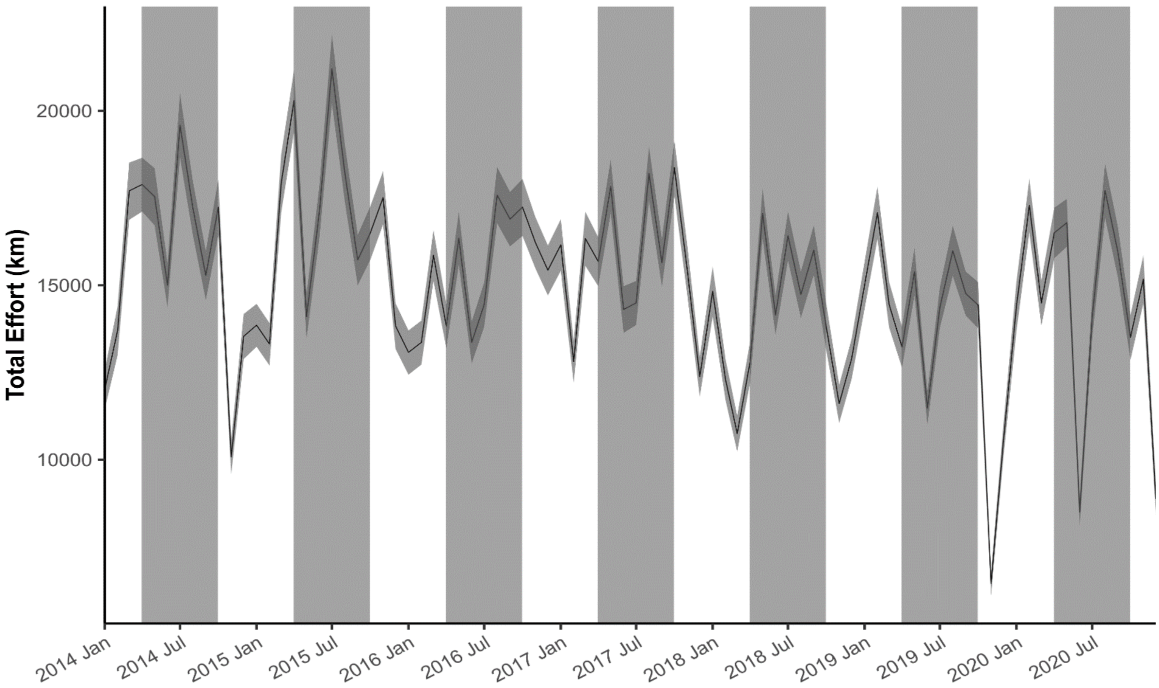


Figure 3.5 Time series showing the evolution of the total monthly fishing effort from vessels with LOA > 14m, as km of nets, along the Portuguese mainland waters. The shaded grey area along the black line represents the 95% Confidence Interval and the vertical shaded bars represent the warmer months (April to September).

Not all vessel LOA classes contributed equally to the total fishing effort, and this contribution seems to be port-dependent and to remain relatively stable throughout the study period. For example, in the port of Aveiro, the vessel LOA class VL1618 had much higher values of effort when compared to the other LOA classes. On the other hand, the difference of effort between classes was not so distinct for the remaining ports where all the 4 LOA classes operated. It is also clear that the bigger vessels LOA class (VL20+) had a higher effort contribution in the neighbouring ports of Sesimbra and Sines. In the fishing ports from the south coast of Portugal, the effort contribution was predominantly from the two smaller LOA classes (Figure 3.6).

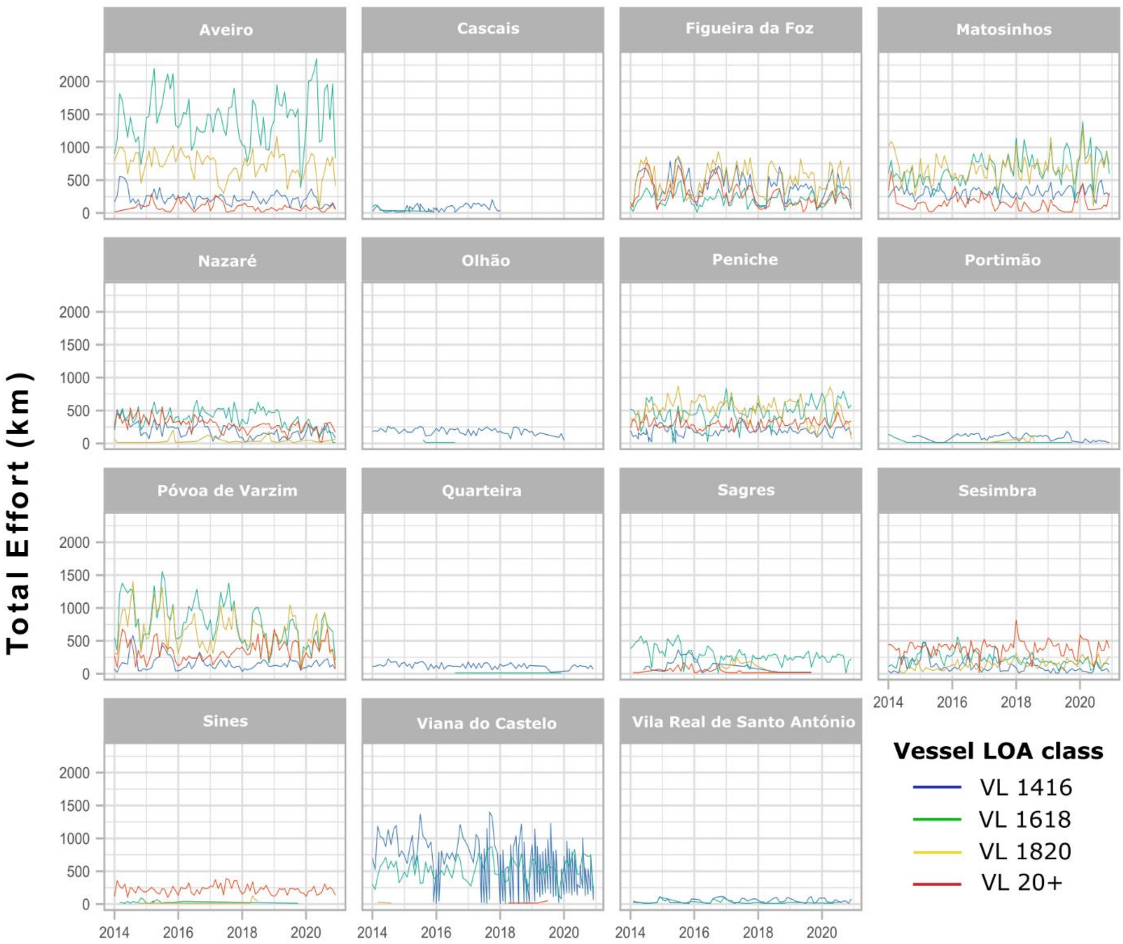


Figure 3.6 Contribution of each vessel LOA class to the overall fishing effort allocated to each port and the total effort with the 95% Confidence Interval. The amount of effort and the effort contribution from each LOA class varies distinctly among ports. Yet, it is observed that the proportion of effort contribution from each LOA class, within each port, remains relatively stable during the study period.

The distribution of net fishing effort remained constant throughout the study region during the studied period. The fishing port that showed highest levels of effort was Aveiro, followed by the port of Póvoa de Varzim and then by the port of Matosinhos. It is evident that the net fishing effort from this fleet segment occurs most predominantly in the upper central and northern region of Portugal, whist the effort in the southwest and south coast of Portugal is evidently lower (Figure 3.7).

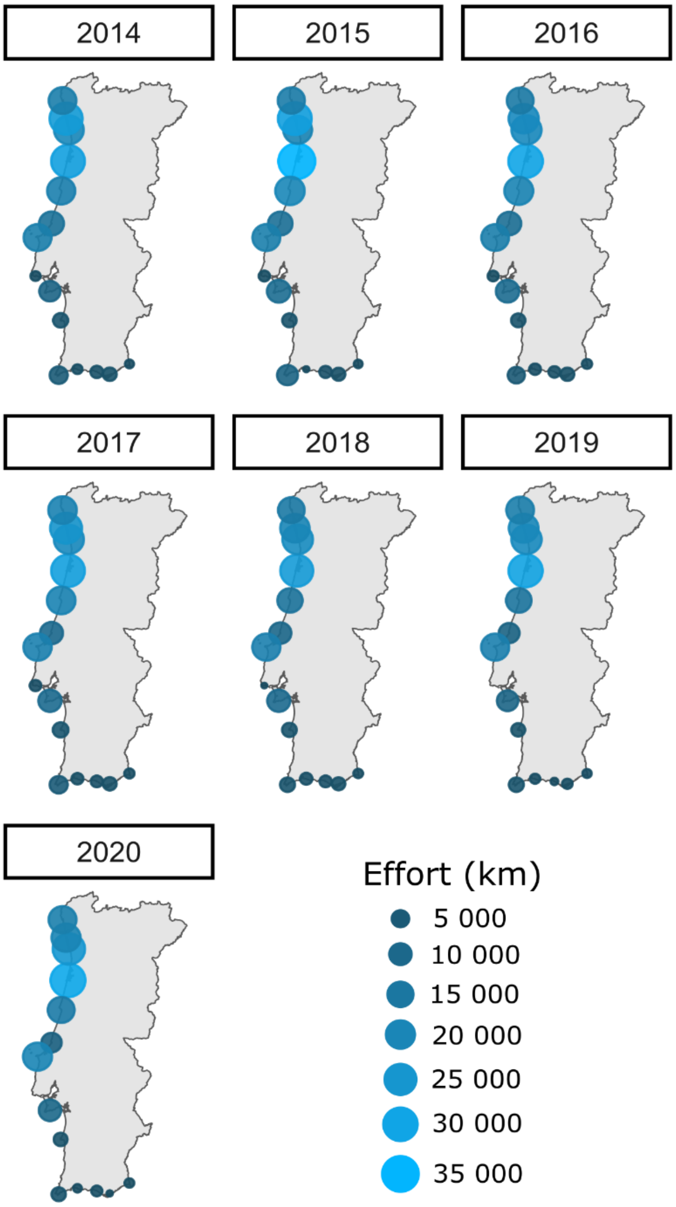


Figure 3.7 Annual values of effort, in km of nets, calculated for the 15 landing ports, during the study period. Landing ports were assumed as a proxy for the region where fishing vessels operated before landing their catches since the majority of these vessels perform daily fishing trips, and when performing longer trips, landing events occur in the port nearest to the fishing ground.

3.5. DISCUSSION

Here we introduce an approach to calculate the nominal fishing effort at high resolution, i.e. length of nets used, at a national level. The approach relies on the combination of two data sources: 1 – a sample of high-resolution effort data derived from classified vessel tracking data, and 2 – fishery dependent data: logbook and landing data. This approach allowed to estimate the fishing effort of a fishing fleet operating static, bottom contacting nets, with a higher resolution than what is common for estimates of fishing effort at broader scales, in this case at national level.

Previous estimates of effort, especially at broader spatial scales, have mostly relied on coarser units of effort, such as the number of vessels, vessel sizes and lengths, engine power, number of fishing trips, fishing days and days at sea. Indeed, these effort metrics can be a good proxy of nominal effort in the absence of high-resolution effort data. The combination of some of these metrics has been acknowledged as an even better approach to improve fishing effort estimates (McCluskey and Lewison, 2008b; Anticamara *et al.*, 2011). For example, under the EU Data Collection Framework (DCF) the fishing effort for each type of gear, is reported at a resolution of engine power (kw) per day (kw*day), vessel size (Gt) per day (Gt*day) or by the number of active vessels (Joint Research Centre (European Commission) *et al.*, 2022, 2023). Indeed, such metrics are, to some extent, good proxies for studying the fishing effort, but they do not necessarily reflect the actual nominal fishing effort for each vessel or each vessel LOA class. For example, and as shown in the present study, smaller vessels do indeed use shorter sets of nets per trips than bigger vessels, but the correlation between vessel LOA class and the length of nets used per trip is not linear. Moreover, using vessel LOA alone does not provide a good estimate of how many km of nets are used per trip. This means that without high resolution effort sampling methods, such as those relying on onboard observers or through the usage of high-resolution vessel tracking data, the average length of nets used by trip, for example, cannot be estimated.

When there is availability of vessel tracking data throughout a comprehensive portion of a fleet, the precise estimate of effort for a fleet segment at national or regional scale has been shown to be possible (Russo *et al.*, 2019a; Leitão *et al.*, 2022). For example, Leitão et al. (2022) studied the spatial trend of LPUE from coastal polyvalent fishing vessels along the Portuguese mainland coast. Russo et al. (2019) was able to map and quantify the fishing effort of the Italian trawl fleet in the Mediterranean Sea. These broad and higher resolution effort assessments are only possible thanks to VMS data (Leitão *et al.*, 2022), or with the combination of VMS and AIS data (Russo *et al.*, 2019a). Yet, VMS data is very hard to be accessed by researchers and its temporal resolution is not ideal for some types of fishing gears, such as passive gears (Mendo *et al.*, 2019b, 2023b; Sales Henriques *et al.*, 2023). Our approach addresses the lack of access to comprehensive sources of high-resolution effort data. It relies on a sample of effort derived from classified AIS data and fishery dependent data to estimate the fishing effort for static nets at the national level, with a higher resolution than has been previously attempted.

The differences between the average effort values obtained directly from the effort sample AIS data and the bootstrapped values were very low, which not only gives us confidence in the AIS classification procedure and the way that we calculated the length of the fishing events, but also allowed us to provide a 95% CI for the effort, when the original distribution of the AvgNet did not follow any known distribution. The resulting values of the AvgNet do follow the expected assumption that bigger vessels use longer nets. Yet, vessels from the LOA class VL20+ operated, on average, considerably longer sets of nets than the remaining LOA classes. The reason for this, has to do essentially with the fact that the trips from these vessels were longer than the remaining LOA classes. An assessment of the classified AIS data (data not shown) revealed that the trips of these vessels, on average, would last around 18 – 19 hours, but could easily take 30 hours. This period allows to operate longer sets of nets and even operate the same net twice within the same trip. For the remaining vessel LOA classes, trips lasted 9.5 - 14 hours on average, which, associated with the smaller space on deck, does not allow setting and hauling of very long sets of nets. Yet, it is important to refer that even though we analysed 108 fishing trips from vessels from the LOA class VL20+, the AIS derived effort data is only from 3 vessels. This means that the effort values per trip need to be considered with caution, as the number of vessels is low and these 3 vessels could have a different behaviour than the remaining vessels from the same LOA class.

To verify if the effort values derived from the AIS data could be reasonable and therefore justify the landing values from this fleet, we followed the approach by Russo et al. (2018), adapted to our case study. Indeed, the predicted monthly effort (*f'*) and the calculated monthly effort (*f*) showed high correlation. It is noticeable nonetheless that as *f* increases the dispersion of *f'* increases as well. This is expected, as with the increase of effort, so does the differences of catches between vessels. These differences result from some vessels having considerably higher or lower monthly values of catches than the average catch of their LOA class, in port p, during month m. These catch differences may be due to many reasons, including the skills of some skippers compared to others which also translate in differences in catch consistency throughout the month, and also because bottom set nets include a variety of métiers, which is reflected in the catch landings species compositions and quantities (Szynaka *et al.*, 2022a). Also, abnormal high or low catches that can influence the overall monthly catch and how much of the catch is actually declared by the vessel can influence these results. Indeed, we did not expect to have small values of dispersion between *f* and *f'* as this is a very complex fishery with many variables that can influence its catches. Yet, from the distribution of the residual values (*f* - *f'*) it is clear that the majority of the values tend to be close to zero, which is also the mean value of the residuals.

The effort intensity along the study period seems to be higher during spring/summer months. This makes sense as this is the period when sea conditions are more favourable for fishing activities, especially in the central and northern coast of Portugal, and when the seafood consumption is generally higher. As expected, spatial distribution of fishing effort from this fleet is higher in the central and northern part of the country and our results corroborate those of Leitão et al, (2022). The fishing fleet in this region, because it is exposed to more adverse meteorological conditions with higher winds and swell heights, is composed of larger vessels. On the other hand, the southern region of Portugal is characterized by more favourable weather conditions and smaller fishing harbours, which makes this region predominantly characterized by small-scale fisheries, with fewer large coastal category fishing vessels. This is supported by our findings, as the two smaller vessel LOA classes operated mostly in the southern region of Portugal.

Another relevant finding of this study is that the spatial distribution of the effort remained stable throughout the study period, and the contribution of each LOA class for the total effort for each port also remained rather stable, supporting the idea of high port fidelity of these vessels.

To be able to extrapolate the overall fishing effort from a high-resolution sample of effort and fishery dependent data, we had to make some important assumptions. The first is that the vessel LOA dictates the length of nets used by trip. This is an obvious and widely used assumption, which is also supported by the results. The second assumption is that vessels, on average, operate the same net length in each trip. Indeed, on some occasions fishers may use more or less nets during a trip, but overall, fishers tend to have the same *modus operandi* within trips. Besides, given that nets operated by these vessels are many km in length, adding or removing one hauled net would greatly impact the time spent at sea. We also used the landing port as a proxy for the region where the vessel fished. Fishing trips within Portuguese mainland waters rarely last longer than a day, which means that fishers normally try to spend less time navigating than fishing and to do so, they need to fish in the vicinity of the landing port.

Given that we are dealing with polyvalent fishing vessels, that can operate more than one type of gear, including within the same fishing trip, and because the algorithm developed by Sales Henriques et al. (2023) is not able to identify which gear was used on a given passive fishing event, we decided to not consider fishing trips where more than one type of fishing gear was used. Using multi-gear fishing trips to calculate the overall fishing effort would overestimate the fishing effort from net fishing by considering the effort of other gears. According to logbook data, of all fishing trips operating nets, only 87% used this type of gear, whilst the majority of the remaining trips operated nets along with pots and traps. This is an important aspect to consider when interpreting the results presented in this paper, which means that the total net fishing effort might actually be underestimated.

There are also some relevant and practical parts of this approach that need to be discussed. The reason we used the gear deployment tracks instead of the hauling of the gear to measure the length of nets used on fishing events, i.e. the length of the fishing event, has to do with the fact that when a vessel deploys a fishing gear, it does it in a very consistent speed and direction, as fishers want the gear to be stretched. When the vessel is hauling the gear, the operation is carried out at a very slow speed and not necessarily in a very constant heading, as many unpredictable events can make the vessel change from the direction of the gear, such as gear fouling on hard bottom, entanglements or bad weather. To consider these changes of heading could overestimate the length of fishing events. Another aspect has to do with the calculation of the AvgNet: this calculation only considered hauled fishing events happening within the trip. This means that, for a given trip, deployed fishing events were not considered in the calculation of AvgNet, unless they were hauled in the same trip they were deployed. The reason for this is that by only considering hauled fishing events, we avoid overestimation of the effort from considering the length of the same fishing event twice, i.e., when it is deployed and when it is hauled. Moreover, hauling events are the most time-consuming parts of fishing trips operating nets, which is a relevant aspect when fishers have to decide how long the fishing trip will be. Also, given that crossing effort data with the landing data was carried based on the landing trips, the obvious procedure is to match the landed catch with the length of hauled nets responsible for that catch.

The assumption that fishing vessels from the same LOA class, on average, operate the same length of nets in each trip does not consider the entire complexity of the system responsible for the variance of the real length of nets used in each trip. Indeed, factors such as the skipper, configuration of the vessel, weather or target species, for example, can affect the length of nets operated in each trip. Yet, in order to extrapolate high resolution fishing effort for an entire fleet based on the number of fishing trips and a sample of AIS derived fishing effort, an average value of nets used each trip for each LOA class needs to be defined. To define an AvgNet for each vessel would only be possible with a complete fleet coverage of classified AIS or any other high resolution vessel tracking data.

Another relevant part of this approach is its dependency on the quality of the data used to calculate the fishing effort. AIS classified data proved to be a reliable source of trip-based effort. On the other hand, this data quality concern is particularly relevant for the fishery dependent data, i.e., logbooks and landing data. For example, if a vessel fails to catch anything during a trip or did not declare its catch, then that fishing trip, will not be in the quantification of effort. Another important concern of this approach has to do with the care with which fishers fill in the logbooks, especially when logging the gear(s) used. If a used gear is wrongly logged, then that trip might, or might not, be considered in the effort estimation. Nonetheless, the mandatory obligation for all vessels to log their logbooks and in the case for Portuguese fishing vessels, to declare their daily landings is a very important and useful circumstance for this approach. Indeed catch composition can assist in identifying which gears were used within a trip (Szynaka *et al.*, 2021; Leitão and Campos, 2022), but in cases when more than one gear is used in the same fishing trips, this approach has proven less accurate.

Given that the current legislation does not require all fishing vessels to be equipped with high resolution and high frequency vessel tracking devices that cannot be switched off by skippers, to improve the resolution of fishing effort for passive fishing gears such as nets at a broad scale, approaches such as the one described in this paper need to be developed and applied. The true assessment of high resolution of fishing effort for all passive fishing gears will only be possible when high frequency vessel tracking devices are mandatory for all fishing vessels. Until then, methodologies such as the one presented in this study can fill an important knowledge gap on the quantification of nominal fishing effort of a very important and complex fishery, which will ultimately assist in improving ocean governance, fisheries management and conservation.

4. **CHAPTER IV:** IMPROVING MONITORING, CONTROL AND SURVEILLANCE EFFORTS THROUGH VESSEL TRACKING AND FISHERY DEPENDENT DATA.

4.1. ABSTRACT

Fisheries are amongst the most extractive and damaging activities impacting the marine environment. To control and promote the sustainability of these activities, different laws and regulations were established. Yet, Illegal, Unregulated and Unreported (IUU) fishing activities are still present to these days and are one of the most threatening problems affecting marine life.

To improve the effectiveness of fishing control and surveillance efforts, risk assessment approaches have been proposed to detect risk units with higher probability of illegal actions, such as vessels, seasons or regions, to which control efforts should be given priority.

Vessel tracking and fishery dependent data have already proved their potential for gathering important information regarding different aspects of fishing activities, such as species distributions or the estimation of fishing effort. Yet, their usefulness for improving monitoring, control and surveillance efforts has not been fully exploited.

Here, we investigate how these two types of data can provide important intelligence, within a risk assessment approach, to identify risk units that have higher probability of failing with landing requirements and how such information can be used to improve fisheries' monitor, control and surveillance efforts.

Our approach is able to identify fishing vessels with higher tendency for not reporting their catches. We saw that a small fraction of fishing vessels are responsible for the majority of unreported landings and that unreported landing events tend to less frequent during the Summer. We also noticed that price variation of sold catches correlates with unreported landing events, which might indicate that it is one of the drivers affecting the seasonality of unreported landing events.

Such information is crucial when planning control and enforcement actions, which should focus on those with a higher tendency to act incompliantly and during the periods when this sort of behaviour is more frequent. By following this approach, such effort become more cost effective, which will strengthen the governance of the marine realm.

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4.2. INTRODUCTION

The primary goal of fisheries regulations is to control fishing activities to make them as sustainable and less environmental damaging as possible. Yet, Illegal, Unreported, and Unregulated (IUU) fishing practices still persist to these days, are widespread, and are considered to be one of the most environmentally threatening activities occurring worldwide (Agnew *et al.*, 2009; Pauly and Zeller, 2016).

It is commonly agreed that to progressively eradicate IUU fishing, strategic policy development and implementation of new approaches, with strong coordination across these levels and with different organizations and countries are needed (Gunningham and Sinclair, 1999; Auld *et al.*, 2023). Under these premises, different treaties and regulations, such as the Agreement on Port State Measures (Hosch *et al.*, 2019), and in the European Union (EU), Council Regulation (EC) No 1005/2008 have been adopted to prevent, deter, and eliminate IUU fishing (Temple *et al.*, 2022). Furthermore, the EU established the European Fisheries Control Agency (EFCA) with the purpose of enhancing and coordinating Monitoring, Control and Surveillance (MCS) operations among EU member states ('Home | European Fisheries Control Agency', n.d.) in 2005.

With the intention of collecting information about fishing activities and their respective catches, the European Common Fisheries Policy (CFP) mandates that fishing vessels' activity and the first sale of all catches to be recorded and reported (Reg (CE) 1224/2009). According to European Regulation (CE) Nº 1224/2009, the activity of some fishing vessels must be recorded by fishers on logbooks, and it is the responsibility of the Member States to ensure that the first sale and record of all catches is done at a fish auction or by registered buyers and organizations (Reg CE 1224/2009).

With regards to "unreported" within an IUU context, it refers to unrecorded fishing and fishing-related activities that have not been reported, or wrongly reported, to authorities. Unreported fishing is one of the most common practices of non-compliance (Pauly and Zeller, 2015; EFCA, 2022). For example, in 2022, 15% of suspected infringements identified by EFCA were related to non-reporting or misreporting (EFCA, 2022), and it is estimated that one-fifth of global catches are not recorded and/or illegally caught (Pauly and Zeller, 2015; Long *et al.*, 2020).

According to EFCA's 2022 annual report, 70.1 million Euros were spent in MCS efforts in 2022, which resulted in the identification of probable infringements in 8.6% of the inspections performed. Indeed, the difficulty in identifying and detecting illegal practices is one of the major challenges when enforcing regulations (Agnew *et al.*, 2009; Petrossian and Pezzella, 2018; Chuaysi and Kiattisin, 2020). That is why the understanding of the associated drivers, the quantification of the impacts and the identification of the many forms of IUU fishing activities is vital to deal with IUU fishing practices (Sumaila *et al.*, 2020; Temple *et al.*, 2022; Widjaja *et al.*, 2023).

On broader scales, there have been several studies addressing the detection, estimation and quantification of IUU activities and their impacts (Sumaila *et al.*, 2006, 2020; Agnew *et al.*, 2009; Liddick, 2014; Pauly and Zeller, 2015; Petrossian, 2015). Yet, in order to improve fisheries management and enforce regulations through MCS efforts, the information on IUU should have higher spatial and temporal resolutions and be disaggregated by region, fleets, target species, or, ideally, by vessel (Macfadyen *et al.*, 2016; Ford *et al.*, 2018b; Temple *et al.*, 2022).

Due to the high costs related with MCS practices and the difficulty in identifying illegal behaviours, which translates to the low effectiveness of MCS efforts (Da Rocha *et al.*, 2012; Pramod *et al.*, 2014; Doumbouya *et al.*, 2017; Cochrane *et al.*, 2020; Standal and Hersoug, 2023), it is agreed that the identification of units, or factors, with higher risk of being associated with IUU activities, such as seasons, gears and metier, fleets, vessels or targeted species, through risk assessments, is necessary to make MCS more cost-effective (MRAG, 2015; Petrossian, 2015; Temple *et al.*, 2022). If risk assessments are made at vessel level for example, with the allocation of enforcement inspections directed to vessels that have been identified as probably non-compliant within a risk assessment framework, instead of simply allocating enforcement efforts randomly, MCS efforts could become more targeted and therefore more cost-effective (Ford *et al.*, 2018b; Temple *et al.*, 2022).

Vessel tracking data, such as VMS and AIS, have been advocated as an important source of information to improve fisheries management and transparency (Dunn *et al.*, 2018; Orofino *et al.*, 2023). Different studies showed and discussed the usefulness of such data in identifying probable IUU fishing activities, such as transhipment or fishing in conservation areas (Chuaysi and Kiattisin, 2020; Iacarella *et al.*, 2022; Kumar *et al.*, 2022), and identifying vessels with greater likelihood of non-compliant behaviours in order to make MCS efforts more effective (Ford *et al.*, 2018a; Orofino *et al.*, 2023).

Vessel tracking data, when combined with fisheries-dependent data, such as logbook data and landing/sales note data has also been acknowledged as a very useful source of information to improve fisheries management, such as to map fishing activities (Mendo *et al.*, 2019a; Tassetti *et al.*, 2022), assess fishing impacts (Gerritsen *et al.*, 2013), infer the distribution of captured species (Gerritsen and Lordan, 2011; Russo *et al.*, 2018) or to improve estimates of fishing effort (Sales Henriques *et al.*, 2024), for example. However, the combination of these two sources of data and its usefulness in identifying IUU fishing behaviours and making risk assessments to improve MCS efforts is yet to be explored.

In the current work, we exercise and explore how vessel tracking and official landing data can provide important information within an IUU risk assessment approach. We show how the proposed procedure can help identifying vessels that tend to fail to officially land their catches, and how the likelihood of this non-compliant behaviour changes seasonally. Then we hypothesize what might be some of the drivers promoting such behaviour, and we discuss how such information is relevant to plan and allocate MCS efforts in order to identify and consequently penalize non-compliant behaviours more effectively. More efficient MCS efforts will ultimately discourage illegal practices and improve the sustainable use of the marine resources and the marine environment.

4.3. METHODS

4.3.1. Study region and fleet description

The present work focused its approach on the coastal polyvalent fishing fleet operating within mainland Portuguese waters. The size of these vessels ranges from 14m LOA (Length Overall) to 23m LOA, and they operate mostly static nets, trammel and gillnets, pots and traps, and longlines, although the latter has been less used than the other two types of gears (Leitão *et al.*, 2025).

These vessels usually operate on a daily basis, which means that they perform daily fishing trips and it is very rare when they spend more than 24 hours at sea. Their area of operation spans across the entire Portuguese coast, although their prevalence is higher in the central and norther region of Portugal and within the 500m bathymetric range (Figure 4.1).

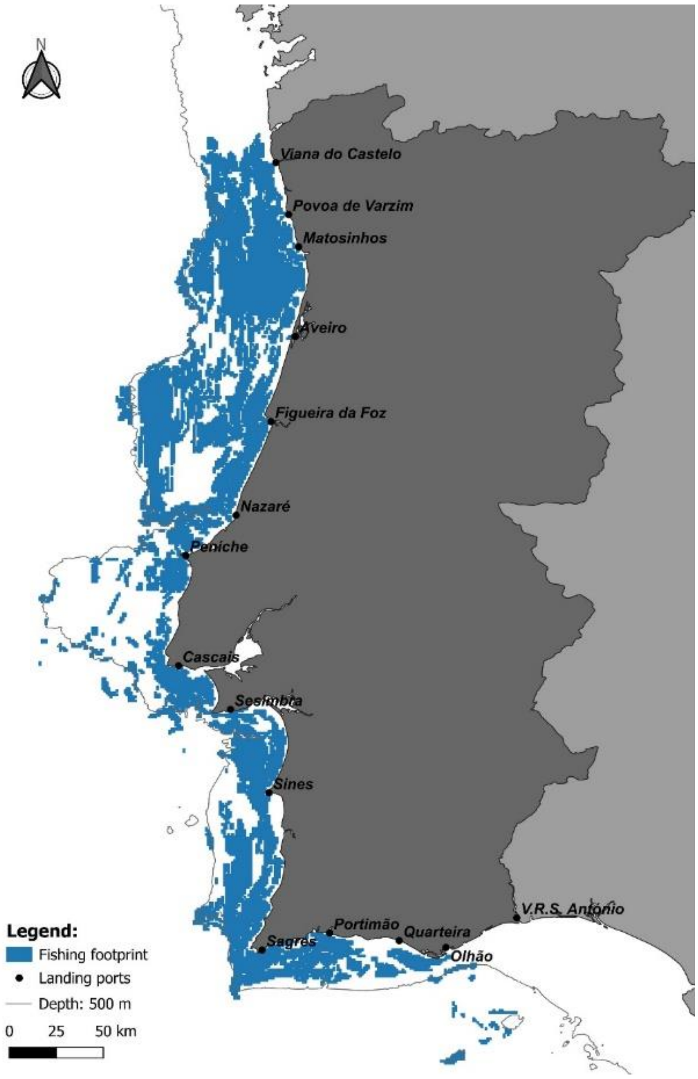

Figure 4.1 Map of the study region, the landing ports and the fishing footprint of the analysed fleet. The footprint was mapped using the methodology developed by Sales Henriques *et al.,* (2023).

This fleet is highly diverse in terms of species it captures. Official landing data accounts for more than 350 species. However, the most landed species, in weight, are the common octopus (*Octopus vulgaris*), the hake (*Merluccius merluccius*), the pouting (*Trisopterus luscus*) and the monkfish (*Lophius spp.*).

4.3.2. Data description

This work combines sales notes/landing data (from here on end referred to as landing data) and vessel tracking data (AIS – Automatic Identification System) from the Portuguese polyvalent coastal fishing fleet operating within Portuguese mainland waters.

Daily landing data, from the period of 2014 to 2020, was provided by the Directorate-General for the Natural Resources, Safety and Maritime Services (DGRM) and it contained information about the vessel, the landing/sale date, landing port, landed species, their amount in kg and the value of the auctioned catch in Euros.

Under the approach developed by Sales Henriques *et al.* (2023), AIS data from coastal polyvalent fishing vessels operating nets and pots and traps, during the period of 2014 to 2020 was split into isolated fishing trips: a fishing trip started from the moment a vessel left port and ended when it returned to any given port. Then the AIS data was interpolated at regular timestamps of one minute and classified into the four main behaviours a polyvalent fishing vessel performs during a fishing trip: navigation, gear deployment, slow navigation/drifting, and hauling of the gear. The aforementioned approach was able to identify and classify 13224 fishing trips from 84 coastal polyvalent fishing vessels during the 7-year period (Sales Henriques *et al.*, 2023).

4.3.3. Assumptions and rational of the approach

According to EU regulation CE 1224/2009, Member States are responsible for ensuring that all fishing products are weighed and recorded and that the first sale and record of all landings is done at a fish auction or by registered buyers and organizations. Moreover, the Portuguese government decreed that landings and the first sales of all fishing products has to be carried out at DOCAPESCA by registered buyers (DL 81/2005), which is a State operated company responsible for the provision of services related to the first sale of seafood across the Portuguese mainland (http://www.docapesca.pt/).

Under the assumption that vessels follow the aforementioned regulations, we assume that for a given fishing trip in which fishing gears were hauled, the most likely scenario is that landing records for a given fishing trip, performed by that given vessel, should be present within the landing data recorded at DOCAPESCA.

4.3.4. Data fusion

The first step to combine the vessel tracking data with landing data was to select, within the classified AIS data, only the fishing trips where hauling of fishing gears occurred. This means that fishing trips without gear-hauling events were removed from the vessel tracking dataset, as these should not return any catch.

Due to the inherent problems of AIS data that affects the consistency of good quality data, such as poor data reception, the ability to turn OFF the AIS transponder by the skipper and the data quality and consistency requirements by the classification procedure (Shepperson *et al.*, 2018; Emmens *et al.*, 2021; Sales Henriques *et al.*, 2023), the number of tracked and classified fishing trips varied greatly, ranging from 3 to 475 trips depending on the vessel. Therefore, to conduct an analysis where all fishing vessels had a representative number of fishing trips, we opted to proceed with the analysis only for vessels with more than 50 fishing trips within the classified AIS dataset.

The next step was to combine, for each vessel, the spatiotemporal information of fishing trips, i.e., the classified AIS data, with the respective landing data. This procedure was based on the date and time of arrival to port of each fishing trip, i.e. the end of each trip, within the AIS data (obtained from the last AIS datapoint of each trip) and the sale date stated on the landing dataset. Given that the present fleet does not freeze their catches, we assumed that the date of the catch sale to be the same as its landing date. However, due to the different schedules of the auctions in the different port facilities, it could happen that a vessel lands its catch later in the day, and because the next auction is in the following day, there would be a mismatch between trip data and landing data. Therefore, in order to avoid such situation, we only match track and landing data of fishing trips that arrived in port at least one hour before the last auction happening within the same day as the date of port arrival. Given that different ports have different auction schedules, which can be consulted in http://www.docapesca.pt/, this data cleaning process was performed for each landing port.

4.3.5. Risk assessment at vessel level – unreported landing events

Under the reporting regulations described above, we assume that in a compliance scenario, for each fishing trip where gears were hauled, a record of the landing data should be present. Under this assumption we investigated, for each vessel, the number and percentage of fishing trips without records on landing data, from now on referred to as unreported landing events.

Given that combining vessel tracking data with official landing data allows to quantify the proportion of fishing trips without reported landing events, we decided to explore how such approach can be useful within a risk assessment approach. We aimed to identify the fishing vessels, i.e., the risk units, that are more likely to not follow with the aforementioned landing obligation. We follow the assumption that vessels with a higher percentage of unreported landing events are more likely to ignore such regulations (Vallejos B *et al.*, 2023), which makes them preferential targets of MCS efforts.

Those "high-risk" vessels were identified based on a threshold that corresponds to the mean value of the percentage of unreported landing events from all analysed vessels. Which means that fishing vessels with higher percentage of unreported landing events than the mean value of the analysed fleet were identified as risk units, making them preferential targets for MCS efforts.

4.3.6. Seasonal variation of unreported landing events

To study the seasonal variation of unreported landing events, we used the combined vessel tracking with landing data, to calculate the total number of fishing trips captured with the AIS data and the proportion of those trips (percentage) without a corresponding landing event, in each month, by each vessel, during the period of 2014 – 2020. To study how the percentage of trips without landing events varies throughout the year, we fitted a Generalized Additive Model (GAM), with a Gaussian error distribution, to model the percentage of unreported landing events against the covariate month and considering the factor "vessel" as predicting variable with a random effect, when fitting the model to the data (Figure 4.2).

The number of fishing trips recoded with the AIS in each of the 12 months for each vessel varied from 1 to 75 trips. Given that the aim was to model the variation of a proportion, this wide distribution of the number of fishing trips per month caused unwanted noise on the proportion values when there were few AIS-recorded fishing trips on a given month. Therefore, to provide a more robust analysis when modelling the variation of unreported landing events, we established a threshold of a minimum of fishing trips carried out by each vessel, for each of the 12 different months, during the period of 2014 to 2020.

This threshold was defined through an iterative approach of model selection, where the resulting Akaike Information Criterion (AIC) and Deviance Explained were monitored across increasing thresholds of minimum number of fishing trips used in the different GAMs. The minimum number of fishing trips was established when the rate of the model's AIC decreased or stopped to improve, and the rate of its Deviance Explained started to stabilize (Pedersen *et al.*, 2019). Under this approach, a threshold of 19 fishing trips was defined as the minimum number of fishing trips carried out by each vessel, for each of the 12 different months, during 2014 to 2020. For a graphical representation of the iterative model selection process, check the Appendix section, Figure A1. Moreover, the response variable (proportion of trips with unreported landing events) was transformed (arcsine square root) in order to comply with the GAM's assumptions (Zuur, 2012). The descriptors of the model, resulting adjusted R^2, Deviance Explained, "and the residual plots can be consulted on Appendix section Table A2 and Figure A2, respectively.

To try to understand if the variation of the auctioned catch value could have an effect on the seasonal variation of the unreported landing events, we modelled the variable "price per kg" of all species landed by this fleet against the variable month. Again, we fitted a GAM and considered the factor "species" as predicting variable with a random effect when fitting the model to the data and transformed (square root) the dependent variable to comply with GAM's assumptions. The model description and its results can be found in the Appendix section (Table A2 and Figure A3).

4.4. RESULTS

4.4.1. Summary of the combined data

The classified AIS data returned 11847 fishing trips from 66 different polyvalent coastal fishing vessels, the number of fishing trips per vessel varied from 53 to 475 with a mean number of trips per vessel of 180 and a median of 142. Landings were reported for 84.1 % of these trips, i.e., landing records from the trips tracked with AIS were present within the landing dataset (Table 1). The remaining 15.9% of tracked trips had no landing records, which is a value that falls close to the 15% of infringements related to non-reporting or misreporting detected by EFCA in 2022 (EFCA, 2022).

Table 4-1 Summary table from the data used in the current work. Unreported landing events were identified when there was no landing record from fishing trips (recorded with AIS) that had gear-hauling events.

Data summary	
Number of trips with hauling events (classified AIS data)	11847
Number of vessels	66
Mean number of trips per vessel	180
Median number of trips per vessel	142
Number of trips with unreported landing events	1885
Total % of trips with unreported landing events	15.9

4.4.2. Risk assessment at vessel level – unreported landing events

On average, landings of 14% of all fishing trips tracked with AIS data, from the 66 vessels, were not reported. This means that fishing vessels with more than 14% of unreported landing events (23 out of 66 vessels) were identified as risk units. These vessels, which represent 1/3 of the analysed vessels, were responsible for nearly 85% of unreported landing events identified in the present analysis.

It is also noteworthy that vessels showed a wide difference regarding the proportion of trips without landing records: some vessels did not miss any landing event in all their AIS recorded trips (0% of unreported landing events), whereas some vessels did not land their catch more than 30% of their AIS recorded trips. There was even one vessel that showed 61.4% of unreported landing events (Table 4-2 and 4-3).

Table 4-2 Summary table regarding the unreported landing events. The overall mean percentage of trips with unreported landing events was 14% which was the threshold % value defined to classify fishing vessels as risk units. The number of vessels with more than 14% of unreported landing events was 23 out of 66 and were responsible for nearly 85% of the detected unreported landing events.

Summary of unreported landing events	
Mean % of unreported landing events	14.0
Median % of unreported landing events	7.0
Maximum % of unreported landing events (vessel level)	61.4
Minimum % of unreported landing events (vessel level)	0.0
Number of vessels with > 14% unreported landing events	23
Total % of unreported landing events from identified vessels	84.6

Table 4-3 Table with the first 20 vessels and the number of fishing trips recorded with AIS data. Fishing vessels with more than 14% of unreported landing events are highlighted. The IDs of the vessels are anonymized due to confidentiality agreements. The complete table of all 66 vessels can be found in the Appendix section, table A1.

Vessel ID	Number of trips - AIS	Number of trips without landing event record	% of trips without landing event record
ID-1	***475***	***137***	***28.8***
ID-2	***437***	***118***	***27***
ID-3	***433***	***142***	***32.8***
ID-4	***396***	***243***	***61.4***
ID-5	381	9	2.4
ID-6	***379***	***114***	***30.1***
ID-7	322	7	2.2
ID-8	286	11	3.8
ID-9	279	9	3.2
ID-10	275	9	3.3
ID-11	274	19	6.9
ID-12	***269***	***101***	***37.5***
ID-13	268	3	1.1
ID-14	***259***	***60***	***23.2***
ID-15	***257***	***81***	***31.5***
ID-16	256	12	4.7
ID-17	255	16	6.3
ID-18	253	5	2
ID-19	252	6	2.4
ID-20	***248***	***74***	***29.8***

4.4.3. Seasonal variation of unreported landing events

The percentage of fishing trips with unreported landing events throughout the year showed a non-linear behaviour (Figure 4.2). The beginning of the year until mid-spring had the highest values in percentage of trips with unreported landing events, with a noticeable decrease during the Easter months of March and April. Then, after May, the percentage of unreported landing events decreased rapidly, reaching its lowest value in August. This means that there was an evident increase of reported landing events (in percentage) during the second half of Spring until August. From September to November, a steady increase of unreported landing events, is observed and in December, a slight drop in the percentage of unreported landing events is again observed.

The price per kg of auctioned catch showed a quite fluctuating behaviour throughout the year and contrary to the behaviour of unreported landing events (Figure 4.2). It started the year with a decreasing tendency, until mid-Spring (May) when it reached its lowest value, except during the Easter months (March and April) when a slight increase of the price was observed. After that, it spiked until it reached its maximum during the Summer (August). From September until November the price decreased again and turned to increase in the last month of the year (December).

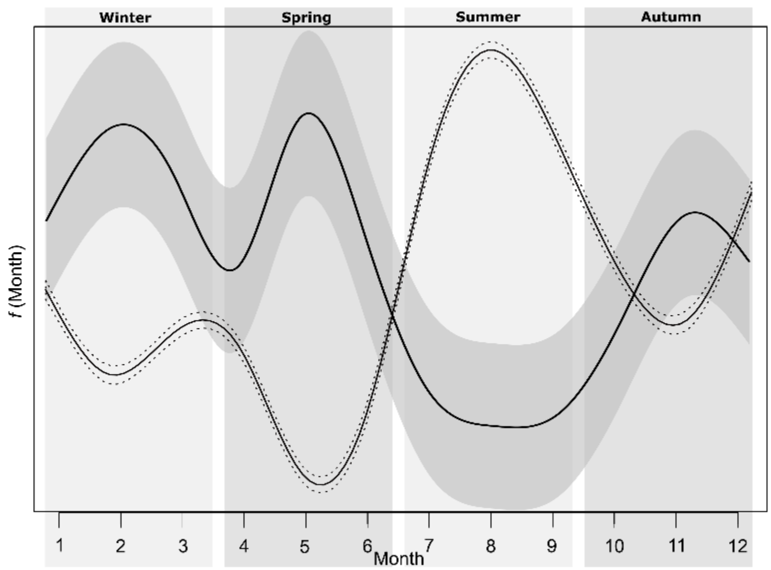

Figure 4.2 Seasonal variation of the percentage of trips with unreported landing events (shaded CI) and the variation of the price per kg throughout the year (dashed CI lines). The four seasons are highlighted. The description of the models, with formulas, variables, R^2 and Deviance Explained can be found in Appendix section, Table A2. The plots and histograms from the resulting residuals can also be found in Appendix section Figure A1 – Unreported landing events and Figure A2 – Price of landed species.

4.5. DISCUSSION

The wide variation in the percentages of unreported landing events amongst the different vessels seems to indicate that vessels behave very differently regarding their obligation of officially landing and selling their catch. This difference in behaviour, aligned with its seasonal variation, associated with the high costs and low effectiveness of MCS effort, corroborates with the statement that supports the need for improvement in MCS efforts which needs to be better allocated instead of being randomly deployed.

There have been other studies with the intent to acquire information that would translate into more cost-effective MCS efforts. Ford *et al.* (2018), for example, used AIS data to study loitering behaviours and rank vessels with higher probability of engaging in such behaviour. Iacarella *et al.* (2023) combined AIS data with aerial surveillance data to detect and estimate illegal fishing activities within conservation areas. Hosch *et al*. (2019) combines AIS data to infer vessel activity and their visit to major landing ports to make a risk assessment, at port level, to identify ports with higher risk of IUU-caught seafood passing through them.

Methodologies combining vessel tracking data with fishery dependent data to gather intelligence to improve MCS efforts are still very undeveloped. Moreover, the majority of IUU risk assessments have been done at wider resolutions, such as country, region or port level. Here, we discuss how these two types of data allow to make a risk assessment at a narrower resolution and identify vessels that could be more prone to fail with their landing obligations and when the probability of that happening is higher. Through the identification of such vessels and time periods, MCS effort can be better allocated by prioritizing the control and inspection to the identified vessels and seasons within the risk assessment.

We observed an evident discrepancy, at vessel level, on the proportion of trips without reported landing events, where one third of the analysed vessels (23 out of 66) were responsible for the majority (85%) of the detected unreported landing events. Which means that identifying such vessels with higher probability of failing to follow a given regulation and prioritizing MCS effort towards them might be a good starting point to better allocate MCS efforts. This is particularly relevant within a risk assessment context, as those who have the tendency of not following a common regulation also tend to not follow other regulations that are transversal to all (Vallejos B *et al.*, 2023).

In the present study, we defined a threshold to identify vessels as preferential targets for MCS efforts based on the average percentage of unreported landing events from the analysed fleet. This value was established merely as an example and can be tuned and adapted to management needs. Stakeholders, such as those responsible for controlling fishing activities, can define higher or lower thresholds based on different factors, such as the number of vessels they intend to inspect or the available budget allocated to MCS activities, for example.

It is important to stress that this approach does not aim, neither is able, to prove if a vessel is committing any illegality or if it is being fully compliant with regulations. Indeed, the absence of landing data after a fishing trip may not be related with incompliancy. For example, if a vessel, after a trip where gears were hauled, does not officially land any catch, there is always the possibility that the vessel neither captured nor kept any catch in that trip. Although possible, this is very unlikely, because these vessels haul more than 10 km of gears per trip (Sales Henriques *et al.*, 2024), and they always capture more than one species with commercial value.

Another reason for the absence of landing record on the same day of a fishing trip could be related to the lower prices of some species during the period when they were fished: some species, like the *Octopus vulgaris*, can be frozen and sold afterwards without losing its market value. Which means that fishers may freeze their catch on land facilities and legally sell it when the demand and prices are higher for those species. Yet, given that we are dealing with a polyvalent fishing fleet that operate different gears, targeting and catching different species, the proportion of fishing trips capturing one single species is inexistent. So, in case when a given species would be stored/frozen to be sold when its price is higher, the remaining species that were caught on the same trip would still have to be officially landed when the vessel arrives to port.

Another incompliant behaviour that this approach is not able to detect, is when a vessel officially lands some, but not all, of their catch. This might be particularly relevant for high-value species, like lobsters (*Palinurus elephas*) for example. Which may be sold through other means than the official and legal one.

It is important to refer that given that we used AIS as vessel tracking data, which can be easily switched OFF by the skipper, if a fisher is aware of such an approach to identify unreported landing events, and in case the skipper does not intend to officially land his/her catch, he/she could make a fishing trip without AIS data being transmitted. This would result in the non-identification of the unreported landing event as the geospatial data from the fishing trip would not exist. Vessel tracking systems where the skipper is not able to switch OFF the track signal, such as VMS (Vessel Monitoring System) or other closed systems, would provide more robust results and indeed should be the preferential source of data used in risk assessments to plan MCS efforts.

Besides the identification of IUU risk units at vessel level, we also aimed to study how the seasons could affect and explain changes of unreported landing events. We saw that during the Summer, there is an evident reduction of the proportion of trips with unreported landing events. This result suggests that MCS effort would have a higher probability of detecting unreported landing events if deployed during Autumn, Winter and Spring’s first half.

Given the seasonality of seafood consumption, which is higher during late Spring, Summer and festive seasons such as Easter and Christmas, which consequently increases the demand for these products (Macdiarmid, 2014; Love *et al.*, 2023), the seasonal variation of unreported landing events is contrary to what the authors would initially expect. We would expect that the unreported landing events would increase during high-demand seasons, especially during late Spring and Summer, as, due to higher demand, and overall higher prices, it is easier to sell seafood products through other means than at auction, like directly to restaurants for example, which usually returns higher profits and allows fishers to avoid paying taxes. However, higher prices may also play an inverse role in this behaviour. The fact that the prices of seafood increase during Easter, Christmas and especially the Summer could play an important role on the reduced proportion of unreported landing events during these periods. Indeed, fishers may feel more compelled to land and sell their catch officially, since they will get higher profits than during the periods when the seafood prices are lower.

There is another important aspect within the Portuguese legislation that may have an important role in this result. According to the regulation nº 14 694/2003, which establishes the conditions for the annual renewal of vessel's fishing licences, a fishing vessel must prove that it maintains a regular activity throughout the year. To do so, vessels must have legally sold a minimum value that is equal to *V*, which is calculated as: $V = (T - 1) \times 12 \times NMW$; where *T* is minimum mandatory number of crewmembers onboard the vessel, and *NMW* is the National Minimum Wage of the current year. In other words, vessels must prove that they are able to pay the salary of its crew, as minimum wage, during the entire year.

Another very relevant aspect of this regulation, is that the period of fishing licencing renewal ends on the 31st of August of each year. Meaning that vessels must have officially sold at least a value that is equal to *V* by the end of August to be able to renew their licence. With that in mind, we hypothesise that another possible reasons that the proportion of reported landing events increase during Spring until the end of August has to do with the fact that fishers are officially selling more seafood products to reach the minimum selling value that will enable them to renew the vessel's fishing licences.

4.6. CONCLUSION

Combining vessel tracking data with fishery dependent data, such as landing data, has shown that it has the potential to unravel some of the human behaviours that are inherent to fishing activities, how fishers comply with regulations and how complex it is to monitor and control their behaviour. To be able to identify and to understand the drivers behind uncompliant behaviours and to know how they are performed across actors and seasons is vital to improve MCS efforts. We have seen that not all vessels behave the same way regarding the obligation of officially landing their catches and that the rate of unreported landing events varies considerably across the year. We also noticed that seafood price fluctuation and national regulations, with their requirements and timing may be important drivers behind unreported landing events. This type of information is vital to identify IUU risk units within a risk assessment and therefore to make MCS efforts more effective. Moreover, since past behaviours are a good predictor of present and future behaviours, especially when control and surveillance practices are ineffective (Vallejos B *et al.*, 2023), this approach, which relies on past data, can still be used in a risk assessment to assist future MCS plans.

As we discussed, the use of AIS data in the presented approach might be a relevant aspect to consider when making such risk assessments. Indeed, the use of vessel tracking devices that cannot be switched OFF by the skipper, would be more appropriate. However, data such as VMS is confidential and very difficult to be accessed by researchers. Nonetheless, It is important to state that that the main scope of this work is to explore the usefulness of combining vessel tracking data with fishery dependent data in improving our knowledge on incompliant behaviours and to assist the improvement of the cost-effectiveness of MCS efforts.

Fishing activities are very complex, and the different drivers responsible for certain types of illegal behaviours do differ from fishery to fishery, species to species, and especially from country to country (Temple *et al.*, 2022). This is why this sort of analysis are important so that we can better understand why and how illegal fishing practices are being carried out throughout the different fisheries around the world.

Another important conclusion that can be drawn from this study, yet slightly out of the main scope of this work, relates with the reliability of fishery dependent data when used to estimate fishing metrics, such as the fishing effort, for example (Ballesteros *et al.*, 2024). Given that nearly 16% of all fishing trips, (15.9% of unreported landing events) would have not been detected through landing data, such estimates consequently may underestimate the real values. Moreover, this aspect may be even more relevant in studies at vessel level, given the evident discrepancy among the different vessels.

Increasing our knowledge on the complexity of IUU activities is the first step to improve the fight against them. By allocating MCS efforts to risk units with higher probability of committing IUU practices will increase the cost-effectiveness of MCS efforts in detecting and punishing illegal behaviours. This will then contribute to discourage such practices and ultimately, improve the governance and sustainability of fishing activities and the conservation of the marine environment (Cabral *et al.*, 2018).

5. **CHAPTER V:** ON THE ACCURACY OF SELF-REPORTED DATA FOR FISHING EFFORT ESTIMATES - A CASE STUDY FROM A POLYVALENT COASTAL FISHERY.

ABSTRACT

The quantification and the analysis of fishing activity is one the most important features in fisheries sciences and ocean management, and fishery-dependent data has always been the main source of information used to that end.

Within the different types of fishery-dependent data, self-reported logbook data provides vast amounts of different information about fishing activities. Despite their enormous importance, the quality and reliability of these data are surprisingly understudied. Yet, the accuracy and consistency of this type of data are sometimes difficult to quantify.

With the purpose of studying how logbook data can be a reliable source for fishing effort quantification, here we estimate and compare, for the Portuguese mainland coastal polyvalent fleet, the fishing effort of each vessel from two types of fishery-dependent data: 1- logbook data and 2- official landing data.

The results showed a difference of 22.7% between the overall number of fishing trips from both data types. In particular, vessels had a significantly lower number of fishing trips logged on logbook data than the trips estimated from official landing data.

Our findings support the concerns regarding the accuracy of logbook data, especially for estimating fishing effort. As far as effort inference is concerned, we suggest that the estimation of fishing effort from data logged and recorded from a third party, like official landing data, is a more reliable source of information than self-reported data.

Published in Fisheries Research

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5.1. INTRODUCTION

Fishery-dependent data is one of the most vital sources of information used to provide scientific advice for decision making in fisheries management. Important information such as catch trends, stock abundance indexes, by-catch estimates, fishing intensity and distribution can be inferred from different types of fishery-dependent data (Punt *et al.*, 2000; Pons *et al.*, 2010; Eigaard *et al.*, 2016a).

The analysis of fishery-dependent data has been the main source of information for the estimation, control and monitoring of fishing effort, an important part of fisheries management (Bordalo-Machado, 2006; Maunder and Punt, 2013). To ensure a sustainable management of fishing activities and of the marine environment, accurate estimates of fishing effort are required as they are vital to, for example, assess stock biomass and variation, study fisher's profitability and market trends (McCluskey and Lewison, 2008b; Peterson *et al.*, 2017). Also, the estimation of fishing effort and its distribution allows the development of comprehensive marine spatial plans, establishing effective marine protected areas and the identification of vulnerable habitats and species (Campbell, 2004; Halpern *et al.*, 2008; Campbell *et al.*, 2014; McCauley *et al.*, 2016; Vespe *et al.*, 2016).

There are different methods for collecting fishery data, which can be grouped into three major categories: 1 – data that is self-reported, known as self-report data, which can either be mandatory, like logbook data, or non-mandatory/voluntary, like self-reported data from fishing apps for example, 2- data that is reported and logged by a third party like onboard observers, official port landings and official sales notes and 3- data that is recorded automatically, like Electronic Monitoring (EM) data such as CCTV footage or vessel tracking data.

Self-reported data is an inexpensive way of collecting vast amounts of valuable information on fisheries, such as catches, discards, details of fishing activities such as the number of fishing trips, and the start, end and location of fishing events. Among the different self-reporting data collection as self-reporting methods, some are voluntary or non-mandatory, such as through mobile apps or unofficial logbooks. Others are mandatory, including official logbooks and electronic logbooks, which certain vessels and fisheries are legally required to use for recording their activities. The latter has been the most commonly used form of self-reported data. Yet, an important concern intrinsic to this type of data is that its accuracy and consistency inherently depend on those who report it (Granberg and Holmberg, 1991; Klebanoff *et al.*, 2001; Murray *et al.*, 2013; Mion *et al.*, 2015). On the other hand, third-party logged data, even though costly and usually collected in specific infrastructures, like ports or at auctions, or by people that presumably do not have any conflict of interest with the reported data, tend to be less biased, more consistent and usually more accurate (Walsh, 2000; Walsh *et al.*, 2002, 2005).

Developments in collection and analysis of EM data, such as vessel tracking data, like VMS – Vessel Monitoring System or AIS – Automatic Identification System (Russo *et al.*, 2011b, 2016c; Tassetti *et al.*, 2022; Galparsoro *et al.*, 2024), now allow more accurate estimates of fishing effort (Walsh *et al.*, 2005; Bastardie *et al.*, 2010; Russo *et al.*, 2016c; Sales Henriques *et al.*, 2024). Yet, given the novelty and complexity of such approaches, allied with narrower fleet coverage and the difficulty in obtaining some of the vessel tracking data, much of effort estimates still rely on either data reported by third parties, or on logbook data (Fonteneau and Richard, 2003; Verdoit *et al.*, 2003; Sari *et al.*, 2021).

Logbook data has been commonly used to estimate and map fishing effort (Grilli *et al.*, 2021; Raup *et al.*, 2021; Reis-Filho *et al.*, 2021). Yet, given that the accuracy and consistency of logbook data are highly dependent on those who log it, i.e., fishers, (Sampson, 2011) there is a need to understand the accuracy of the information that can be inferred from this type of data (Cotter and Pilling, 2007; Sampson, 2011). There have been studies addressing the accuracy of self-reported fisheries data. For example, Palmer and Wigley (2009) compared the stock distributions when inferred from VMS (Vessel Monitoring System) data compared with logbook data. Results showed that, when fishing activities occurred in different areas, logbook data was less accurate than VMS data to allocate stock. Moreover, logbook data was quite inaccurate when used to allocate stocks of less abundant species. Roman *et al*. (2011), compared logbook data with validation data from fishers self-sampling programs. One of the findings suggests that the latter is more accurate to estimate fishing effort than logbook data.

This work presents a case study focuses on a Portuguese polyvalent coastal fishing fleet operating throughout its mainland waters. These vessels operate mainly on a daily basis, meaning that they perform fishing trips shorter than 24 hours and they use primarily three types of gears, which are nets (gillnets and trammel nets), pots and traps, and longlines. Although a multi-species fishery, the main targeted/caught species are the common octopus (*Octopus vulgaris*), the pouting (*Trisopterus luscus*), the hake (*Merluccius merluccius*), the jack mackerel (*Trachurus trachurus*) and rays (*Rajidea*).

In this case study where we estimate the fishing effort at vessel level, inferred from two different data sources: 1 – logbook data and 2 – landings/sales notes from official fish auctions. We then compare the fishing effort inferred from self-reported data with that from data logged from a third party. We then discuss the implications of estimates of effort from both data sources on managing fishing activities and resources.

5.2. RATIONAL OF THE APPROACH

In this approach, we compare the number of fishing trips of each vessel, a commonly used fishing effort unit, that can infer from self-reported fishery-dependent data, i.e., official and mandatory logbooks, and a third-party logged fishery-dependent data, i.e. official landings data. Daily landings/sales notes (from here on referred to as landings data) and landing records from electronic logbook data from polyvalent coastal fishing vessels operating within Portuguese mainland waters from 2014 to 2020 were provided by the Directorate-General for the Natural Resources Safety and Maritime Services (DGRM). Both these datasets contained information regarding the vessel ID (anonymised), the landing dates, landing port, landed species and their amount in kg.

Under the EU's Common Fisheries Policy (CFP), fishing vessels must report their catch and log their fishing activity either on manual or electronic logbooks (EU regulation CE 1224/2009). Moreover, under the Portuguese legislation and during the study period, all catches must be landed and have their first sale at a DOCAPESCA (DL 81/2005) auction. DOCAPESCA is a State-operated company responsible for providing services related to the first sale of seafood in mainland Portugal (http://www.docapesca.pt/).

As far as this work is concerned, the important difference between the two datasets, has to do with the fact that landings data are logged and reported by DOCAPESCA, without the intervention of the skipper, which means that the only requirement for the existence of a landing record regarding a given fishing trip is the vessel to land any catch at the designated and mandatory landing place - DOCAPESCA. On the other hand, logbook data requires the skipper or someone else to manually log and report the information about the fishing activities and catches.

To compare the number of fishing trips of each vessel logged in the two types of fishery-dependent data, we assumed that each landing event, registered with the same landing date on both datasets, represents one fishing trip. Under an ideal scenario, the number of landing records of each vessel, from landing and logbook data, should be identical. Following this assumption, we assume there should be a perfect, or nearly perfect, linearity between the number of fishing trips estimated from both datasets for each vessel when fitting a linear regression model to these variables. In other words, the expected regression line from a fitted linear regression should have a slope of x=y and a R value equal to 1. To do so, we used the "stats" package and "*lm*" function from R software (R Core Team, 2024). The fitted linear regression and number of fishing trips of each vessel from both datasets are displayed in Figure 1.

Additionally, to check if there are significant differences between the number of fishing trips depending on the data collection method, i.e. landings and logbook data, we tested this hypothesis using the non-parametric Wilcoxon test (normality of the number of fishing trips not met) (Wilcoxon, 1945).

Due to exemptions within EU CFP control regulations regarding logging and reporting logbook data, special care was taken before comparing the number of fishing trips logged based on the two data types. According to EU regulation CE 1224/2009 article 14th, only catches with more than 50kg of each species are required to be logged in logbooks. This means that catches less than 50kg may not be logged in logbooks. Due to this exemption, in order to avoid uneven numbers of landing records between logbook data and landing data, only landing events with at least one record with more than 50kg of any given species were considered in both datasets.

Under article 15th from the same regulation concerning the logging and reporting of logbook data, all fishing vessels with a LOA equal or above 12m are required to log and report their activity through electronic logbooks. However, it is also stated in paragraph 4 that Member States may exempt vessels under 15m LOA (Length Over All) from logging and reporting logbook data if a vessel only operates within national waters and who's fishing trips do not last longer than 24 hours. Given the characteristics of the Portuguese polyvalent coastal fishing fleet, that carry out daily trips within Portuguese waters, some vessels with LOA under 15m could be exempt from logging and reporting logbook data. Therefore, to avoid having more recorded landing events within landing data than from logbook data, only data from vessels with LOA above 15m was analysed.

5.3. RESULTS

The present work analysed logbook and landing data from 157 polyvalent coastal fishing vessels over a period of seven years (2014-2020). The number of fishing trips inferred from both types of fishery dependent data differed significantly ($p < 0.05$, Wilcox test). Overall, we could detect 90873 fishing trips from landings data, whereas 70743 fishing trips were identified from logbook data, corresponding to 22.7% fewer fishing trips detected from the self-reported data (Figure 1).

As expected from the results above, the majority of vessels (132) had more landing records on landings data than on logbook data. On average, and at vessel level, we identified more 133 fishing trips on landings data than on logbook data. On the other hand, 24 vessels had more landing records on logbook data compared to landing data, and only one vessel showed the same number of landing records in both datasets (Figure 1A). The fitted linear regression model also indicates that a lower number of fishing trips was inferred from logbook data (slope < 1) and the $R = 0.88$ indicates, as expected, a strong, although not perfect, correlation between the number of fishing trips identified in both datasets.

The distribution of the difference of number of fishing trips, at vessel level, detected on both datasets showed a skewed pattern (Figure 1B). It ranged from 633 less fishing trips logged on logbooks

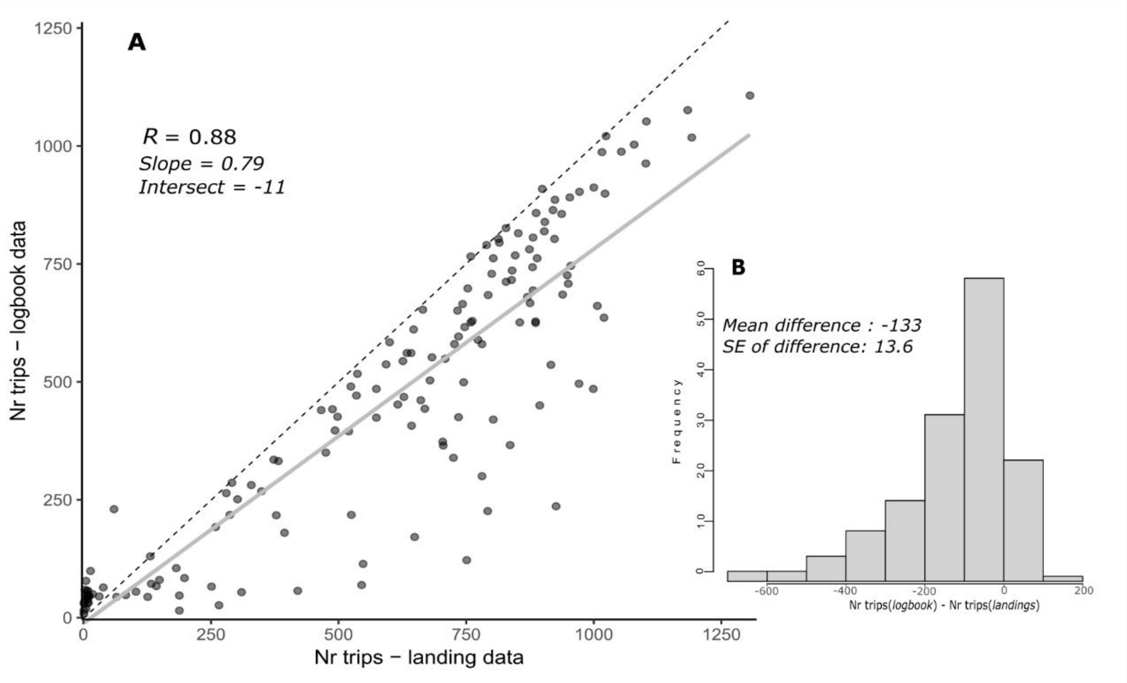

Figure 5.1 A - Number of fishing trips inferred from landing data and logbook data, during the period of 2014-2020, for each of the 157 analysed vessels. Only one vessel showed the same number of fishing trips from both datasets, whereas 132 vessels had lower numbers of fishing trips logged on logbooks than those registered in landings data. The remaining 24 vessels had more landing events logged on logbook data than on landing data. The fitted linear regression model (light grey line) and the R value are shown. To compare the slope of the linear regression model with the expected slope = 1, a x = y line (dashed black line) is also displayed; B – Histogram showing the distribution of the difference of fishing trips estimated from both datasets for each of the analysed vessels.

than on landings records to 170 more fishing trips detected on logbooks compared to those detected on landings data.

5.4. DISCUSSION AND CONCLUSIONS

Concerns about the quality of logbook data is not new and there have been different studies addressing this issue with different conclusions. For example, Bishop *et al.*, (2008) found that logbook data, when used to standardize catch rates, was systematically incomplete and sometimes unreliable. On the other hand, Mion *et al.* (2015) compared e-logbook data with observer's data and concluded that self-reported logbook data agreed with observer's data and that it allowed the description of the spatiotemporal patterns of target species. Emery *et al.* (2019a) also found congruence between

Electronic Monitoring (EM) and logbook data on catches. However, this congruence differed between retained and discarded catches. Sampson (2011) analysed reported fishing locations and catches with official landing records from Oregon trawlers. He concluded that logbook data on depth and location was sometimes inconsistent and that the logbook records on retained catches were inaccurate relative to the official landing data. Furthermore, the study also concluded that the factor vessel, among other variables like year and quarter, was the main explanatory variable explaining the variance of the accuracy and consistency of the logbook data.

In the present work, we observed a significant difference between the effort estimated from both types of data. In an ideal scenario, we would expect that the number of fishing trips inferred from both datasets to be nearly identical and therefore, the R from the regression model to be closer to 1. Moreover, the R^2 value of 0.77 indicates that there is variation in the number of landing records in both datasets, throughout the analysed fishing vessels. In other words, some vessels had a lower discrepancy in the number of landing records in both datasets, whereas other vessels had a quite evident discrepancy.

These results are not surprising as logbook data requires that fishers manually log, and in a correct way, the information about the fishing trips. This means that the existence of such data is dependent on many variables, such as the willingness, motivation and consistency in logging and reporting logbook data in a precise manner; the computer literacy of fishers to operate electronic logbooks; and the correct working conditions, such as internet connection of the computer with the electronic logbook or software related problems that may fail to transmit the logged information by the skippers. If one of these variables fails, the most likely scenario is the absence of logbook data for a given fishing trip. Moreover, if the vessel is targeting a species subject to quotas or catch limits, fishers may also avoid reporting the catch of those species to avoid reaching the official catch limit. On the other hand, for the existence of landing records in official landing data, the only requirement dependent on fishers, is that fishers land their catch where they legally must, which is a rather straight forward process, as the landings of catches happens when vessels arrive at the fishing port.

Considering the arguments stated above, the fact that 24 fishing vessels had more records on logbook data than on landings data might be unexpected. Although we cannot prove why these vessels had more landing records on logbook data than on landings data, the geographical location where these vessels usually land their catch might gives us a clue. These vessel all operate in neighbouring regions to Spain. So, we can hypothesize that these vessels may land their catch in Spanish ports, which will result in the absence of official landing records in the analysed official landings data, whilst the logbook records, that are always transmitted to the vessels' flag country, are still existent for a given fishing trip that landed their catch in Spain.

Regarding the quantification of the fishing effort, our results support the concerns about logbook data quality. Since fishing effort is an important aspect when managing fisheries and the ocean space (Trudeau *et al.*, 2021; Demirel *et al.*, 2023; Orofino *et al.*, 2023), the underestimation of this activity might bring erroneous and undesirable conclusions that might jeopardize the design and implementation of management plans (Omori *et al.*, 2016; Sondita, 2020; Hiddink *et al.*, 2023).

Indeed, the fact that there are many probable reasons for the absence of logbook data for a given fishing trip makes logbooks, as far as effort quantification is concerned, a less reliable source of information. Moreover, the reporting exemptions allowed by the EU CFP regulation, such as for vessels between 12 and 15m LOA that only operate within national waters and for no longer than 24 consecutive hours is also a relevant limitation of logbooks as a source of information. Another limitation from logbooks, although not directly related with effort estimates, relates with the fact that, according with the same regulation, only catches with more than 50kg of each species are mandatory to be logged in logbooks. The logging exemption for catches below 50kg of each species may result in the underestimation of catches of some species or for particular fisheries if logbook data is the only source of information. However, if catch report is mandatory for all catches, as it happens in other regions around the world, regardless of how much of each species is caught, logbook data might be a more reliable source of information to estimate catches and stock abundances. Which means that the usage and conclusions drawn from logbooks alone should be considered cautiously and to take in considerations the reporting requirements and exemptions.

On the other hand, using official landing data, collected from an official entity at an official landing site, for which fishers are not responsible neither for the logging nor the reporting of the data, seems a more reliable source of information to estimate the fishing effort. Having designated personnel and/or infrastructures responsible for the collection of fishery data, such as onboard observers and, in the Portuguese case for example, a state operated company responsible for the collection of landing data seems a more reliable source of information. Indeed, these data sources are more costly than self-reporting data, which is their major disadvantage, and we recognize that it is not feasible to have onboard observers in every vessel. The establishment of entities or infrastructures that can be responsible for data collection is not an easy task either. Another important drawback from this form of data collection is its temporal and spatial coarse resolution. Indeed, if logbook data is correctly and accurately logged, this data collection method can provide very important information that official landings data cannot.

However, thanks to recent developments in data collection, storage and analysis of EM data, other tools can be used to improve the collection of and make inferences from fishery dependent data. For example, vessel tracking data can be used to estimate fishing effort with much higher resolution (Jennings and Lee, 2012; Eigaard *et al.*, 2016a; James *et al.*, 2018; Sales Henriques *et al.*, 2024). Electronic monitoring with CCTV cameras has already been used to estimate discards and interactions and accidental catches of protected species (Emery *et al.*, 2019a), which until now could only be reliably collected through onboard observers. Moreover, the presence of EM onboard fishing vessels has shown to improve the quality of logbook recordings by the skippers (Emery *et al.*, 2019b).

Indeed, each type of fishery-dependent data poses its advantages and disadvantages. EM despite its already acknowledged potential, has its disadvantages, such as its novelty, which makes it still far from being broadly implemented throughout fishing fleets. Furthermore, the large volumes of data it generates and the complexity in their analysis are some of the challenges that will need to be addressed in the near future. Moreover, a well-trained, experienced and motivated observer or fisher in logging fishery dependent data will always be a very important data source with a wide range of capabilities that an automatic logging device will hardly be able to compete with. This is why we argue that in order to improve the quality and quantity of information used in fisheries management, the approach to follow is to 1- acknowledge the advantages and disadvantages of each type of fishery dependent data and 2 - to combine these different types of data, as has already been done (Bastardie *et al.*, 2010; Russo *et al.*, 2016c, 2018; Sales Henriques *et al.*, 2024), to make more reliable inferences that will improve the management of fishing activities and of the marine environment.

6. GENERAL DISCUSSION

The combination of vessel tracking data with fisheries dependent data is a promising approach which has seen increasing usage over the last few years. However, such approaches dedicated to polyvalent fisheries have received less attention, especially compared to other types of fisheries, such as trawl fisheries.

With that in mind and focusing on the Portuguese mainland coastal polyvalent fishing fleet, the main purpose of this thesis was to develop new methodologies to 1 – advance the knowledge on polyvalent fishing effort, 2 – to assist in making MCS efforts more cost-effective and 3 – to analyse the quality of fishery-dependent data when used in such approaches to estimate fishing effort.

In this last chapter an overall overview of the main findings from this study is provided. Then the implications of such findings and recommendations for future management are discussed and it ends with potential research ideas based on the capabilities of the approaches developed in this thesis.

6.1. Summary of the Results

6.1.1. Chapter II - Development of a Vessel Tracking Data classification approach to map and quantify the fishing effort of polyvalent fisheries

Chapter II addresses the lack of methodologies capable of classifying vessel track data that allow to map and quantify, as soak time, the fishing effort of polyvalent fishing fleets operating static gears. This new methodology was developed and applied to the Portuguese polyvalent fishing fleet operating two different types of fishing gears: nets and pot and traps.

This new data classification approach relies on its ability to classify vessel tracking data into the four main behaviours expected from a vessel operating passive fishing gears: steaming, gear deployment, drift/slow navigation and hauling of the gears. By applying this methodology to an entire fleet, it allows to map its fishing footprint, to quantify and study the spatiotemporal dynamics of the fishing effort, as soak time, at a high resolution.

One of the highlights of this methodology is that it allows to calculate the full duration of passive fishing events, i.e., the soak time. Which, as already discussed, is highly important within a fisheries management and research context (Briand *et al.*, 2001; Ward *et al.*, 2004; Bacheler *et al.*, 2013; Peterson *et al.*, 2017), which until now, was only possible through onboard observers or through logbook data. Moreover, this methodology was set up to be applied to a polyvalent passive fishery, regardless of which gear, as long as their operations follow a set of assumptions. This is particularly relevant is multi-gear fleets, such as the analysed one, where only a very small fraction of vessels reported the use of only one type of fishing gear during the study period.

The developed methodology also allows to understand how different fishing gears are operated. As seen by the results, nets are usually deployed for less than 24 hours, whereas pots and traps have a much wider distribution of soak time. Moreover, this approach might also be useful in providing important information for monitoring and control of how fishers comply with regulations that limit the maximum soak time of each type of fishing gear.

As already verified by Leitão *et al.* (2022), the results of this study demonstrate that fishing activities carried by this fleet occur essentially within the continental shelf and in the upper part of the continental slope and it is spread along the entire coast. The fishing effort on the other hand, has a patchy distribution, where the northern part of the country is subjected to higher fishing pressure, whereas the South coast has shown lower fishing effort by this fleet.

Despite the important and useful information that this approach is capable of delivering, this study was only able to map and quantify a small portion of the total fishing activity carried out by this fleet (12.1% of fishing trips). Indeed, approaches such as the one presented in this chapter are highly dependent on vessel tracking data availability and quality, which, in this case, is seriously compromised by the different disadvantages inherent to AIS data (Russo *et al.*, 2016c, 2019b; Shepperson *et al.*, 2018; Emmens *et al.*, 2021).

In an ideal scenario, estimates of fishing effort, regardless of its resolution, should focus on the entire fleet's activity (Bastardie *et al.*, 2010; Batista *et al.*, 2015). However, more comprehensive vessel tracking datasets than the one used in this chapter are required. Alternatively, to combine vessel tracking data with other types of data that have a more comprehensive coverage throughout a given fleet or fishery, such as logbooks or landings data, could also be a valid approach to quantify the fishing effort at a high resolution (Russo *et al.*, 2019b).

6.1.2. Chapter III – Estimation of the national fishing effort with high resolution

In the third chapter of this thesis the aim was to complement the information on fishing effort obtained in the previous chapter. Therefore, another approach was developed that allowed to study other fishing effort metrics and to make more comprehensive fishing effort estimates, at high resolution, without depending on the full coverage of AIS data.

This approach relies on the combination of two types of data: 1 - official landings data, which we assumed to be a comprehensive source for fishing effort estimates of a given fleet, although without the desired resolution, and 2 - previously classified AIS data, which, as we saw, is not a comprehensive source for effort estimates but, on the other hand, is able to provide unprecedented resolution for fishing effort estimates.

The novelty of this approach relies on the fact that it is able to comprehensively estimate the fishing effort with a higher resolution than what is usually done at a broad scale. It provides the first estimates of the total length (km) of nets used by these vessels along the Portuguese coastline. The results also provide information on the seasonal variation of fishing effort, which seems to indicate that the net fishing effort is higher during the spring and summer months. As was also shown in the previous chapter, the distribution of fishing activity is higher in the central and northern part of the country (Leitão *et al.*, 2022), it remains constant throughout the analysed period and so does the contribution of each vessel LOA class for the total effort in each region.

An important fact to consider when analysing these results is that the effort assessment done in this study only considered the fishing trips that only operated nets and no other fishing gear. Given that we are dealing with a polyvalent fishing fleet, in many cases, vessels operate more than one type of gear within the same fishing trip. Since the AIS data classification approach developed on chapter II is not able to distinguish which gear was used, this effort estimation did not consider a relevant portion (13%) of fishing trips, which were the ones that used both gears. This was done to avoid overestimating the net fishing effort estimates by considering fishing trips where nets and pots and traps were used within the same fishing trip. This means that the present results underestimate the total km of nets used by this fleet along the Portuguese coastline.

Although innovative in its approach and results, this methodology is inherently dependent on the quality and reliability of the data it uses for effort extrapolation. Whereas the AIS classified data has shown to be reliable for trip-based effort estimates, the data quality concern is of particular relevance for the logbook and landings data when used to extrapolate the entire fishing effort (Mion *et al.*, 2015; Emery *et al.*, 2019a). Even though it is mandatory to log and report both data sources, their quality and consistency is strongly dependent on whether or not fishers have any catch to land at the end of the trip, if they officially land their catch and if they correctly log and report the fishing trip information on logbooks.

As for any fishing effort assessment approach relying on fishery dependent data such as logbooks and landings data, the concern on the quality and consistency of such data is a reality (Bishop *et al.*, 2008). This makes it vital to understand the level of compliance with regulations related with fisheries data collection (Verdoit *et al.*, 2003; Thomas-Smyth, 2013).

6.1.3. Chapter IV – Risk assessment and estimation of unreported landing events

Chapter IV explores how combining classified vessel tracking data (AIS) with fishery dependent data, in this case, official landings data, can be a useful approach to improve the cost effectiveness of MCS efforts.

The combination of these two types of data allows to understand which actors (vessels) have a higher tendency to not land their catch where they should and to understand in which periods/seasons these uncompliant behaviours are more likely to occur. Some of the probable drivers that may influence this behaviour are also explored in this chapter.

The results of this study revealed a very wide distribution in the proportion of trips without landing data at vessel level, meaning that vessels behave very differently regarding their obligation to officially land and sell their catch. Following this result, it was also shown that a small fraction of the analysed vessels was responsible for the majority, i.e., 85%, of the detected unreported landing events and that the tendency for this behaviour decreases during the summer season. This is quite relevant information when planning MCS efforts, as, given the limited resources for such control actions, these efforts should be better allocated in order to increase their chances to detect and consequently penalise these uncompliant behaviours (Fujii *et al.*, 2021; Auld *et al.*, 2023).

It is important to stress that the described approach does not aim, nor is able to identify uncompliant behaviours, as there are some other reasons other than those related with incompliancy, for the absence of landings data at the end of a fishing trip. This is why this is in fact a risk assessment approach to identifying vessels and seasons with higher tendency of failing to land and sell their catch officially. Given that past behaviours tend to be a good predictor of present and future behaviours (Vallejos B *et al.*, 2023), the information derived from risk assessments such as the one described should be used when planning future MCS efforts (Petrossian, 2015; Hosch *et al.*, 2019; Kumar *et al.*, 2022).

Although slightly beyond the main scope of this particular study, an important conclusion for this thesis relates with the quality and consistency of official landings data when used to estimate the fishing effort, as was done in the previous chapter. Indeed, we saw that nearly 16% of the fishing trips recorded through the vessel tracking data would not have been detected through landings data. This means that using landings data alone to quantify the fishing effort may underestimate the true value of fishing effort.

6.1.4. Chapter V – assessment of the data quality of self-reported data (i.e., logbook data, when used to estimate fishing effort)

Fishery dependent data is a vital source of information to manage fisheries (Punt *et al.*, 2000; Verdoit *et al.*, 2003; Grilli *et al.*, 2021; Thatcher *et al.*, 2024), including the estimation and monitoring of fishing effort (Bastardie *et al.*, 2010). This is why it is important to understand its quality and reliability when used to make such inferences (Sampson, 2011; Thomas-Smyth, 2013).

Both types of data, i.e., official landings and logbook data, have been used throughout this thesis, and we saw in chapter IV that official landings data is incomplete. This means that effort estimates based on this type of data will always be underestimated.

Logbook data has also been widely used to study fishing effort (Cotter and Pilling, 2007; Gerritsen and Lordan, 2011; Punt, 2019). However, given its self-reported nature, there are many concerns on its quality and consistency (Sampson, 2011; Mion *et al.*, 2015).

In chapter V we assessed the consistency of logbook data when used to estimate the fishing effort for the studied fleet. To do so, and for each vessel, we compared the number of trips logged on logbooks with the number of fishing trips recorded on official landings data. As far as this study is concerned, logbook and landings data differ essentially in that the first is a form of self-reported data, whereas the latter is logged and reported by an official 3rd party.

The results corroborated the general concern regarding the consistency of self-reported data. The estimated fishing effort from logbook data was 22.7% lower than the effort estimated from official landings data.

As shown in chapter IV, due to unreported landing events, official landings data fails to provide the real values of fishing effort. Given that logbook data provides underestimated effort values when compared to an already incomplete source of effort, it is important to acknowledge that fishing effort estimates based on logbook data alone could be even more incomplete than estimates based on other forms of fishery-dependent data, like official landings data. Moreover, it is also relevant to recognize that the logging and reporting exemptions that are predicted under the CFP do also contribute to the underestimation of fishing effort if only logbook data is used to that end.

6.2. Relevance of this work - Implications and perspectives for management

The increasing usage of the marine environment demands improved management systems compared with those existing today (Ahlquist *et al.*, 2025; Hunt and Hilborn, 2025; Morales-Saldaña *et al.*, 2025). To effectively manage a system, it is vital to have timely and precise information on resource usage and its users (Lewin *et al.*, 2006). Indeed, efforts for fisheries data collection and analysis must be strengthened as they are key for evidence-based fisheries management (FAO, 2024).

The broad understanding of fisheries distribution and the precise quantification of fishing effort is fundamental to improve current fisheries management frameworks (Fonteneau and Richard, 2003; Dunn *et al.*, 2018; Kroodsma *et al.*, 2018; McSpadden *et al.*, 2024). Moreover, and to improve overall ocean governance, to plan and deploy MCS efforts need to rely on risk assessments in order to make such efforts more cost-effective (Petrossian et al., 2015; Temple et al., 2022). However, precise and accurate information and means to get such information are still too lacking, especially for polyvalent fleets when compared with other fishing fleets (Oliveira *et al.*, 2015; Bastardie *et al.*, 2021; Couce Montero *et al.*, 2021; Rosa *et al.*, 2021; Papageorgiou *et al.*, 2024).

The fishing effort estimation approach developed in chapter II, and others that came after it (ICES, 2023; Mendo *et al.*, 2023b; Rufino *et al.*, 2023; Samarão *et al.*, 2025) allow to obtain broad and vital information about polyvalent fisheries at an unprecedented scale and resolution. Thanks to this vessel tracking data classification methodology it is now possible to understand the operational distribution and which areas are more important or used by this type of fishing fleet. This is particularly important in terms of marine spatial planning for example, as it allows mitigation of the conflicts arising from the establishment of offshore infrastructures, such as windfarms or aquaculture areas, that compete in terms of space with the fishing sector (Lang *et al.*, 2025; Shi *et al.*, 2025). This sort of information is also vital from a marine conservation perspective, as it allows to understand which areas and habitats are more impacted by this type of fleet (Le Pape *et al.*, 2014; Birchenough *et al.*, 2021; Horta e Costa *et al.*, 2022; Karnad, 2022; Rangel *et al.*, 2025).

Given that this approach allows to completely understand how passive and static fishing events are performed, such as the location, soak time and length of deployed gears, it provides the sort of information that could only be obtained, until now, from onboard observers and/or through logbook data. As already discussed, this is vital information for fisheries research, such as stock assessments, and for monitoring fishing activities(Hilborn, 2003; Punt, 2019; Cadrin, 2020; Saul *et al.*, 2020).

This sort of information, when obtained using this approach has an important advantage compared with the same type of information coming from onboard observer programs, which is its broader vessel coverage. Compared with logbook data on the other hand, vessel tracking data-derived information, which is automatically logged, reported and analysed, is expected to be more accurate, as it is independent from a self-reporting system like logbooks that can be inaccurate, biased and incomplete (Emery *et al.*, 2019a; Domínguez-Bustos *et al.*, 2025).

Despite the advantages of vessel tracking data and the approach developed in this thesis, the information derived from this methodology was as complete as the data used in it. Indeed, in order to take the full advantage of this approach, a more complete dataset of AIS data would have been required. The reasons for the incompleteness of AIS data are well studied (Hinz *et al.*, 2013; Russo *et al.*, 2016c; Malarky and Lowell, 2018; Emmens *et al.*, 2021). They range from lack of reception antennas (for land-based AIS) which affects the spatial coverage of the AIS signal, to meteorological conditions and the ability of the skipper to switch the AIS transponder off. VMS systems, when compared with land-based AIS, have the advantage of relying on satellite signal and, moreover, VMS systems are not easily switched off by the skipper, which aligned with the legal requirement of being used by vessels of smaller sizes (starting from 12m LOA, compared with 15m LOA for AIS), makes this form of tracking data a more inclusive source of data. However, the low data frequency generated by these devices is not suitable for extracting the information on passive gear fishing events, as the approach developed in this thesis is able to do (Mendo *et al.*, 2019b).

This conclusion is of particular relevance given the new Common Fisheries Policy regulation (Regulation (EU) 2023/2842). According to this new regulation, all fishing vessels, including small-scale fishing vessels and recreational fishing vessels, must be equipped with a vessel tracking device until 2030. This is a major development in terms of fisheries data collection. However, the requirements on the frequency of data transmission concerning the location and movement of fishing vessels is yet to be determined (Regulation (EU) 2023/2842).

The results of this thesis and those from other studies (Mendo *et al.*, 2019b; ICES, 2023; Rufino *et al.*, 2023) suggest that the vessel tracking data frequency from these devices should be much higher than the frequency of actual VMS devices in order to be able to completely track, and therefore identify, the entire duration of passive gear fishing events. This makes it important to stress that if the new mandatory vessel tracking systems generate the spatial data with the same low frequency as the current VMS systems, then a great potential of extracting highly valuable information from most of the EU fishing vessels (polyvalent vessels) will be missed.

Another relevant aspect to consider when establishing the technical specifications of these new devices regards its ability to be easily switched OFF by the skipper. Given that the data provided by these new devices will not be publicly displayed/transmitted, then these devices should not be easily switched OFF, like in AIS transponders. Otherwise, if fishers do not want to disclose their whereabouts, regardless of the motive, his/her activity will easily be hidden and unreported to control agencies. Therefore, to leverage the potential of vessel tracking data to improve fisheries management, control and research, data transmission frequency and the device's ability to be manually switched off should be thoroughly considered.

Since the availability of vessel tracking data alone did not suffice to have a comprehensive understanding of the total fishing effort of the studied fleet, we combined the classified AIS data with landings data to improve the knowledge of fishing effort of this fleet. The results from this approach are particularly useful as they allow to understand the passive net fishing effort on a broad scale, i.e., national scale, with a resolution that has not been previously achieved at such a large geographic scale. This is particularly relevant for stock assessments for example, as they depend on accurate fishing effort estimates in order to provide more precise estimates of fish stocks (Chen *et al.*, 2003; Nishimoto *et al.*, 2024; van Denderen *et al.*, 2024; Kalhoro *et al.*, 2025; Kunimatsu *et al.*, 2025). When stock assessments are made at a broad scale, which is the most common spatial scale for stock assessments (Lleonart and Maynou, 2003; Methot and Wetzel, 2013; Cadrin, 2020), the most common effort metrics have rather coarse resolutions (Methot and Wetzel, 2013; Kalhoro *et al.*, 2025), which may lead to less reliable stock estimates (Chen *et al.*, 2003).

This approach also allows improved understanding of the seasonal fluctuation of fishing effort, which is vital within a fisheries management system that takes into account the economic and social dimension of fishing activities (Ben-Hasan *et al.*, 2018, 2019; Guiet *et al.*, 2019). For example, if effort seasonality is combined with seasonality of landings or revenues, it allows an understanding of how the profitability of this fishery behaved throughout the year. Which is something important to consider when planning regulatory closures or the establishment of fishing seasons, for example (Ben-Hasan *et al.*, 2018, 2019).

The results from chapter III show that the central and northern ports of the Portuguese mainland are the most important for this fishing sector. To understand which ports are the most used by a given fishery allows not only to understand which regions are more important and impacted by this fishing fleet, but that they are also important locations to monitor and control such fishing activities. Moreover, they are also important sites for fisheries data collection and also to promote best fishing practices (Mrčelić *et al.*, 2023). Which means that such ports, as the port of Aveiro, Matosinhos or Póvoa de Varzim for example, should be given priority when engaging with this sector. It can be for controlling and monitoring purposes, to collect data or to promote collaborations between this sector and NGOs or researchers, for example.

The absence of reported catch and landing data has many undesirable consequences for an effective management of fishing activities (Pauly and Christensen, 1995; Pitcher *et al.*, 2002; Jacquet *et al.*, 2010; Pauly and Zeller, 2016; Rudd and Branch, 2017; Temple *et al.*, 2022). These can translate into underestimation of total catches, which is particularly relevant for species that are managed through TACs and quotas. It may also lead to inaccurate estimates of population sizes and, if landings data is used as a proxy for fishing effort estimates, then the fishing effort may be underestimated. This is why the fight against IUU fishing and in this case, against unreported landing events, is vital to improve fisheries management.

Relying on risk assessments to guide MCS efforts in order to improve their cost-effectiveness has been acknowledge as a path to follow (Petrossian, 2015; Booth *et al.*, 2020; Temple *et al.*, 2022). We showed that through the combination of vessel tracking data with fisheries-dependent data it is possible to identify vessels with a higher tendency to fail to land their catches and during which months such uncompliant behaviours are more likely to occur. This information is of extreme use as, instead of randomly allocating MCS efforts throughout all vessels and seasons, these efforts can focus on those particular vessels and seasons identified as at greater risk of incurring less compliance by the risk assessment approach (Soyer *et al.*, 2018; Ford and Wilcox, 2022; Hosch *et al.*, 2023). According with our results, MCS efforts should primarily focus on a small fraction of vessels that were responsible for the majority of unreported landing events. These efforts should also be more prevalent during the winter, the first half of spring and also during the second half of the autumn season.

If MCS efforts become more effective in detecting and consequently penalizing incompliant behaviours, they tend to have a snowball effect: as those that have not been punished by this enforcement tend to reduce their incompliant behaviour due to fear of being punished. This means that to improve the compliance by fishers, MCS efforts do not need to target all vessels or fishers, but should target those that are more likely to be punished if engaged by authorities. On the other hand, if enforcement acts continue to be highly ineffective, incompliant behaviours will likely continue to exist (Doumbouya *et al.*, 2017; Castillo *et al.*, 2024).

This study also allows to understand to what extend the absence of landings data occurs in fishing trips. If fishing effort estimates are based on landings data, as in chapter III, we can conclude that the total estimation of effort, although unprecedented in its resolution, is underestimated. Indeed, it is important to understand how reliable and complete the data is when used to make such estimates as it allows to have a better idea of the accuracy and reliability of such estimates (Chen *et al.*, 2003; Birchenough *et al.*, 2021).

Self-reported data, conceptually speaking, is a very good way to get highly diverse and important information about the activity it reports. Fisheries management and research has long been relying on self-reported data in the form of logbook data, which is the responsibility of fishers to log and report it. However, and corroborating with the wide concern about its accuracy due to its self-reported nature (Walsh, 2000; Walsh *et al.*, 2002; Emery *et al.*, 2019a), it was demonstrated that this form of data is highly incomplete when used to estimate fishing effort. Official landings data, on the other hand, can be a more complete source of information for effort estimates, although not being free from unreported landing events, as we have seen in chapter IV. However, when both types of data are available, and the same estimate can be calculated from both types of data, the results suggest that official landings data should preferably be used over logbook data as it provides more reliable estimates for fisheries management and research.

As seen in chapter V, the lack of self-reporting of fishing activity is not a neglectable or trivial issue. Indeed, to improve the monitoring of logbook logging and reporting it would be advisable to improve the quality and consistency of the information derived from this data collection method. Such improvement could also be based on a risk assessment approach, as the one developed in chapter IV. The simple comparison of records from landings and logbook data for each vessel, as was done in chapter V, can provide valuable insights on who is more prone to misreport their fishing activity and should consequently be made preferential targets for inspection regarding this particular issue.

It is also important to conclude that the reason for the better data quality, as far as estimates of effort are concerned, from official landings data, has to do with the fact that, in the Portuguese case, there is an official entity responsible for recording and reporting all the information related with fisheries landings and that do not have any conflict of interest with such data, i.e. the DOCAPESCA. Although this is certainly a much more expensive way of collecting data than self-reported data, it is less exposed to the reasons that make self-reported data inaccurate, biased or incomplete (Pollock *et al.*, 1995; Walsh, 2000; Bishop *et al.*, 2008; Sampson, 2011). However, this is not a data collection approach that is feasible in many countries, especially in the developing ones. Nevertheless, this data collection approach has the advantage of not relying on the fisher's willingness to accurately log and report their catch, which can help to overcome the flawed estimates derived exclusively from self-reported data.

The innovative approaches developed in this thesis have shed light on important features, such as the fishing effort, compliancy with landing and reporting regulations and on the quality of fisheries-dependent data from the analysed fleet. However, to fully leverage the potential of such approaches, better vessel tracking and fisheries-dependent data are needed. At the present time, when the technical details of the new CFP regulations are being drawn, there is an important opportunity to improve the current methodologies of data collection which should not be missed. Improvements will surely be possible and hopefully they will not fall short on the technical requirements of the new vessel tracking, and other electronic monitoring devices, that need to be put in place in order to significantly improve our knowledge of the polyvalent fishing sector, which is an important fishing sector throughout the EU and the rest of the world.

6.3. Research potential of the developed approaches and further research

This thesis, more than just aiming to improve the knowledge on a given fishery, aimed to develop new methodologies that can provide new and better information about polyvalent and passive gear fisheries. With that in mind, and given the results from this thesis, this section outlines some potential research areas that may be useful to explore to improve even further our knowledge on these fisheries:

1- The vessel tracking data classification approach developed in this thesis has the unprecedented capability of identifying the entire *modus operandi* of passive gear fishing events. Such information is vital to better understand fishing métiers, which are an important characteristic of multi-gear and multi-species fisheries (Szynaka *et al.*, 2021, 2022b; Leitão and Campos, 2022). Therefore, to cross the information on fishing events, such as the gear used (obtained from logbook data), the length of the gear, the soak time, the time of the day and the date, with other external variables, such as depth, and habitat type, could provide interesting patterns on how these complex fisheries operate. Moreover, if this information is crossed with the respective landings data, the understanding on the different métiers used by these fleets could be greatly improved.

2- To estimate the fishing effort by combining the metric of gear length and the gear soak time. Through the high resolution of both metrics, their combination would provide an even more accurate estimate of effort for passive fishing gears. Such effort estimates could then be used in an exercise to carry out stock assessments and compare the results with the same stock assessment approach but based on a coarser resolution of fishing effort.

3- Given the existing regulation within the Portuguese legislation that limits the total allowed length of nets used per trip, to check how vessels comply with the regulation could provide important intelligence for enforcement entities. Since the vessel tracking data classification algorithm allows measurement of the length of the deployed gears, it would be possible to check which vessels violate the gear length limitations. A risk assessment can be developed to identify which vessels have a higher tendency of ignoring such gear limits, which should then be made preferential target to be engaged by enforcement authorities.

4- Since landing ports are important sites to monitor and control fishing activities, it is central to understand in which ports there is higher prevalence of uncompliant behaviours, such as unreported landing events. In chapter IV of this thesis, a risk assessment of unreported landing events was done at vessel and seasonal level. However, such an assessment could have also been done at port level. The information from such an analysis could help to understand if the presence of this sort of behaviour is also dependent on the landing port. If that would be the case, then enforcement and management entities could increase the control and sustainability awareness in such ports in order to discourage such behaviour and promote better practices.

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8. APPENDICES

8.1. Chapter II – Appendix

Section 1 – Data

To select the AIS data from the desired vessels, we used the vessel identifier MMSI - Maritime Mobile Service Identity. From the EUfleet Registry database (www.webgate.ec.europa.eu). We sorted the Portuguese vessel's IDs (MMSIs) based on their size, i.e., LOA >12m and by licenses for all gears except the active gears, such as trawls, seines, and dredges. After selecting the polyvalent vessels with the desired sizes, we then used logbook data to filter the vessels that only used the desired gears (nets and/or pots and traps) during the study period.

Table S8.1.1: Summary statistics of the raw AIS data from the period of 2014 to 2020.

	Value
Number of AIS datapoints	85 385 152
Number of vessels with AIS data	205
Average number of AIS datapoints per vessel	780 119
Median number of AIS datapoints per vessel	591 216
Maximum number of AIS datapoints per vessel	2 800 946
Minimum number of AIS datapoints per vessel	1
Average frequency of AIS datapoints (minutes)	3
Median frequency of AIS datapoints (minutes)	0.7
Maximum Δt between consecutive AIS datapoints (minutes)	413 533
Minimum Δt between consecutive AIS datapoints (minutes)	0

The extracted raw AIS data varied in its frequency between generated datapoints (Table S8.1.1) and it contained two types of information: 1 – dynamic information, such as vessel location (Latitude and Longitude), course and speed at each time stamp, and 2 - static information, the MMSI, which is a unique vessel identification number. To train and validate the classification models, two sources of data were used: 1. onboard GPS collected data and 2. manually labelled AIS data. The onboard GPS data was collected from 32 fishing trips, from 9 different fishing vessels, of which 5 used nets (gill nets and trammel nets) and the remaining 4 vessels operated pots and traps. Fishing trips were classified into four different phases: Steaming, Deployment, Hauling and Slow navigation. The latter corresponds to when a vessel is either drifting or slowly navigating, usually waiting for a gear to fish before starting the hauling process.

The selection of the different phases was based on the onboard observer's direct observation and experience, and with discussions with the skippers regarding the types of expected behaviours from a vessel within a fishing trip. When selecting AIS data to manually label the fishing trips, we assured that we selected trips where the logbook information regarding those trips was present. Other criteria to select these training AIS tracks was that the fishing vessels would only operate one type of fishing gear, i.e, either nets (trammel or gill nets) or pots and traps. In total, we were able to collect and classify 74 fishing trips from 11 different vessels, of which 40 trips were used to train and set up the parameters for the classification model and the remaining 34 were used to assess the classification accuracy of the model.

Section 2 – Data pre-processing

2.1 - Data cleaning

The erroneous data points, such as those located on land, repeated datapoints or with unrealistic values of speed and course, were removed from the initial AIS dataset.

2.2 - Split data into fishing trips

The first stage of the data processing was the identification of the fishing trips (or tracks) for each fishing vessel. To split the data into single fishing tracks, the procedure relied on the moment the vessel would leave a harbour (start of the track) until the time it would return to any given harbour (end of the track) (Russo *et al.*, 2011b, 2011a, 2014a).

2.3 - Remove inadequate fishing trips

Despite the recognized potential and advantages of using AIS data, there are also disadvantages, with the lack of consistency of spatial and temporal coverage of the AIS signal one of the most relevant (Shepperson *et al.*, 2018). Following the identification of the fishing trips, tracks were removed from the data set if there was a time gap greater than 60 minutes between consecutive data points. We relied on an interactive approach, where we visually assessed the accuracy of the interpolated tracks given the size of the temporal gap between datapoints to establish the maximum time gap. The aim of this procedure was to keep the most complete tracks in order that the interpolation would reconstruct the tracks as accurately as possible, while not losing too much information from the initial dataset.

2.4 - Interpolation

To reconstruct fishing tracks to have a timely consistence of datapoints, the remaining tracks were interpolated using the algorithm developed by Russo et.al., (2011a, 2014a) that relies on the Catmull-Rom approach, a modification of the hermit cubic spline algorithm. The interpolation was set to generate data points at one minute intervals, as this frequency has shown to be best suited to identify passive fishing events (Mendo *et al.*, 2019b). One of the advantages of this approach is that it allows synchronizing the AIS signal for the different vessels, aligning the temporal coordinates of AIS ping to the same timestamp.

Section 3 – Set up the Classification Variables

After pre-processing the AIS data, a preliminary analysis of the speed distribution of the training datapoints for each of the 4 phases of the fishing trips was carried out (Figure S8.1.1).

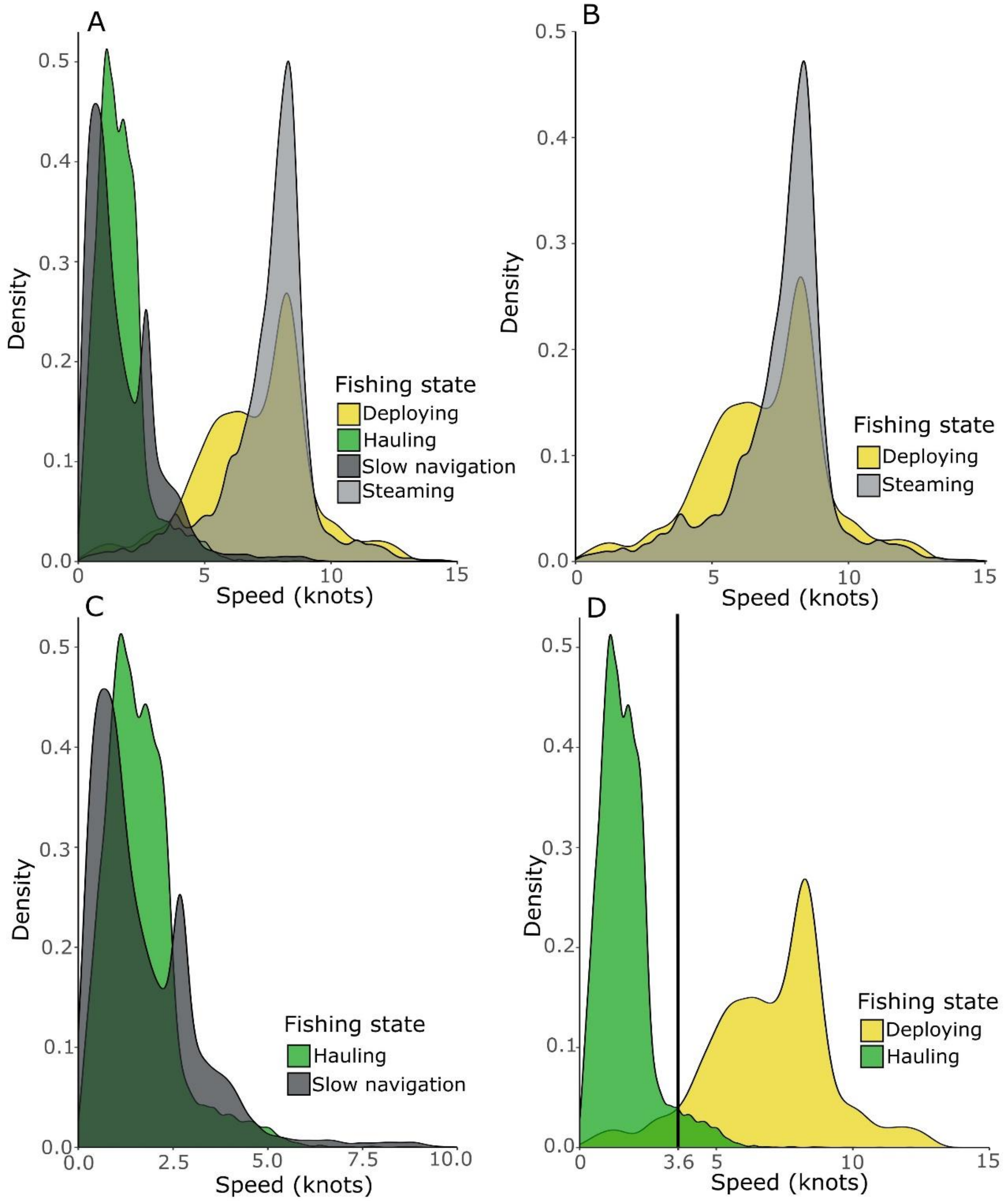


Figure S8.1.1: Density distribution of speed values for each of the fishing states from the training data, with two clearly distinct groups based on speed profile (A): the fast-speed states - Steaming and Deploying (B); and the low-speed states (C): Haul and Slow navigation. In plot D the start (deployment) and end (haul) of fishing events are represented with the highlighted value where the maximum speed value of the hauling state crosses the minimum speed value of the deploying state. The intersection of both density distributions was used to establish the speed threshold between slow-speed and fast-speed values used throughout our approach.

Given the distribution of speed values for each state of a fishing trip, we grouped the four states (Figure S8.1.1A) into two groups: 1- the fast speed group, composed of the steaming and deployment states, given that both these states are carried out at a fast speed (Figure S8.1.1B); and 2- the low-speed group, where the hauling and slow navigation/drift are included. The hauling of the gears is carried out at a slow speed, just like when the vessel is slowly navigating or drifting, so these two states were included within the same group (Figure S8.1.1C). To separate the datapoints into the slow or fast speed groups, a speed threshold had to be established. It was defined as the intersection point between the density distributions of the states we primarily aim to identify: deployments and hauling (Figure S8.1.1D). Under this approach, datapoints with speed values below 3.6 knots were included in the slow speed group, and datapoints with speed equal or above 3.6 knots were grouped into the fast speed group.

Given the overlapping distributions of speed profiles between steaming and deploying and between slow navigation and hauling, the classification of the datapoint into the four states using speed values alone would not be possible. Therefore, another set of variables had to be used.

To be able to distinguish the deployment events from steaming and hauling events from slow navigation or drifting, we rely on the fact that if a gear is deployed, it must be hauled and the vessel runs the same path when deploying and hauling a given gear. In other words, both deployment and hauling tracks overlap in space and they are dependent on each other. This means that both tracks need to be present in the data to be identified as the beginning (deployment) and end (haul) of the fishing event. Strictly speaking, to identify a deployment of a fishing gear, there must be an overlap with a hauling track (carried out at a slow speed), that happens in the future in relation to the deployment track. Conversely, to identify the hauling of a gear, there must be an overlap with a deployment track (carried at fast speed), that happened in the past in relation to de hauling track (Figure 3).

Given the previous rational, we had to determine a distance to establish if two datapoints overlapped. First, we assessed the minimum (overlapping) distance between datapoints from deployment and respective hauling events within the training data. To do so, we calculated the distance of 3620 deployment datapoints to the closest hauling datapoint, within the same fishing event and conversely, 14690 distances from the hauling datapoints to their closest deployment datapoints of the same fishing event (Figure S8.1.2).

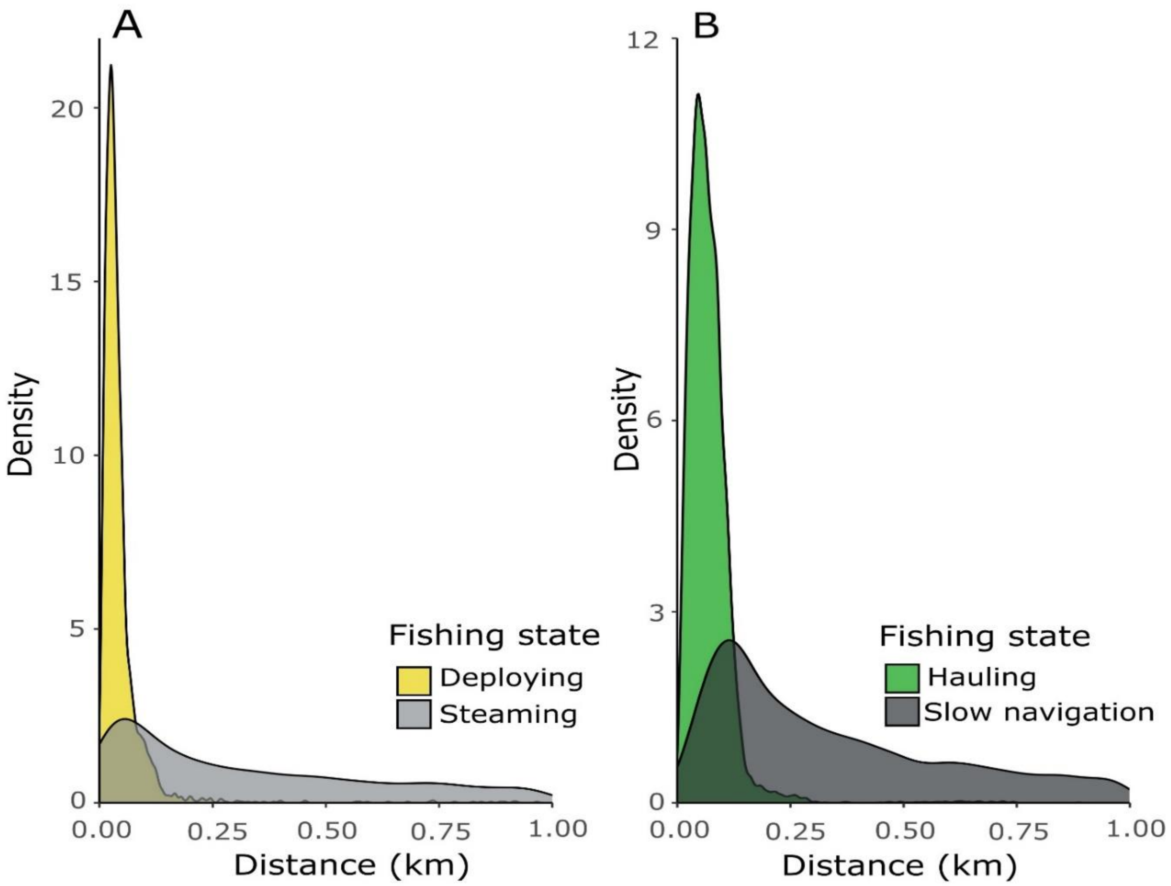


Figure S8.1.2: Plot A - Density distributions of the minimum distances between fast-speed datapoints (deploying and steaming) and slow-speed datapoints generated in the future in relation to the fast-speed datapoints; Plot B – Distribution of the minimum distances between slow-speed datapoints (hauling and slow navigation) and fast-speed datapoints generated in the past in relation to the slow-speed datapoints.

With the calculated distances we defined two threshold distances: 1- Future Overlap Distance (FOD) which is the threshold distance from a deployment datapoint to a hauling datapoint occurring in the future in relation to the deployment datapoint; and 2- Past Overlap Distance (POD) corresponding to the threshold distance from a hauling datapoint to deployment datapoint that occurred in the past in relation to the hauling datapoint. These threshold distances were then defined using the Normal distribution to model the distance value at which P $(X \leq x) = 0.99$, using the mean and standard deviation obtained from the calculated distances. The established distance values for FOD and POD were 150m and 235m, respectively (Figure S3).

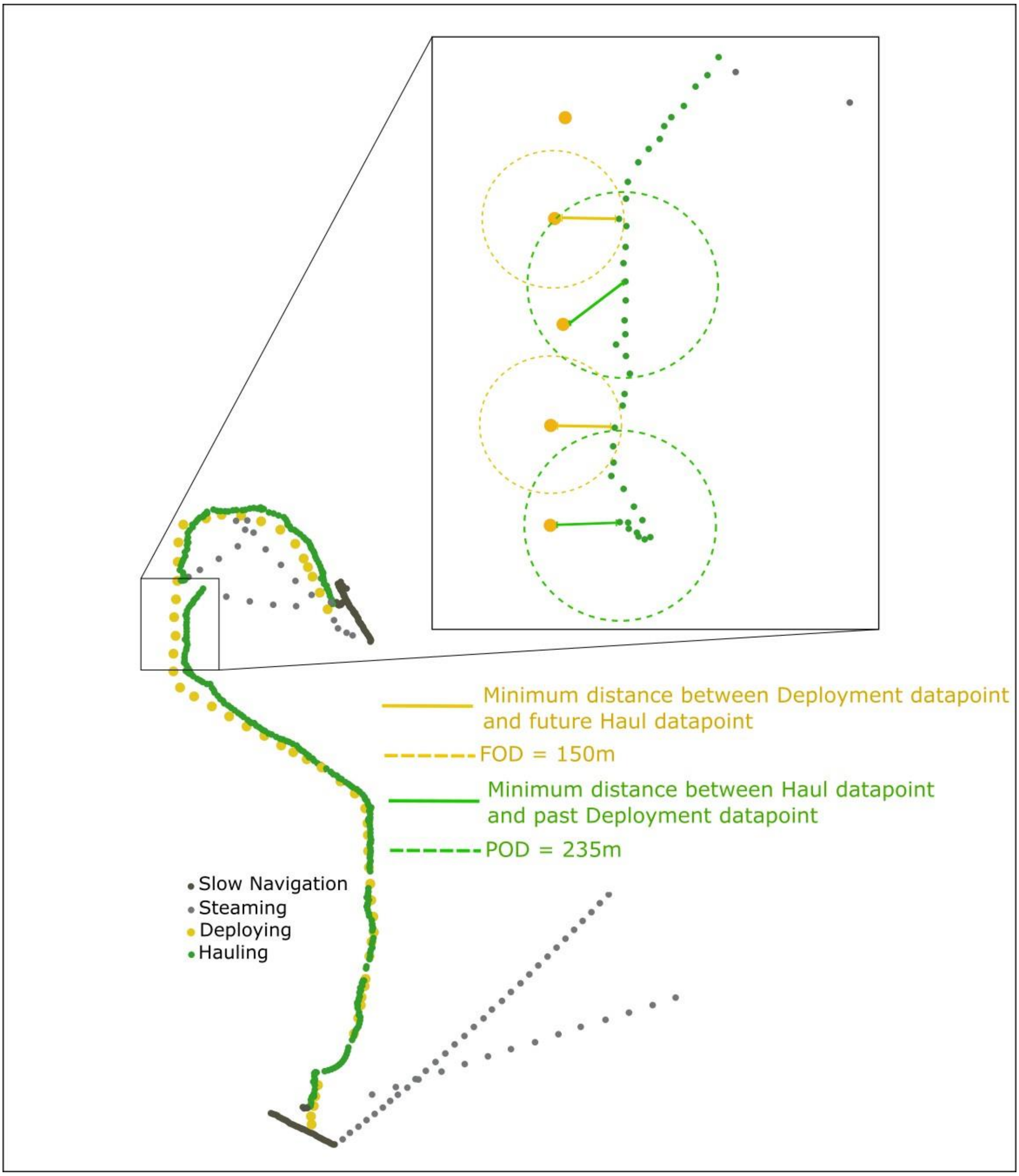


Figure S8.1.3: Schematic representation of the assignment of the FOD - Future Overlap Distance and POD - Past Overlap Distance. These thresholds were established based on the minimum distances between deployment and hauling datapoints from the same fishing event. The AIS data was interpolated at a rate of 1 datapoint per minute. For that reason, datapoints corresponding to deployment events (carried at fast speed) are considerably less than datapoints from hauling events, which are carried at a very low speed.

After establishing the overlap threshold distances, two binary variables were assigned to the datapoints to assist their classification into deployment and hauling states: 1- FO (Future Overlap) where FO = 1 means that the current datapoint is overlapped by a future datapoint; and 2 – PO (Past Overlap) where PO = 1 means that the current datapoint was overlapped by a datapoint occurring in the past.

Under this approach, the deployment datapoints (from the training data) had a P(FO=1) = 0.99 and the hauling datapoints a P(PO=1) = 0.99. Nonetheless, and because the aim is to apply this procedure to non-classified data, there are some other parameters that need to be taken in consideration when assigning these binary variables to the non-classified data.

When calculating the minimum distances between datapoints, an important aspect to consider is the time frame of fishing events, i.e., how long a fishing event can last. Given that our approach aims to identify fishing events for vessels using nets, pots and traps, the range of the soak time of these two types of gears is very wide. Therefore, to identify the overlapping deployment and hauling datapoints, we precautionarily selected a time window that spanned from 90 minutes to 20 days. This window assumes that after a deployment, the gear is fishing for at least 90 minutes (in the case of nets) and that it can be soaking/fishing for up to 20 days (pots/traps).

Considering the parameters and assumptions previously described, for each datapoint with speed values corresponding to possible deployment or steaming events (≥ 3.6 knots), we assigned a value equal to one to the binary variable Future Overlap (FO). The assigned value of one means that for that given datapoint, there is an overlapping datapoint within the established threshold distance, at a low speed (< 3.6 knots), 90 minutes to 20 days ahead in time to the referred datapoint. For high speed datapoints without overlapping datapoints and all low speed datapoints were assigned zero for the FO variable. Conversely, for low speed datapoints (possible hauling or slow navigation/drifting datapoints) we assigned the Past Overlap (PO) binary variable, where value 1 means the existence of an overlapping datapoint, with speed of a deployment datapoint (≥ 3.6 knots) that was generated 90 minutes to 20 days in the past, in relation to the low speed datapoint. Low speed datapoints without overlapping datapoint and all datapoints with speed values ≥ 3.6 knots were assigned zero for the PO variable.

We are aware that in the case of pots and traps, fishers do not always haul the entire gear on deck and then deploy it elsewhere. Instead, fishers may run slowly along the line checking if there is any catch in each trap/pot whilst leaving the entire set in the water, and this behaviour can be repeated indefinitely for a given gear. This means that the overlapping tracks are all performed at a low speed. At the present, the identification of this particular fishing behaviour is beyond the scope of our approach.

Section 4 – Data classification and model validation

4.1 – Data classification with HMM

MomentuHMM is capable of multivariate HMM analyses with different data streams. Classical HMM approaches have been relying on positional data alone, such as step-length and turning angles, but MomentuHMM can integrate different sources of data, such as environmental or biotelemetry data, for example (McClintock and Michelot, 2018).

We used three different variables in the HMM analysis: 1- Speed, 2- Future Overlap (FO) and 3- Past Overlap (PO). MomentuHMM allows the use of different distributions to model the different variables. So, to model speed values, we used the positive gamma distribution and given that datapoints were interpolated into regular time intervals of 1 minute, we used the standard approach of MomentuHMM and converted speed values into distance values between datapoints (step length) as a proxy for speed. The distribution parameters of each fishing state, calculated from the training data, were used as the initial distribution parameters of the HMM model.

Since the FO and PO were established as binary, we used the Bernoulli distribution to model these two variables. After assigning the Overlap variables to the training data, we assessed the probability of FO = 1 and PO = 1 for each of the four states. Just like for the step parameters, these probability values, directly calculated from the training data were used as initial parameters for the HMM model.

When fitting the HMM model, we used MomentuHMM's "formula" argument, which is a regression formula for the transition probabilities covariates. By default, the formula argument applies to all transition states unless functions such as the "toState" function are used, which, in this case, allows to specify the formula to the transition from all states to a particular state. With this feature in mind, we specified the presence of PO = 1 as a regression of the transition probability to the state Hauling and the presence of FO = 1 for the transition probability to the Deployment state McClintock and Michelot, 2018). This feature will improve the identification of true positives for both of the fishing states but will also increase the number of false positives.

After establishing the prior values for each of the three variables, we interactively ran the HMM analysis on the training data while tuning the final distribution parameters with the aim of maximizing the classification accuracy of the deployment and hauling states. This procedure was carried consecutively until we reach the highest values of Sensitivity (recall) for both states. Once the final distribution parameters were determined, we used MomentuHMM's "fixPar" function, which fixes the distribution parameters throughout the classification procedure. This option also made the overall data classification running time to decrease.

4.2 - Clean false positives

Despite an overall classification accuracy for the training data of more than 90% for the deployment and hauling states, the results are likely to be affected by the presence of false positives for both states. There are several reasons for this: one has to do with how the model was set up (explained above) and the other with the high probability values of Overlap variables assigned to each of the two (deployment and hauling) states. For example, when two tracks, a fast speed and a low speed, crossed, it was commonly observed that at least one or two datapoints were labelled as one of the two fishing states. For these cases we applied a smoothing procedure to each fishing trip, where if there were up to two different labelled datapoints from the previous and subsequent five datapoints, these isolated datapoints would be labelled as the same state of the previous and next datapoints.

It was also observed that datapoints were sometimes labelled as deployments when there was no co-dependent classified datapoint (hauling datapoint) within the vicinity. Particularly, some datapoints were classified as hauling without the existence of corresponding classified deployment datapoints within the overlap threshold distance. Under our approach, both events need to be present within the defined overlap threshold distances. So, after the smoothing procedure, deployment datapoints without any classified hauling datapoint within the FOD were labelled as the other fast speed state: steaming.

Datapoints classified as hauling without a classified deployment datapoint within the POD were labelled as the remaining slow speed state: slow navigation.

4.3 - Model Validation

After establishing the distribution parameter for the three variables considered in the HMM analysis, and developing the procedure to clean false positives, we ran the entire classification analysis on the validation dataset. The rational of the assessment of the performance of the classification procedure is based on the comparison of the accuracy of the procedure's output with the onboard groundtruthed and the manually labelled data, used as test dataset to assess the model performance.

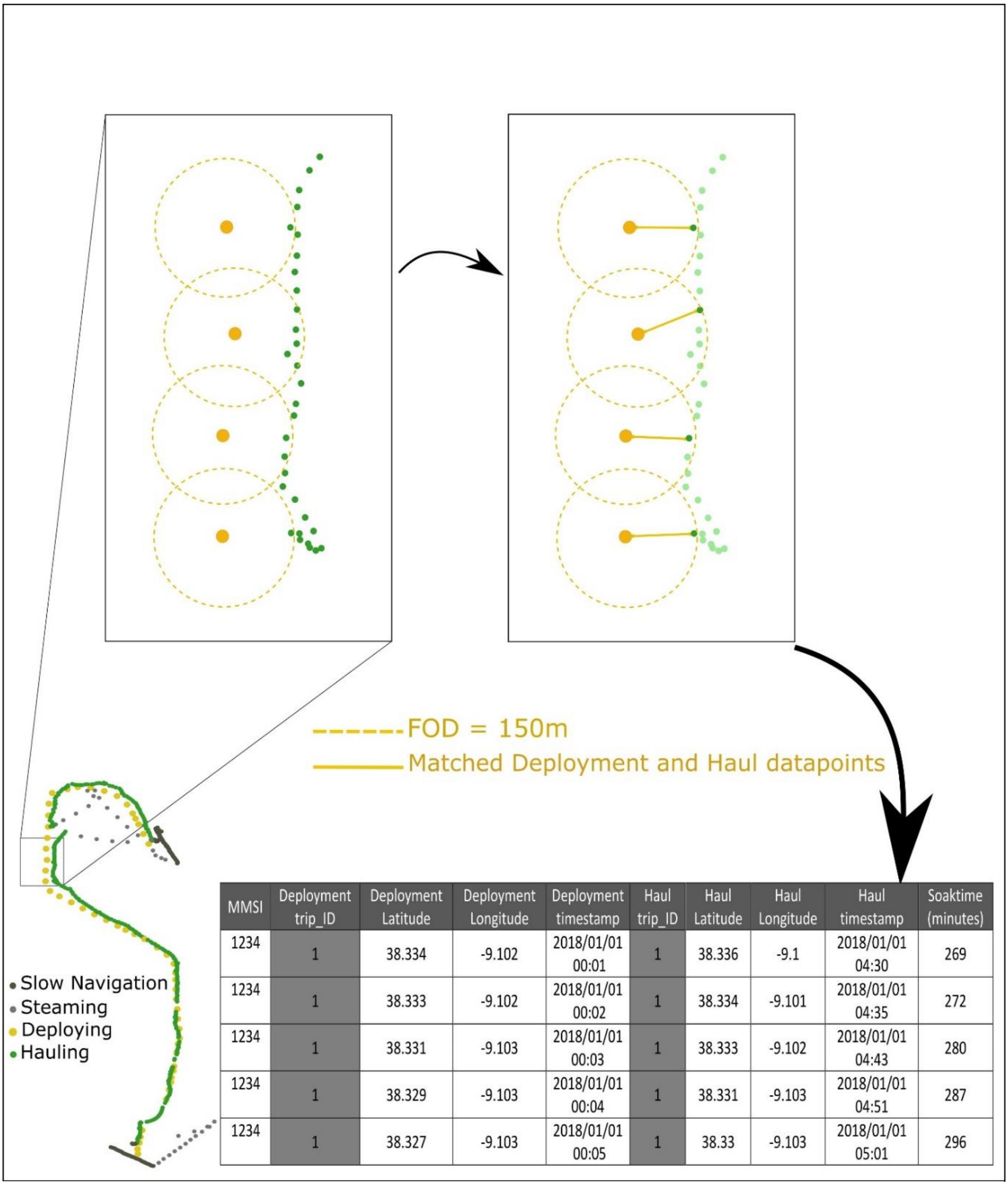
The validation dataset was composed of 34 different fishing trips in which only one type of gear was used: 1- trips operating only nets or 2- trips using only pots and traps. Given that our approach aims to identify the beginning and end of a fishing event, regardless of the type of gear being used, we assessed the classification accuracy through confusion matrices, on all 34 trips. The confusion matrix analysis provides us with the rate of true positives (Sensitivity) and the rate of true negatives (Specificity) for each state. The accuracy, i.e. Balanced Accuracy, is then calculated as the average of the Sensitivity and the Specificity of the model. Moreover, and due to the big disparity of number of datapoints from different states, i.e., the number of datapoints from hauling state is much greater than that from the deployment state, we also assessed the overall model performance through Cohen's kappa coefficient (McHugh, 2012).

Because we are dealing with a polyvalent fishing fleet, in this case using two types of gears, after the first validation assessment, we then assessed the classification accuracy for each type of gear to assess if the model performs equally well regardless of the type of gear. To do so, we repeated the validation procedure for the fishing trips using only nets and using only pots and traps, separately (Figure 2.4 and Table 2-1).

After confirming that the model was able to classify the deployment and hauling datapoints with an accuracy of more than 90%, we then run the classification procedure on the entire dataset.

Section 5 – Footprint and Effort assessment

The approach to identify the fishing events was carried for each vessel, by matching each classified deployment datapoint with the most recent hauling datapoint that falls within the pre-established time window (90 minutes to 20 days) ahead of the deployment datapoint timestamp and within the FOD in relation to the deployment datapoint. The information of both deployment and haul datapoints, such as trip ID and timestamp were combined into a table, and the soak time was calculated as the difference between the timestamps of the paired hauling and deployment datapoints (Figure S8.1.4).



MMSI	Deployment trip_ID	Deployment Latitude	Deployment Longitude	Deployment timestamp	Haul trip_ID	Haul Latitude	Haul Longitude	Haul timestamp	Soaktime (minutes)
1234	1	38.334	-9.102	2018/01/01 00:01	1	38.336	-9.1	2018/01/01 04:30	269
1234	1	38.333	-9.102	2018/01/01 00:02	1	38.334	-9.101	2018/01/01 04:35	272
1234	1	38.331	-9.103	2018/01/01 00:03	1	38.333	-9.102	2018/01/01 04:43	280
1234	1	38.329	-9.103	2018/01/01 00:04	1	38.331	-9.103	2018/01/01 04:51	287
1234	1	38.327	-9.103	2018/01/01 00:05	1	38.33	-9.103	2018/01/01 05:01	296

Figure S8.1.4: Schematic representation of the procedure to match deployment and hauling datapoints. The most recent hauling datapoint within the FOD was paired with the respective deployment datapoint. The information of both datapoints, such as trip ID and timestamp were combined into a table. The soak time was then calculated as the difference between the timestamp of the hauling and deployment datapoints.

Due to the complexity and the myriad of fishing behaviours present in these types of fisheries (Figure 2.3), simply combining deployment with hauling datapoints does not allow us to identify individual fishing events (unique fishing gear sets). To do so, we started by grouping consecutive deployment datapoints (from here on: deployment groups) from the same trip, and if there was a time gap of more than 15 minutes between consecutive deployment datapoints, then a new deployment group was created. From these deployment groups, the ones that lasted less than 15 minutes were discarded under the assumption that a gear deployment always takes more than 15 minutes to be carried out.

By analysing the length of the deployment events from the training data, no deployment took less than 17 minutes to be carried out. Based on this information we took the conservative assumption that the deployment of gear, for this class of fishing vessels, does not take less than 15 minutes to be carried out. This procedure allowed us to discard false positives. Then, a subsequent grouping procedure followed based on three variables: 1- the ID of the deployment fishing trip; 2- the ID of the deployment group and 3- the ID of the haul fishing trip. By doing so, we were able to group datapoints that correspond to deployments of the same trip and the same deployment group where the hauling event occurred in the same trip. Again, in the case of the existence of final groups with less than 15 minutes of duration, these groups were discarded, under the same assumption that a gear never takes less than 15 minutes to be deployed.

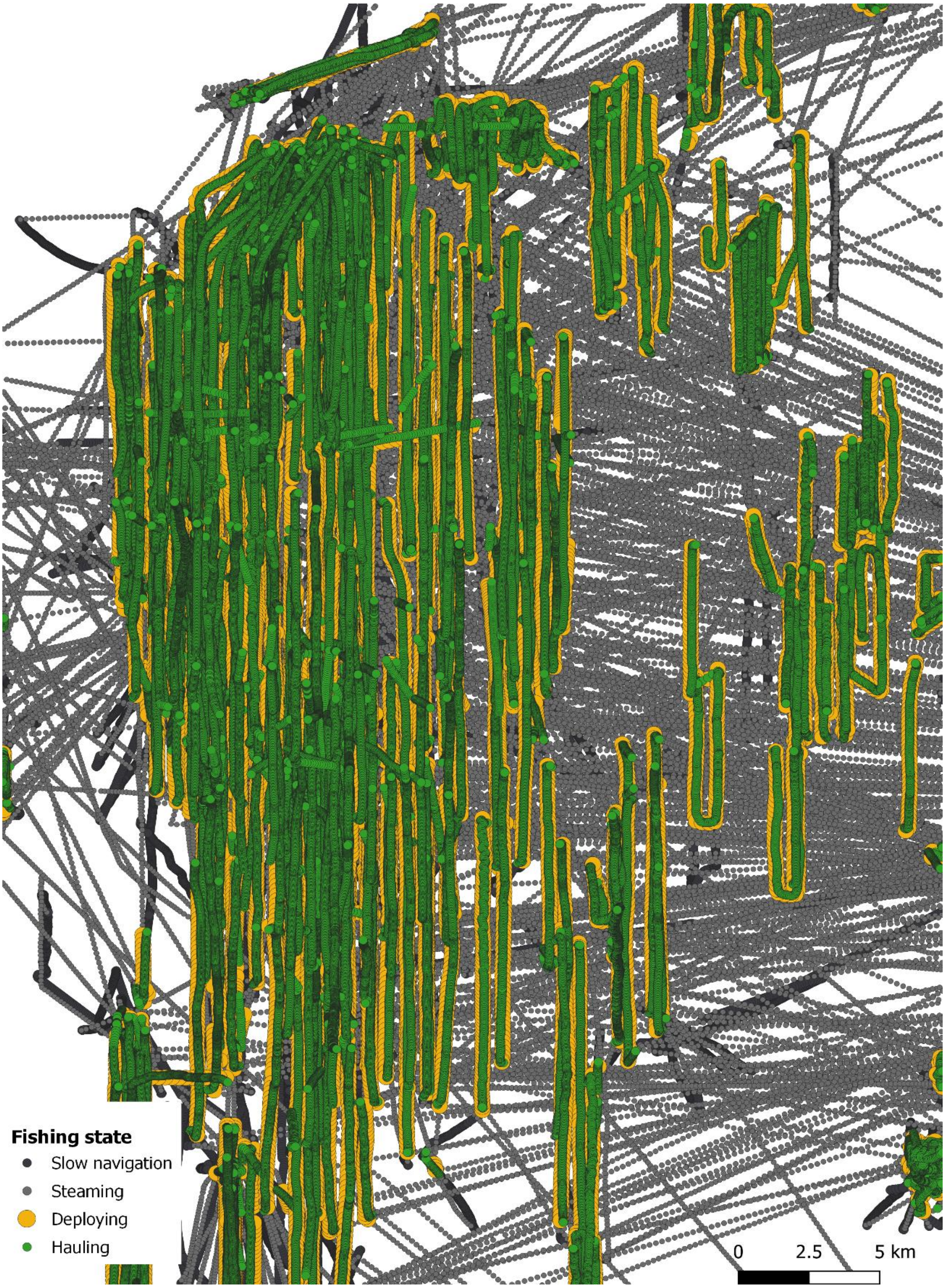


Figure S8.1.5: An example of the AIS data, after being classified by the HMM and cleaned of false positives. The year, coastline and coordinates are not displayed to not disclose the exact location of the fishing operations.

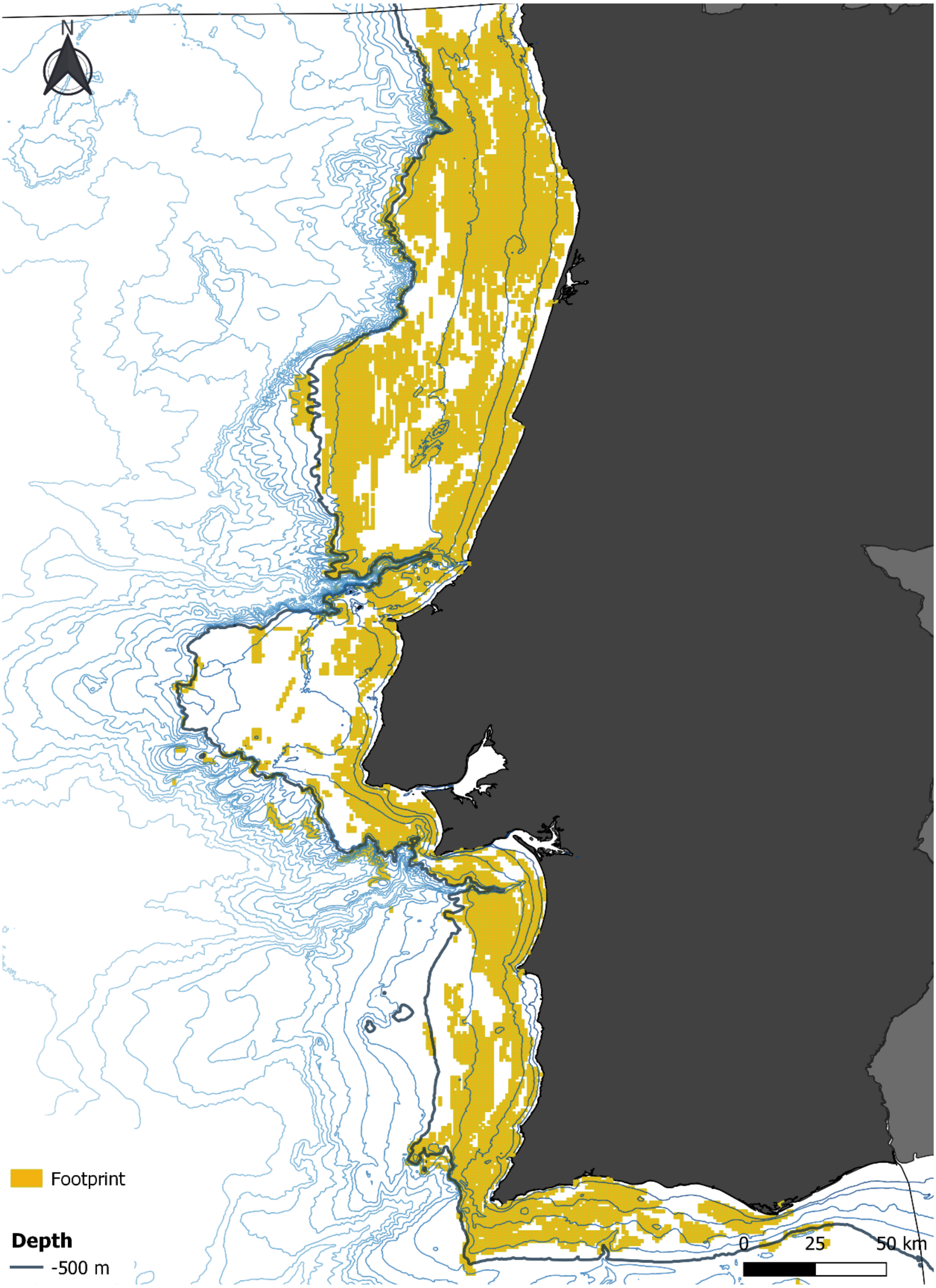


Figure S8.1.6: Fishing footprint of coastal fishing vessels using nets and/or pots and traps. The footprint was obtained from 13224 fishing trips carried by 84 vessels, during the period from 2014 to 2020.

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8.2. Chapter III – Appendix

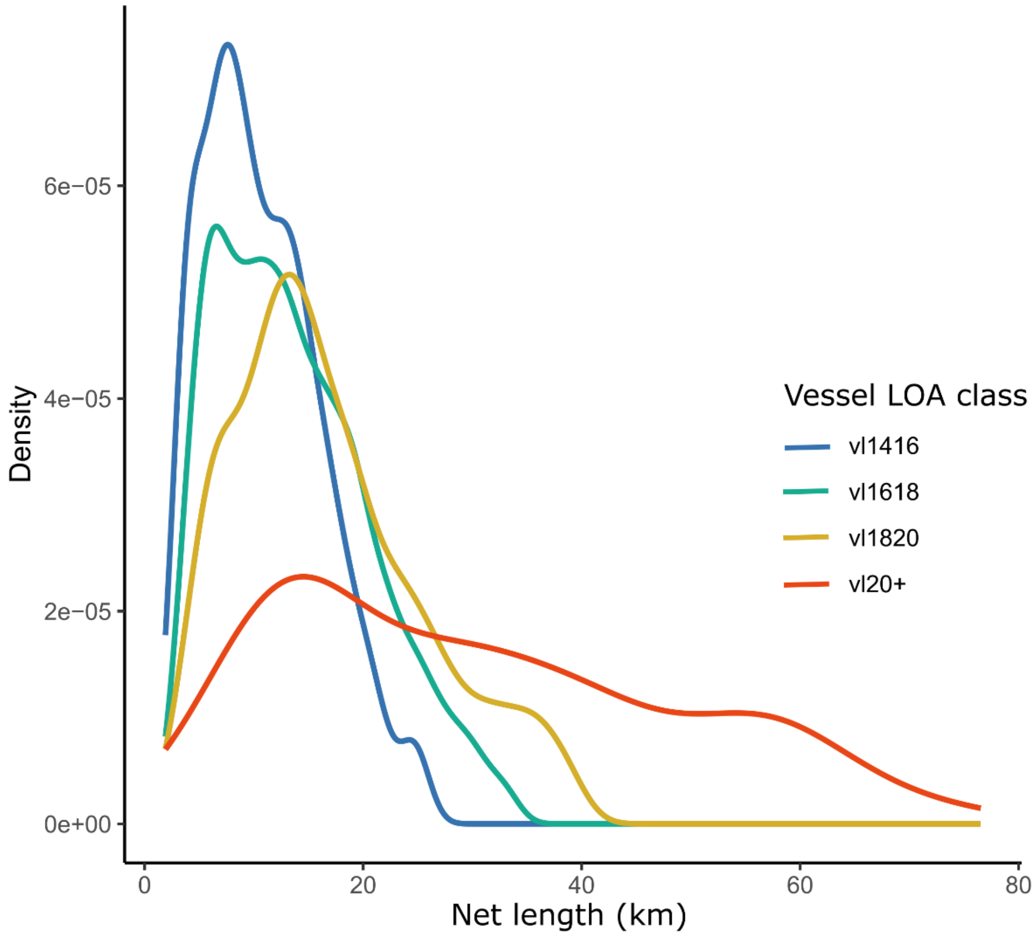

Figure s8.2.1: Distribution of the length of nets used per trip, for each vessel LOA class. The length of fishing events, i.e. the length of nets used within each fishing trip was calculated using the AIS data, that was classified under the approach developed by Sales Henriques et al. (2023).

8.3. Chapter IV - Appendix

Table A1: Table with the 66 vessels included in the analysis and the number of fishing trips recorded with AIS data; the number of fishing trips without recorded landing events and the percentage of fishing trips without recorded landing events. Fishing vessels with more than 14% of unreported landing events are highlighted. The IDs of the vessels are anonymized due to confidentiality agreements. Vessels are ordered by the number of recorded fishing trips with AIS data.

Vessel ID	Number of trips – AIS recorded	Number of trips without landing event record	Percentage of trips without landing event record
ID-1	**475**	**137**	**28.8**
ID-2	**437**	**118**	**27**
ID-3	**433**	**142**	**32.8**
ID-4	**396**	**243**	**61.4**
ID-5	381	9	2.4
ID-6	**379**	**114**	**30.1**
ID-7	322	7	2.2
ID-8	286	11	3.8
ID-9	279	9	3.2
ID-10	275	9	3.3
ID-11	274	19	6.9
ID-12	**269**	**101**	**37.5**
ID-13	268	3	1.1
ID-14	**259**	**60**	**23.2**
ID-15	**257**	**81**	**31.5**
ID-16	256	12	4.7
ID-17	255	16	6.3
ID-18	253	5	2
ID-19	252	6	2.4
ID-20	**248**	**74**	**29.8**
ID-21	**246**	**43**	**17.5**
ID-22	218	4	1.8
ID-23	211	3	1.4
ID-24	**206**	**58**	**28.2**
ID-25	**189**	**86**	**45.5**
ID-26	188	5	2.7
ID-27	183	10	5.5
ID-28	176	3	1.7
ID-29	174	14	8
ID-30	**158**	**35**	**22.2**
ID-31	**152**	**54**	**35.5**
ID-32	**147**	**23**	**15.6**
ID-33	145	8	5.5
ID-34	139	1	0.7
ID-35	138	1	0.7
ID-36	134	7	5.2

ID-37	129	9	7
ID-38	127	3	2.4
ID-39	123	8	6.5
ID-40	123	10	8.1
ID-41	122	3	2.5
ID-42	**121**	**89**	**73.6**
ID-43	119	3	2.5
ID-44	117	4	3.4
ID-45	116	14	12.1
ID-46	114	3	2.6
ID-47	110	3	2.7
ID-48	109	3	2.8
ID-49	106	12	11.3
ID-50	**95**	**14**	**14.7**
ID-51	**89**	**19**	**21.3**
ID-52	89	12	13.5
ID-53	88	15	17
ID-54	**87**	**45**	**51.7**
ID-55	86	7	8.1
ID-56	86	9	10.5
ID-57	73	4	5.5
ID-58	71	0	0
ID-59	70	5	7.1
ID-60	68	4	5.9
ID-61	**66**	**11**	**16.7**
ID-62	64	5	7.8
ID-63	59	4	6.8
ID-64	55	9	16.4
ID-65	**54**	**24**	**44.4**
ID-66	53	3	5.7

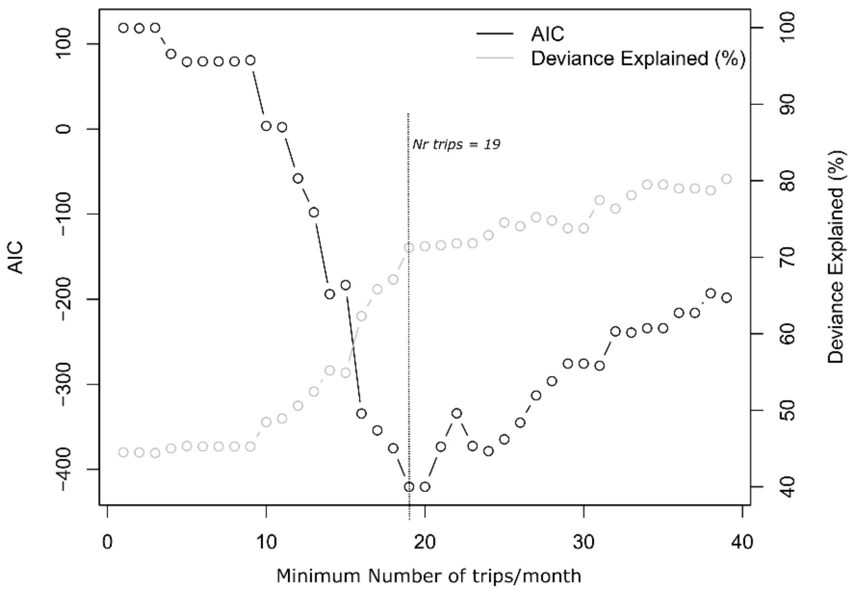

Figure A1: Iterative model selection: process for the selection of the minimum trips per month of each vessel to fit the GAM. GAM models were fit with increasing values of minimum number of fishing trips per month and the AIC and Deviance Explained were calculated for each GAM. The ideal minimum number of fishing trips per month was established as the minimum number of trips where the rate of AIC improvement stopped or was minimal and the rate of increase of the model's Deviance Explained stabilized (Pedersen et al., 2019). Under this approach the minimum number of fishing trips per month used to fit the GAM model was 19. Increasing this threshold would result in overfitting the model without relevant improvements on the Deviance Explained.

Table A2: Description of the two GAMs used to model the variation of the percentage of Unreported Landing Events (ULE) and the Price of landed species, in EUR/kg.

GAMs	Unreported Landing Events (%)	Price of landed species (EUR/kg)
Error distribution	Gaussian (Normal) distribution	Gaussian (Normal) distribution
R^2 (Adjusted)	67.9	76.7
Deviance Explained	70.2%	77.8%
Model formula & variables	***arcsin***($\sqrt{\% \boldsymbol{ULE}}$) = $\int(\boldsymbol{Month})$ + $\int(\boldsymbol{CFR})$ + ϵ Where: ***arcsin***($\sqrt{\% \boldsymbol{ULE}}$) - arcsine square-root transformation of the proportion of trips with unreported landing events ***Month*** – Each month of the year: smooth function with k = 12 (12 knots) ***CFR*** – Vessel ID was used as predicting variable with a random effect on the response variable	$\sqrt{\boldsymbol{price}}$ = $\int(\boldsymbol{Month})$ + $\int(\boldsymbol{Spp})$ + ϵ Where: $\sqrt{\boldsymbol{price}}$ – square-root transformation of the price of the landed species (in Eur/kg) ***Month*** – Each month of the year: smooth function with k = 12 (12 knots) ***Spp*** – Species name was used as predicting variable with a random effect on the response variable

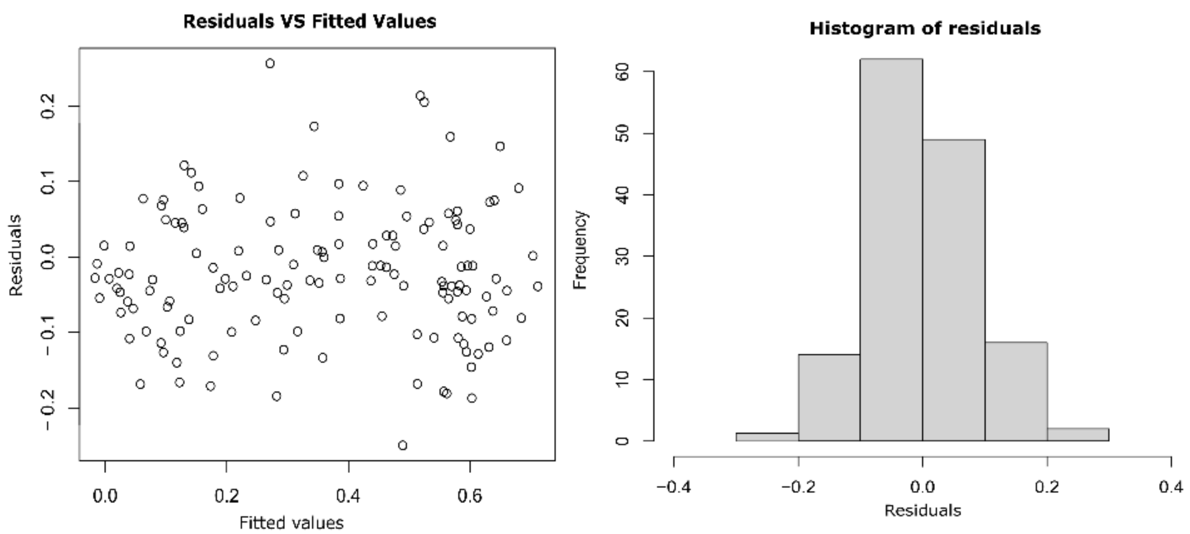

Figure A2: Residual plot and histogram of residuals resulting from the GAM used to model the percentage of Unreported Landing Events.

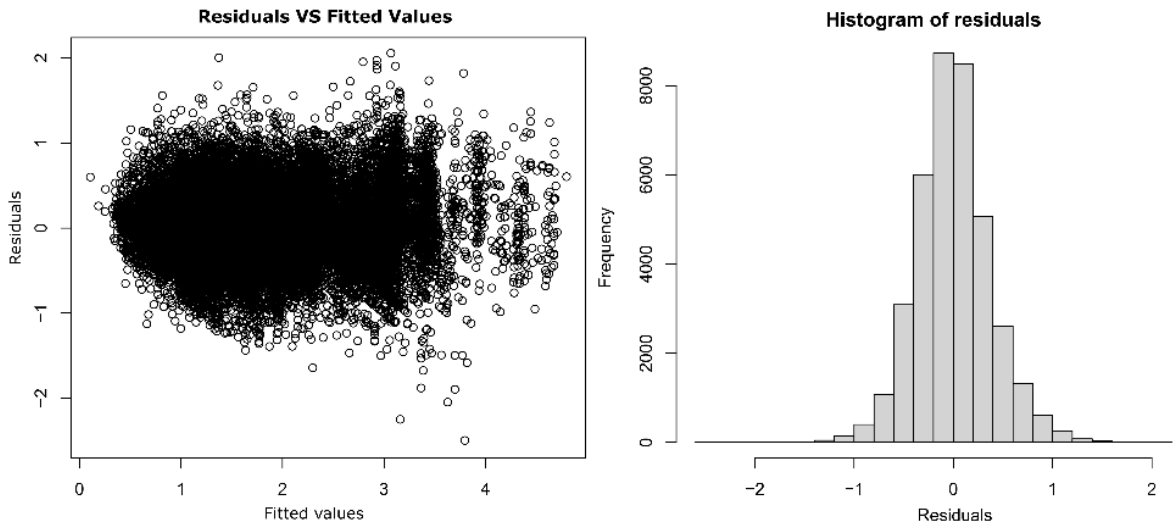

Figure A3: Residual plot and histogram of residuals resulting from the GAM used to model the Price of landed species.