Exploration of unfished areas for Dutch demersal fisheries in the North Sea

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Spatial modelling with VMS-data and survey among fishers to identify why certain areas remain unfished

Authors: Vallina, T., Van de Pol, L.

Wageningen Marine Research

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Summary

To effectively guide decision-making regarding marine spatial planning, it is critical to understand the variables influencing fishers' choices of fishing grounds and their ability to deviate from preferred locations. This research, commissioned by the Ministry of Agriculture, Fisheries, Food Security and Nature (LVVN), supports policy development by investigating unfished areas in the Dutch part of the North Sea. It aims to identify areas with minimal fishing activity by the primary large-scale fleet segments of the Dutch fishing fleet, and explore the underlying reasons for low fishing activity, and seeks to contribute to the knowledge base on the behaviour of the Dutch fishing fleet. Additionally, efforts were made to identify low-intensity areas that could potentially be exploited for future fishing.

The study focuses on the Dutch EEZ outside of territorial waters (within 12 NM of the coast) and outside the plaice box. The studied fleet segments were large beam trawlers, small beam trawlers, bottom otter trawlers, flyshooters and pulse beam trawlers. The research focused on fishing intensity between 2018 and 2022. To quantify fishing intensity, expressed as swept area ratio (SAR), we split the North Sea into 0.05-degree c-square cells, and aggregated the cumulative area in which fishing activity took place, per c-square, per year. Fishing activity was determined by speed profiling (typical fishing speeds per fishing gear type) applied to VMS data. SAR was calculated as the area (km^2) swept by fishing gear within a c-square cell divided by the cell's surface area (km^2). Visualisation of the swept area ratio revealed clear differences in visitation frequency across different areas. We employed both quantitative and qualitative approaches to further examine why certain areas experienced minimal fishing.

Through statistical analyses, we assessed relationships between the chance of an area being fished and various abiotic variables, such as habitat characteristics (such as seafloor characteristics and distance from the coast) and human-made structures (such as pipelines or oil platforms). Marine-protected areas and wind farms were excluded a priori. For some segments, there were very clear reasons on why certain areas were fished less. Examples are the strong statistical relations between gravel and fishing intensity for large beam trawlers and distance to coast for flyshooters. In some cases, maps of the distribution of these abiotic variables already showed a clear visual link to the spatial distribution of a fishery segment. For some of the relations identified, maps of the distribution of these abiotic variables already showed a clear visual link to the spatial distribution of a fishery segment, such as mud content for bottom otter trawlers. For other fleet segments, such as pulse beam trawlers, causes of avoidance of certain areas were less pronounced.

In addition to statistical analysis, it is essential to gather insights from fishers to understand why certain areas are minimally fished. Reasons for low fishing intensity in certain areas were investigated through an online survey among fishers (n=12). The main reasons for avoidance reported by fishers include the absence of target species, bycatch risks, and unfamiliarity with the area. Notably, responses varied across the different regions, with unfamiliarity with the area often cited by fishers as a key factor.

Despite efforts to identify low-intensity areas that could potentially be targeted for future fishing, our findings reveal clear reasons, either from statistical analyses or survey responses, for why certain areas remain underutilized. Notably, for some areas, a significant proportion of fishers reported unfamiliarity, suggesting that these regions might present new opportunities for exploration and could be considered for further research into potential new fishing grounds.

1 Introduction

Human activities in the marine environment have become increasingly intensive and complex in recent years. In the North Sea, the space occupied by marine protected areas (MPAs) and offshore wind farms (OWFs) comes at the expense of available areas for fishing, and the fishing industry competes for space with these other users (Hatenboer, Van den Berg & Holzhacker, 2023). In order to make informed decisions regarding the distribution of space at sea, it is essential to gain insight into the motivation of fishers to move to specific grounds when choosing their fishing location. It is also crucial to understand whether fishers have the ability to deviate from their preferred locations.

Several studies have been conducted on the spatial distribution of bottom-trawling fisheries, often looking at habitat preferences (e.g., van der Reijden et al., 2018; Hintzen et al., 2021). The spatial distribution of bottom trawlers varies by fishing method (Eigaard et al., 2017). At a fine spatial scale (approximately 1 km), the distribution of a fishery is often irregular (Rijnsdorp et al., 1998). This irregularity is caused, among other things, by the accessibility of fishing grounds, which is influenced by the type of seabed, habitat type, seabed heterogeneity, and the presence of the fishery's target species. Fishers often prefer areas where good catches are more frequently achieved. However, what has received less research attention is why some areas in the North Sea are scarcely fished or not fished at all. When visualizing fishing intensity in the North Sea, some areas are conspicuously underfished (CBS, PBL, RIVM, & WUR, 2024, figure 1). The size of these observed unfished areas varies from very large to very small, usually depending on the type of gear used. An estimated 20 to 30% of the North Sea is hardly fished, and approximately 8% remains completely unfished (Vrooman, Van Sluis & Van Hest, 2018).

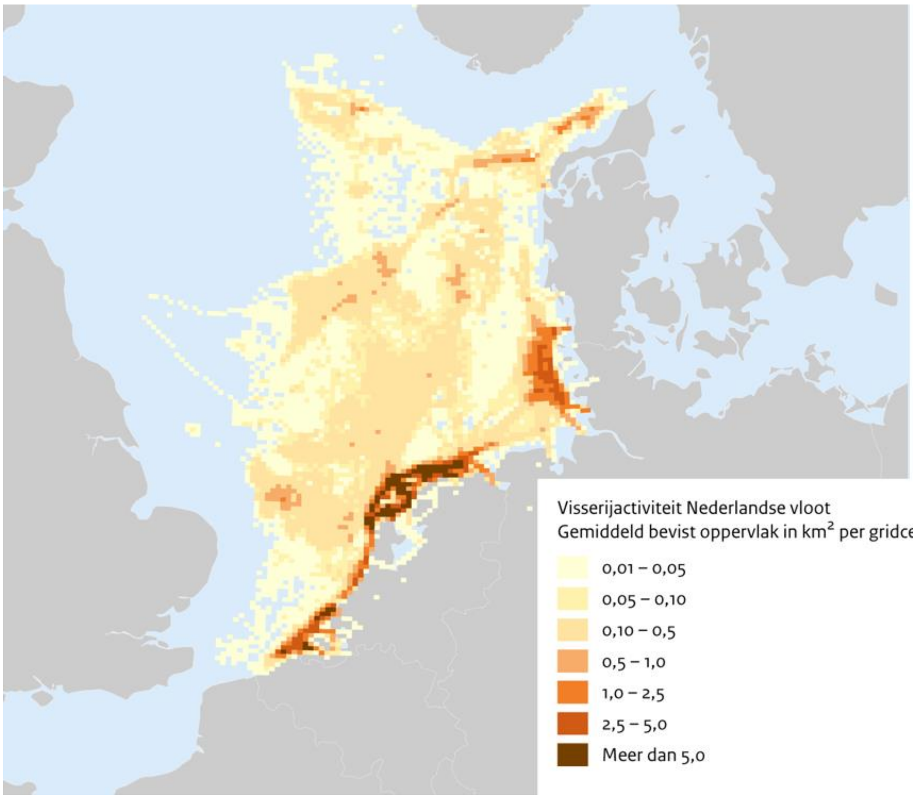


Figure 1. *Intensity of beam trawling 2016-2019. CBS, PBL, RIVM, & WUR. (2024).* Bodemfauna Noordzee en bodemvisserij, 2016 - 2019 (indicator 1251, versie 06, 18 november 2021). *Retrieved from www.clo.nl*

The aim of this research is to identify areas with low fishing intensity, which will be referred to as unfished areas, for the primary fishing gears in the Dutch demersal fleet and to investigate the main reasons why these areas are not being fished. This work seeks to contribute to the existing knowledge about the behavior of the Dutch fishing fleet and to improve our understanding of the spatial distribution of fisheries in North Sea. The main fisheries in the Dutch fishing fleet are beam trawling, bottom otter trawling, flyshooters, and pelagic trawlers.

This research examines the similarities between unfished areas using statistical methods in addition to quantitative analysis, we also gathered experiential knowledge from fishers through an online survey, in which they were asked to identify reasons for avoiding certain parts of the Dutch EEZ. The study considers the potential effects of biotic variables, such as the absence of the target species and the overall productivity of the area, as well as abiotic variables, such as the composition of the seabed and the presence of hard structures, and the presence of other human activities and structures. The focus lies on identifying the variables leading to low fishing activity. Additionally, unfished areas for which no clear predictor can be found will be identified as potential locations for future fishing activities.

2 Assignment

This is policy-supporting research, commissioned by the Ministry of Agriculture, Fisheries, and Food Security and Nature (LVVN) to investigate unfished areas in the Dutch part of the North Sea. The research is meant to inform policy makers, fishers and researchers on the spatial patterns of fisheries in the Dutch EEZ. The aims of this study were to:

- Identify areas of low fishing intensity in the Dutch Exclusive Economic Zone (EEZ).
- Relate these areas of low fishing intensity to biotic, abiotic and human variables.
- Gather experiential knowledge from fishers on their reasons for avoiding the identified areas of low fishing intensity.

3 Materials and Methods

3.1 Spatial and temporal extent

the research was limited to the Dutch Exclusive Economic Zone (EEZ) outside of territorial waters (12 nautical miles off the coast). The twelve-mile zone and the plaice box were excluded from the analysis because fishing is prohibited here for vessels with an engine power exceeding 221 kW. Offshore wind farms (OWFs) were excluded from the analysis because under management regulations at that time fishing was not allowed there. For the fleet segments we focused on, during the time of the study period, there were no further spatial limitations, such as fishing restrictions in Marine Protected Areas (MPAs).

The study used fishing data from the period 2018-2022, ensuring sufficient data to discover overall patterns in fishing effort. For pulse fishing, which was banned in 2021, data from the period 2018-2020 was used.

3.2 Fisheries data

This research focused on the main large-scale fleet segments in the Dutch fishing fleet that operate in the research area (table 1). These area beam trawlers (divided into large and small beam trawlers based on engine power), bottom otter trawlers, flyshooters, and pulse trawl fisheries. These fleet segments represent a large portion of the total Dutch (demersal) fishing capacity. Other fishing techniques within the Dutch fleet were not considered in this study. The reason for this exclusion is that many of these segments, such as beam trawl fishing for shrimp, gillnet fishing, and handline fishing, operate in relatively small areas where the distance to the coast is likely one of the key factors in choosing specific areas.

Table 1*: Grouped gear codes included in the study.*

Gear codes	Vessel engine power	Group
TBB, TBZ, SUM, PUL, PUK	> 225 kW	Beam trawl large
TBB, TBZ, SUM	< 225 kW	Beam trawl small
OTB, TB, PTB, OTT, CTB, OTG, QUA	All	Bottom otter trawlers
SDN, SSC, SB	All	Flyshooters
PUL, PUK	All	Pulse trawl

3.3 Calculating fishing intensity

3.3.1 Calculating SAR

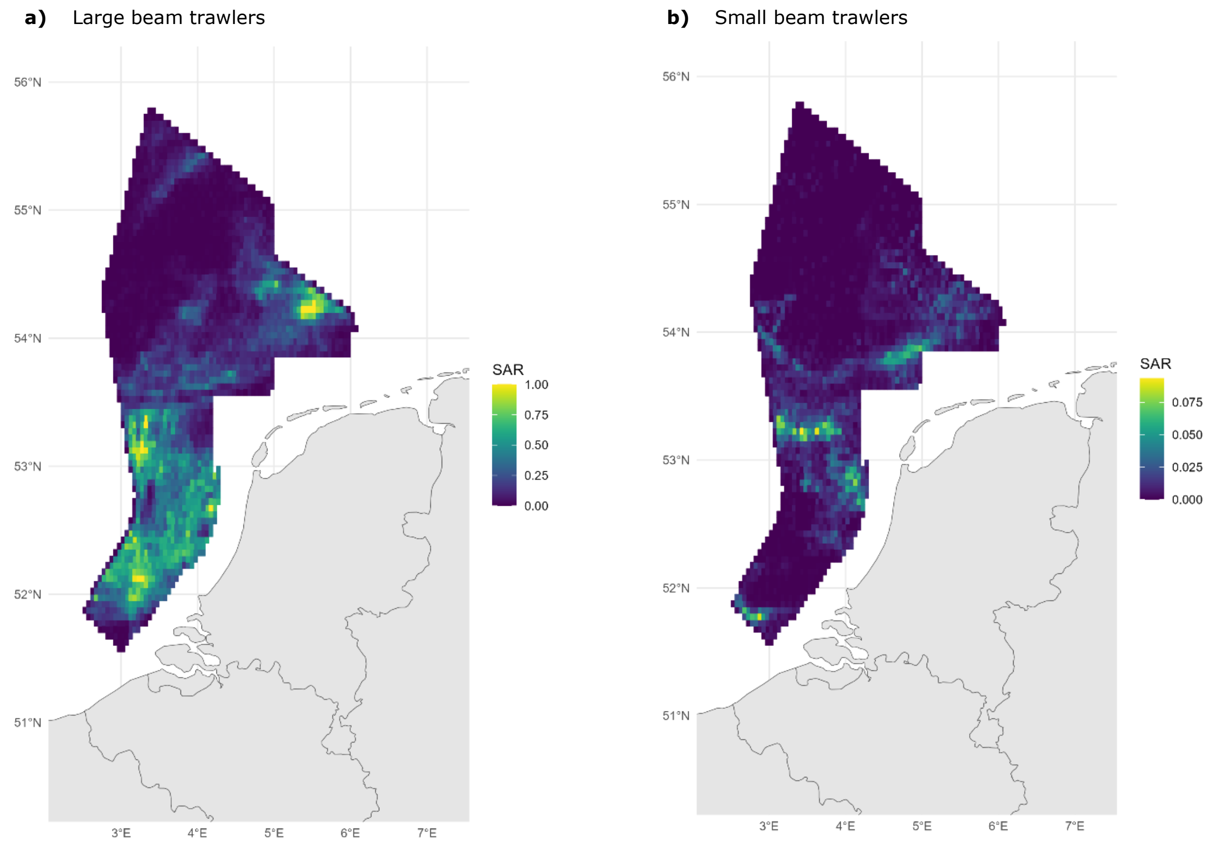
The first step in the research was the cleaning and processing of Vessel Monitoring System (VMS) data. The data was checked for quality based on the criteria proposed in Hintzen et al. (2012). Subsequently, the data was aggregated at the level of c-squares (0.05 degrees latitude × 0.05 degrees longitude), for which the annual swept area ratio (SAR) was determined per gear type.

SAR values are calculated using information on the speed of the vessel and size of and characteristics of the fishing gear, following the approach of Eigaard et al. (2016). SAR is a measure used in fisheries science to estimate the impact of fishing gear on the seabed. It is commonly used to assess the extent of seabed disturbance caused by bottom trawling. To calculate the swept area, the width of the gear (e.g., the width of the trawl net) and the distance it travels along the seabed are used (equation 1). To calculate the Swept Area Ratio, the cumulative total swept area per c-square is divided by the total area of the c-square (equation 2). If an area is trawled twice along the exact same route, the surface area is counted twice in the calculation. Therefore, if an entire area is fully trawled, it is counted the same as if half the area were trawled twice. Since many fishing areas are visited more than once (especially since were calculating yearly swept areas in a cell), SAR values can exceed one. A SAR value greater than 1 indicates that the area is fished on average more than once per year, while a SAR value less than 1 indicates that part of the area remains unfished. Next, the average SAR value per c-square for the study period (2018-2022, 2018-2020 for pulse fishing) was calculated.

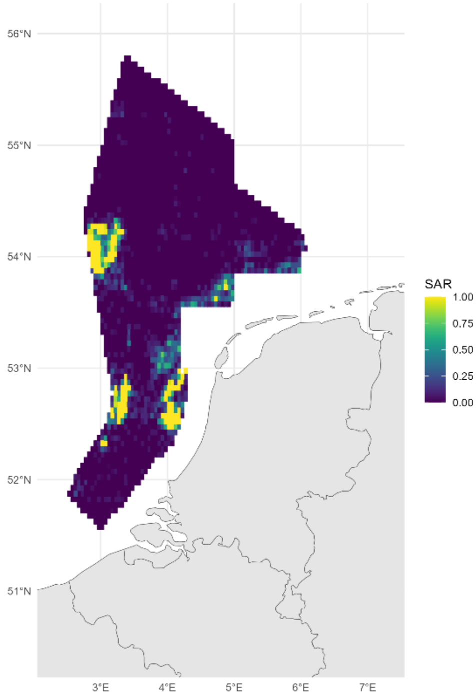
$$Swept\ Area\ =\ Gear\ Width \times Distance\ Towed\ (\mathbf{eq.\ 1})$$

$$Swept\ Area\ Ratio = Total\ swept\ area\ per\ c\text{-}square\ (cumulative\ per\ year)\ /\ total\ area\ c\text{-}square\ (\mathbf{eq.\ 2})$$

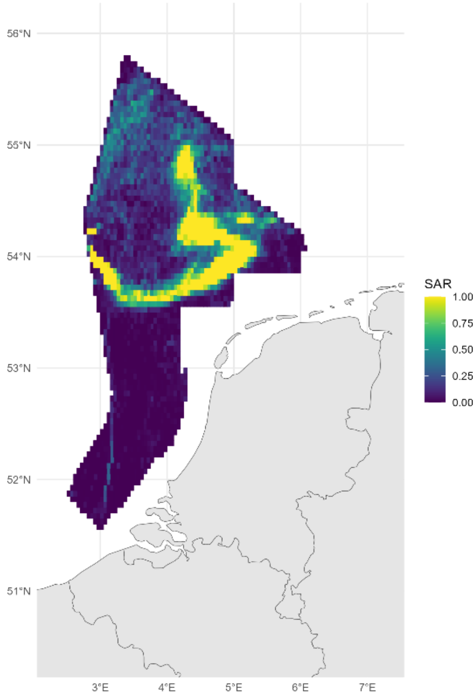
In this study, our primary interest was in identifying unfished areas, rather than regularly fished areas. To focus on this aspect, we transformed SAR values greater than 1 to a value of 1. The mean yearly SAR values for the period 2018-2022 are given in figure 2. The studied fleet segments have distinct spatial patterns: large beam trawlers are mainly active in the southwestern and central part of the Dutch EEZ, and effort is low in the northern parts, as well as the area directly north of the Wadden sea. Small beam trawlers display low fishing effort in general (all SAR are under 0.10), with effort mainly concentrated in the western and central parts of the EEZ. The SAR patterns of flyshooters are highly aggregated in three areas, with low effort in the rest of the EEZ. The bottom otter trawler fishery is concentrated in a band in the northern part of the EEZ, with low effort in the southern EEZ. Pulse fishing in 2018-2020 was concentrated in the southern parts of the EEZ. In part this is due to a ban on pulse fishing north of 55° N.



c) Flyshooters



d) Bottom otter trawlers



e) Pulse beam trawlers

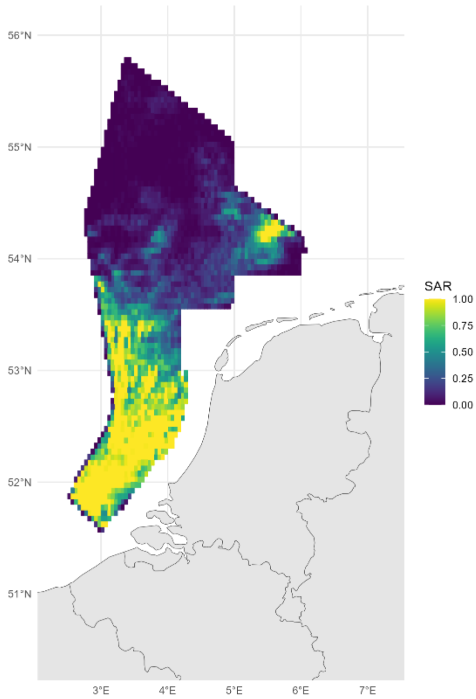


Figure 2: *Mean yearly swept area ratios over the period 2018-2022 in the Dutch EEZ, excluding the twelve-mile zone and the plaice box per fleet segment ("a" to "e"). SAR values higher than 1 were set to 1. For small beam trawlers, SAR values range up to 0.01 because fishing intensity is lower than for the other fleet segments. For pulse beam trawlers (e), the study period was 2018-2020 due to the pulse ban as of June 2021.*

3.3.2 Data transformation

In exploring the variables influencing the non-exploitation of certain areas, our focus was on understanding why specific regions remained unfished. To create the response variable for our analysis, data on fishing intensity for the five fleet segments was transformed into a binary variable, with a cell being either regularly fished (1) or (largely) unfished (0). The specific SAR value used to distinguish between 'fished' and 'unfished' areas varied by fleet segment. This categorization was guided by visual observations and aimed to achieve a balanced ratio of fished and unfished cells within the dataset, which is crucial for developing robust and stable statistical models.

3.3.2.1 Large beam trawlers

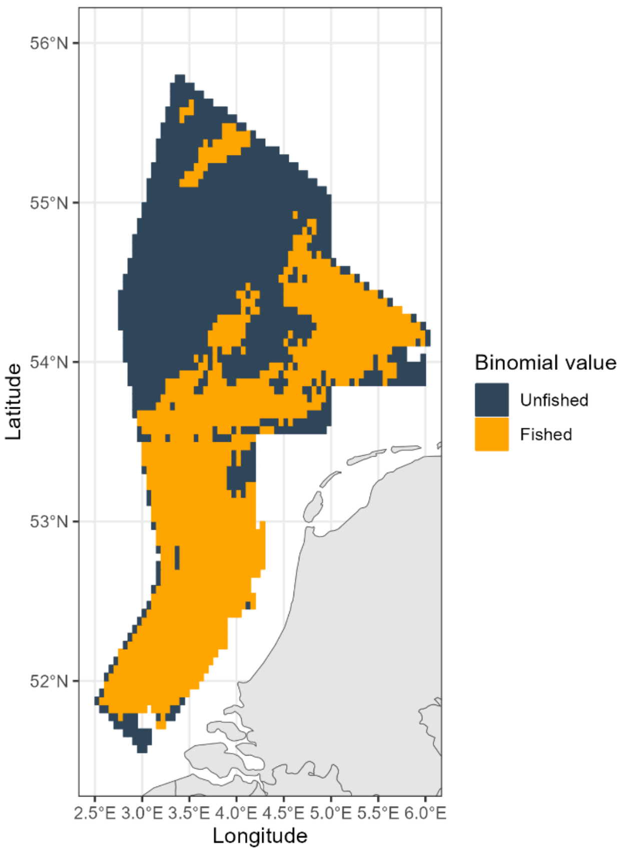


Figure 3: *Spatial distribution of fished (SAR > 0.10) and unfished cells (SAR ≤ 0.10) by large beam trawlers.*

12% of the cells recorded an absolute zero value for the SAR of large beam trawlers. Transforming the continuous response variable into a binomial one, we opted to categorize the data as "fished" when SAR was >0.10 (51%) and "unfished" when SAR was ≤0.10 (49%). This categorization was informed by our visual observations of unfished areas and aimed to maintain a balanced response variable in the dataset of 'fished' and 'unfished' areas. The spatial distribution of the binomial value indicating whether an area is fished or unfished is visualised in figure 3.

3.3.2.2 Small beam trawlers

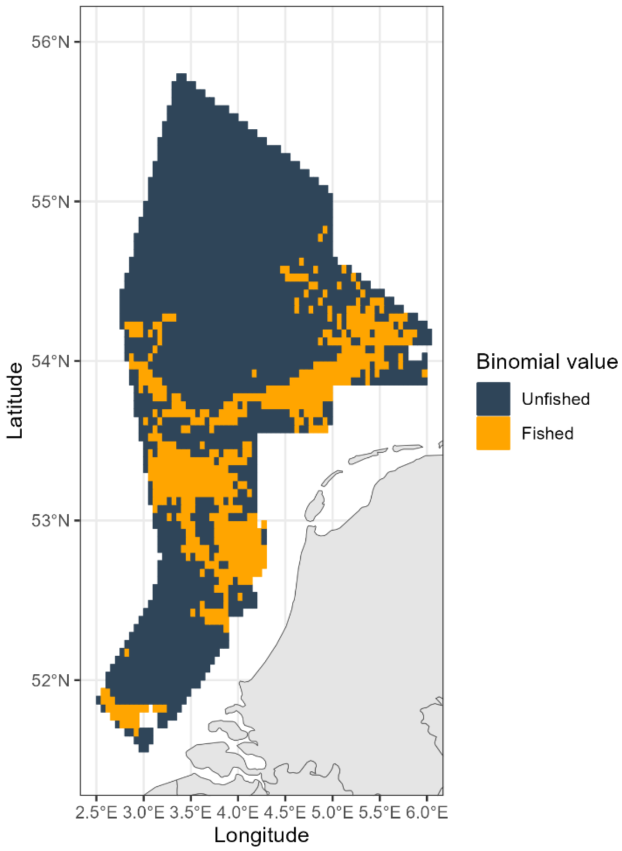


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Figure 4: *Spatial distribution of fished (SAR > 0.01) and unfished cells (SAR ≤ 0.01) by small beam trawlers.*

39% of the cells recorded an absolute zero value for the swept area ratio for small beam trawlers. Transforming the continuous response variable into a binomial one, we opted to categorize the data as "fished" when SAR was >0.01 (33%) and "unfished" when SAR was ≤0.01 (77%). This relatively large difference in area fished compared to large beam trawlers is logical, as the fleet is considerably smaller, and the vessels are smaller as well. The spatial distribution of the now binomial value indicating whether an area is fished or unfished is depicted in a plot (figure 4).

3.3.2.3 Flyshooters

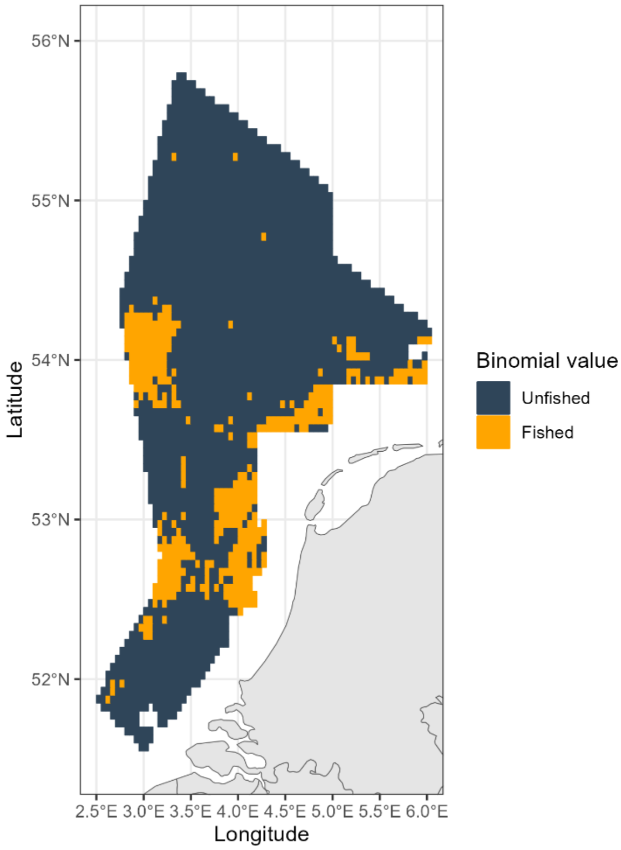

Figure 5: *Spatial distribution of fished (SAR > 0.10) and unfished cells (SAR ≤ 0.10) by flyshooters.*

70% of the cells recorded an absolute zero value for the swept area ratio for flyshooters. SAR values for flyshooters range up 10, though almost all cells show a SAR of less than 1.5. Transforming the continuous response variable into a binomial one, we opted to categorize the data as "fished" when SAR was >0.10 (15%) and "unfished" when SAR was <0.10 (85%). The spatial distribution of the binomial value indicating whether an area is fished or unfished is shown in figure 5.

3.3.2.4 Bottom otter trawlers

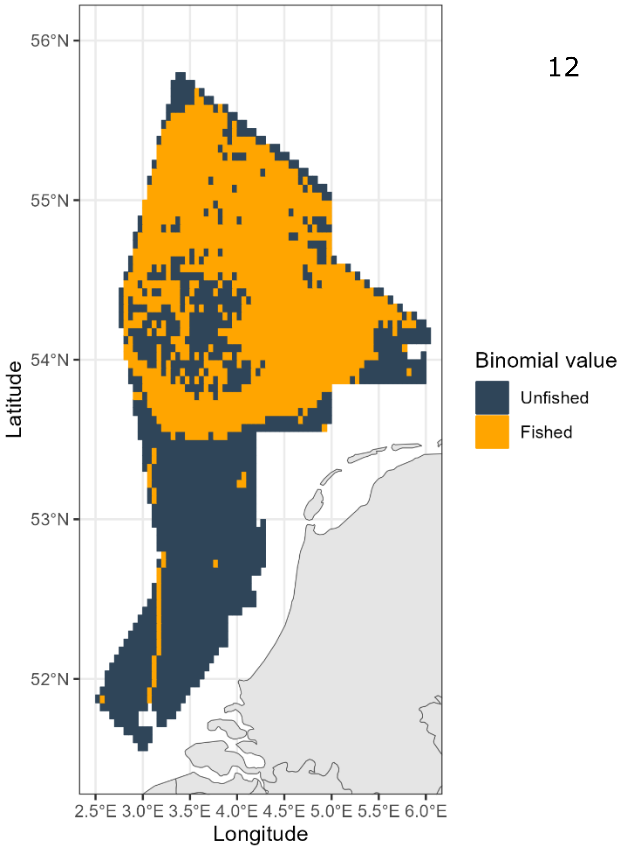

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Figure 6: *Spatial distribution of fished (SAR > 0.10) and unfished cells (SAR ≤ 0.10) by bottom otter trawlers.*

19% of the cells recorded an absolute zero value for the swept area ratio for bottom otter trawlers. Transforming the continuous response variable into a binomial one, we opted to categorize the data as "fished" when SAR was >0.10 (52%) and "unfished" when SAR was <0.10 (48%). The spatial distribution of the now binomial value indicating whether an area is fished or unfished is visualized in figure 6.

3.3.2.5 Pulse beam trawlers

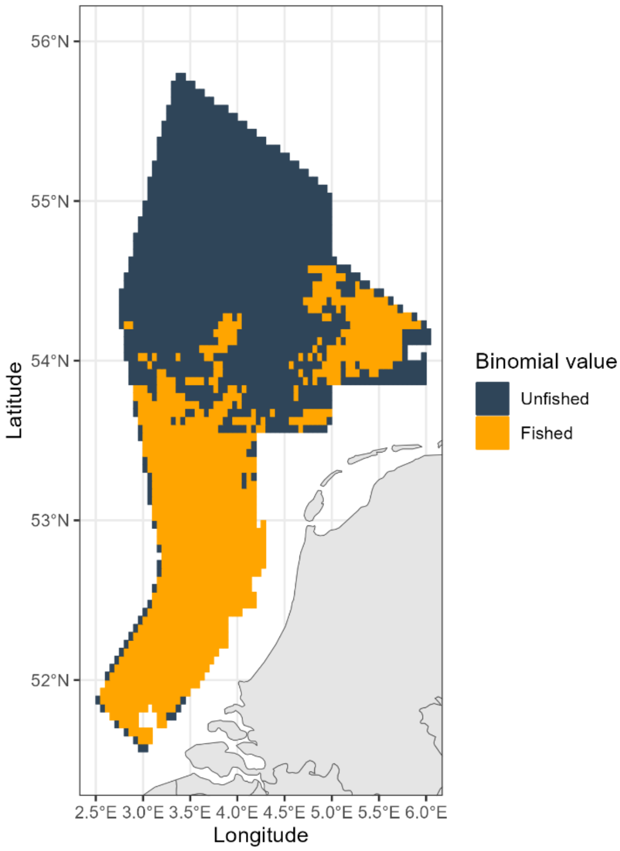


Figure 7: *Spatial distribution of fished (SAR > 0.20) and unfished cells (SAR ≤ 0.20) by pulse beam trawlers.*

18% of the cells recorded an absolute zero value for the swept area ratio for pulse beam trawlers. Transforming the continuous response variable into a binomial one, we opted to categorize the data as "fished" when SAR was >0.20 (44%) and "unfished" when SAR was <0.20 (58%). The spatial distribution of the now binomial value indicating whether an area is fished or unfished is depicted in a plot (figure 7).

3.4 Predictor variables

3.4.1 Data collection

To relate the fishing intensity of the different fleet segments to biological and environmental variables and human uses of the Dutch EEZ other than fisheries, spatial datasets of these variables were collected (hereafter referred to as the predictor variables (table 2). Around offshore installations, such as oil platforms, a 500m buffer zone is present in which fishing is prohibited. Therefore, we calculated the total area of buffer zones per cell based on a dataset of offshore installations (EMODnet). Datasets of electric cables, telecommunication cables and oil and gas pipelines were merged, and the total lengths of these were calculated per cell. Data on shipwrecks in the Dutch EEZ was obtained from Wrecksite.eu, and the number of wrecks per grid cell was calculated. For the biological and environmental variables, an EMODnet dataset was used. This included information on the sand, mud and gravel content, rock cover, depth, distance to the coast and Bathymetric Positioning Index (BPI) for each cell. BPI is a measure of where a referenced location is relative to the locations surrounding it. We used the BPI at a distance of 5 km as an indication of the seabed topography.

***Table 2**: Data, units, and sources*

Variable	Unit	Source
Fishing intensity expressed as SAR	$year^{-1}$	VMS and logbook data, WMR
Offshore installations	km^2	EMODnet
Shipwr**ecks**	Number	Wrecksite.eu
Sand percentage	%	EMODNet via ICES
Mud percentage	%	EMODNet via ICES
Gravel percentage	%	EMODNet via ICES
Rock percentage	%	EMODNet via ICES
Bathymetric Positioning Index	Dimensionless; elevation (m) compared to mean elevation of surroundings at 5 km distance)	EMODNet via ICES
Distance to coast	km	EMODNet via ICES
Depth	m	EMODNet via ICES
Cables and pipelines	km	EMODNet

3.4.2 Data transformation

We checked for non-linear relationships between the predictor and response variables by visualizing the relations individually and fitting a smoother function trough the data points. In case of clear non-linear patterns, the predictor variable was transformed to best fit the relation it resembled: This was only the case for the BPI value, which showed a quadratic relationship with the fishing intensity of the large beam trawler fleet segments. For this segment, BPI was included in the models as a quadratic term.

Next, we checked for abnormalities (like outliers) in our predictor variables. Because there was very low variability in the non-zero observations for the rock content and offshore installations area in the data, the data was transformed into a categorical absence/presence variable. Then, the predictor variables were checked for collinearity by creating scatterplots and inspecting correlation coefficients. In case of (significant) high correlation ($r < -0.4$ or > 0.4), one of the variables was excluded. Under this condition, sand content was dropped from the analysis due to strong correlation with mud content ($r = -0.98$) and depth was dropped due to strong correlation with both distance to coast ($r = -0.4$) and sand content ($r = 0.56$). We chose to include mud content and distance to coast, rather than sand content and depth. This was done because sand is the dominant sediment type in the southern and central North Sea and mud content was therefore deemed more informative. Distance to coast was chosen over depth because it was deemed a more important variable affecting fishers' choice to avoid certain areas. Lastly, we checked whether the categorical variables were balanced. Both the categorical variables for rock content (yes/no) and offshore installations (yes/no) were unbalanced (67 vs 2540 and 207 vs 2400 observations, respectively). This implies that it will be more challenging to detect potentially significant effects on the response variable.

3.4.3 Variable descriptions

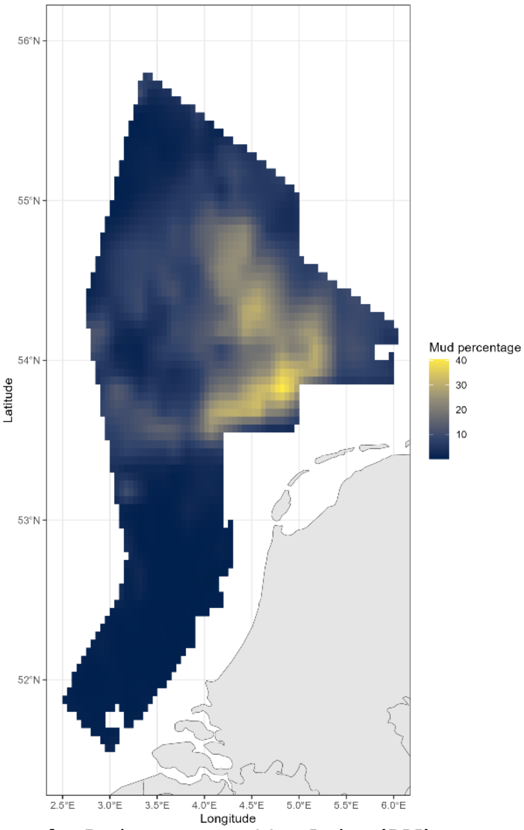
The observations in the study area are based on the 0,05 x 0,05 degree C-squares, that will hereafter be referred to as cells. These cells varied in biological and environmental variables, such mud, sand, gravel, and rock percentages. Additionally, variations are observed in bathymetric features such as depth, distance to the coast, and bathymetric position index. We also collected information on man-made structures, focussing on offshore installations, wreck counts, and cables and pipelines (table 3). A total of 2607 cells are present in the research area, and as there were no missing datapoints in the dataset, this resulted in the collection of 2607 observations per variable.

Table 3: *Summary of the characteristics of cells in the research area (N=2607), used for the statistical analysis. BPI stands for Bathymetry Position Index. Cables and pipelines show the cumulative length of the cables and/or pipelines in that cell. S.D. is standard deviation. 25th pct denotes the 25th percentile, and 75th the 75th percentile of the data. Min and Max specify the minimum and maximum observations.*

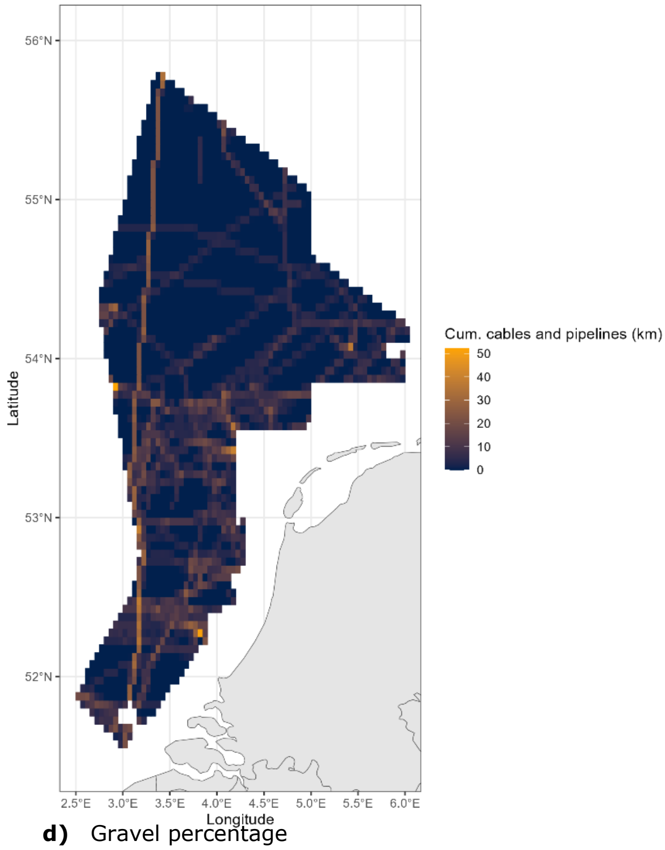
Variable	**Mean**	**S.D.**	**Min**	**25^{th} pct**	**Median**	**75^{th} pct**	**Max**
Mud percentage	8.000	8.100	0.003	1.100	6.000	11.000	40.000
Gravel percentage	0.440	1.600	0.000	0.000	0.003	0.100	18.000
Rock (50 cm) percentage	0.001	0.004	0.000	0.000	0.000	0.000	0.075
Depth	-37.000	7.500	-61.000	-44.000	-38.000	-30.000	-20.000
Distance to coast (km)	120.227	62.649	24.325	68.412	106.110	168.037	288.551
BPI (absolute)	0.670	1.000	0.000	0.110	0.300	0.760	10.000
Offshore installations (km^2)	0.049	0.190	0.000	0.000	0.000	0.000	2.400
Wreck count	0.390	0.880	0.000	0.000	0.000	0.000	14.000
Cables and pipelines (km)	3.800	6.200	0.000	0.000	0.000	5.200	52.000

Figure 8 visualises the spatial distribution of the different data layers that were used in the analysis on the spatial distribution of the fleet segments. The regions with the highest mud content exhibit a curved distribution, with the greatest concentrations located north of the Wadden Islands (figure 8a). Cables and pipelines, identified in 49% of cells, exhibited clear linkages between cells and had a scattered distribution throughout the study area (figure 8b). The Bathymetry Position Index, reflecting depth and terrain roughness, showed higher values toward the outer edge of the study area (figure 8c). 65% of cells contained gravel, often in minimal quantities (figure 8d). The distribution of rocks, which was found in only 3% of cells, was clustered, with a notable hotspot in the south of the study area, surrounding the Borssele windfarm area, which was excluded from the analysis (figure 8e). Offshore installations, present in 8% of cells, were scattered across the research area (figure 8f). Wrecks, which could not be visualised in a plot due data confidentiality, were evenly distributed across the study area.

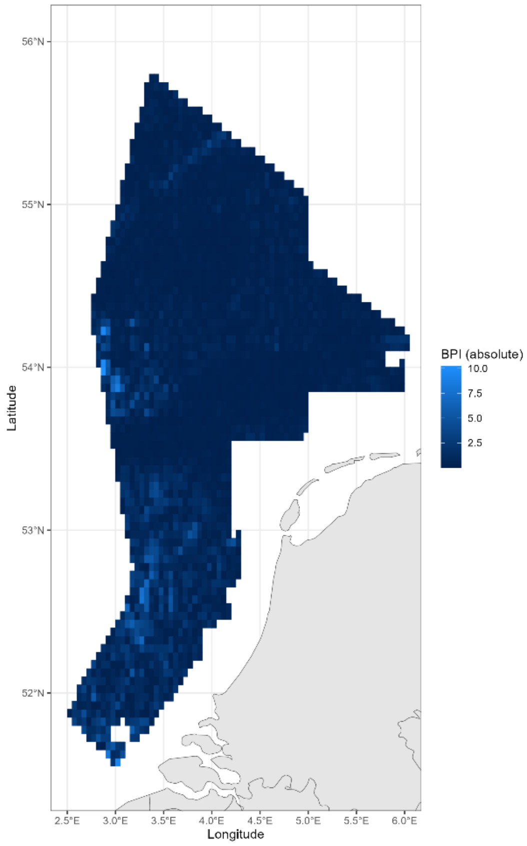
a) Mud percentage



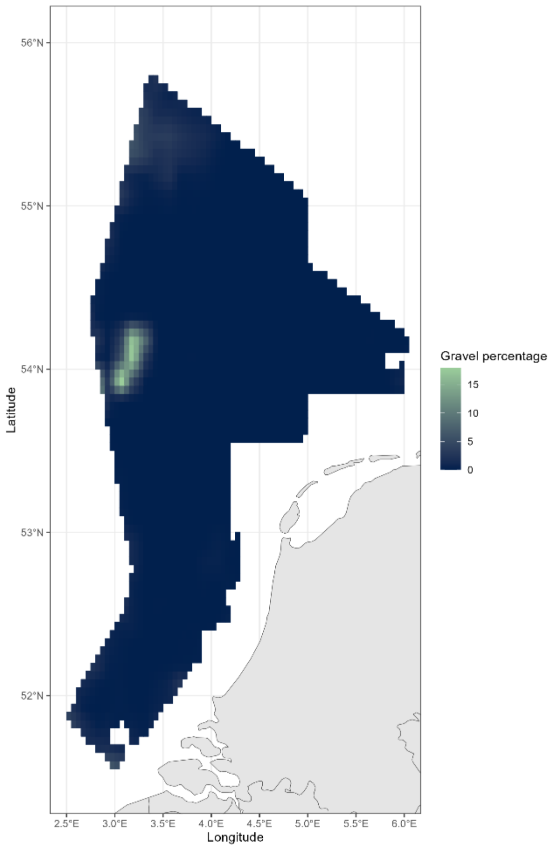
b) Cables and pipelines



c) Bathymetry position Index (BPI)



d) Gravel percentage



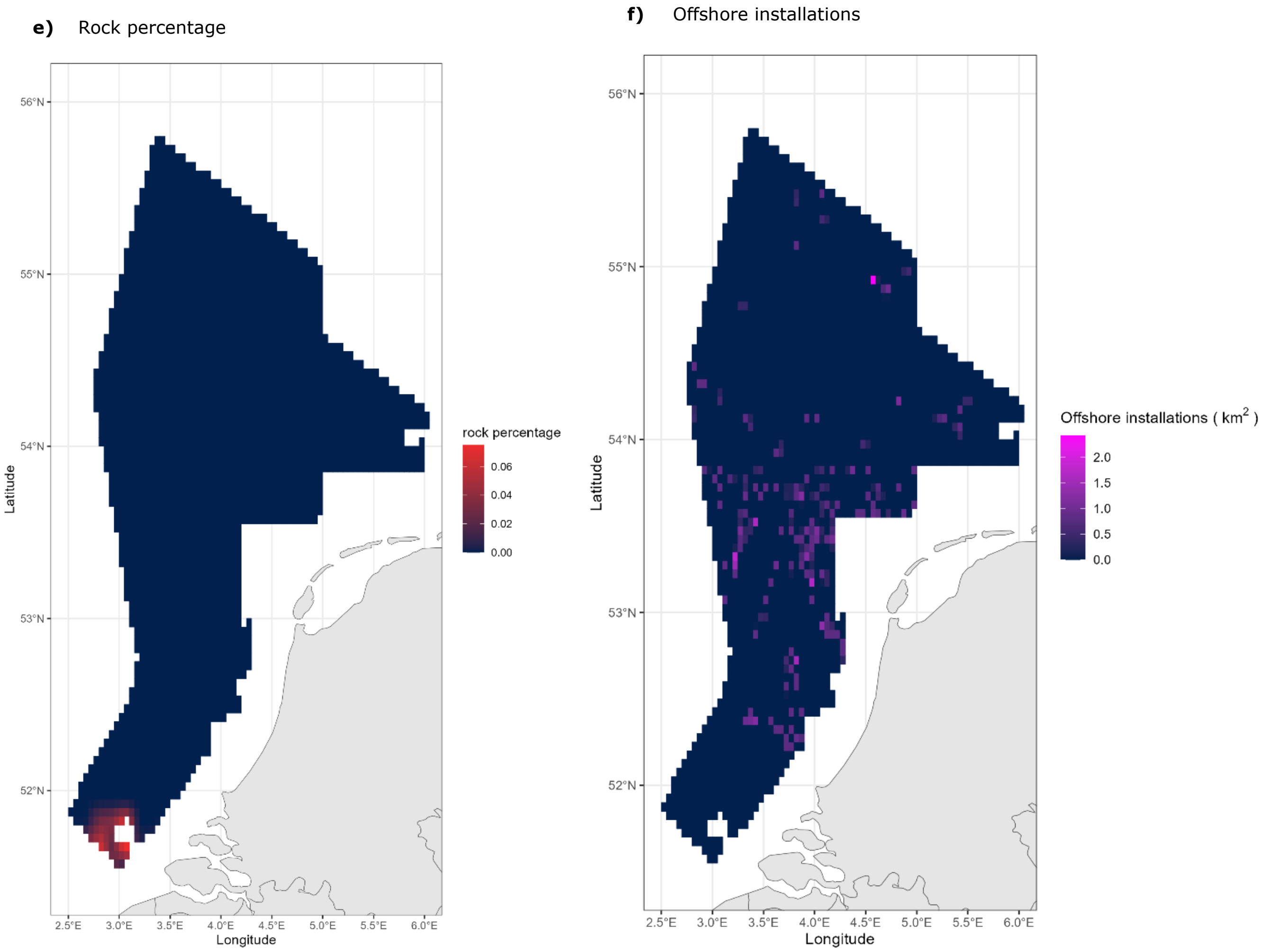


Figure 8: *Spatial distribution of variables of interest in the Dutch EEZ, excluding the twelve-mile zone and the plaice box.*

3.5 Fitting models with INLA

3.5.1 INLA-software

To study which variables affect the fishing patterns, multiple linear regression models were computed. The analysis was conducted using Integrated Nested Laplace Approximation (INLA), a Bayesian methodology (Rue et al., 2009) accessible through the R-INLA package (http://www.r-inla.org). INLA offers computational efficiency and versatility in modeling complex hierarchical structures, incorporating spatial and temporal effects into models. Because of the spatial nature of the response variable, the statistical model likely needs to account for a degree of spatial correlation. Spatial correlation is a form of pseudo replication, since observations are too close to each other to be independent. As a first step, and to test the presence of spatial autocorrelation, a non-spatial approach is taken. Next, we explored two different approach where spatial correlation is accounted for: the geostatistical and areal approaches.

3.5.2 Non-spatial approach

First, models were computed without a spatial random effect. The analysis aimed to investigate which variables influence the absence or presence of fishing, using a binomial error distribution with a log-link function. For each of the five fleet segments, the model was computed:

$$(P|fished)_i \ = Binomial\ (\mu_i)$$

$$logit(\mu_i) = Intercept + \ \beta \times x_i + \ \varepsilon_i$$

Where μ_i is the binomial value, either fished or unfished, for each observation i, β represents the coefficients of the intercept and the predictor variables x_i, and ε_i is a random error term.

The Pearson residuals of the models were computed to create a semi-variogram, which fits a model of the relationship between the distance between observations and the semi-variance between them. If a strong pattern is visible, where variance increases greatly with distance, spatial correlation is present. Strong spatial patterns in the residuals were found for five fleet segments up to 200km, meaning a modelling approach that accounts for spatial correlation needed to be used (see variograms in the appendix).

3.5.3 Areal approach

The first method to account for spatial correlation in INLA is the areal approach, designed for observations in spatial regions (lattice data), such as c-squares. First, a grid is created detailing which cells are neighbours (using queen dependency, i.e., vertical, horizontal, and diagonal relationships). This grid is then transformed into an object readable by INLA. A term for the spatial dependency structure is added to the INLA model:

$$(P|fished)_i \ = Binomial\ (\mu_i)$$

$$logit(\mu_i) = Intercept + \ \beta \times x_i + \omega_i + \ \varepsilon_i$$

Where μ_i is the binomial value, either fished or unfished, for each observation i, β represents the coefficients of the intercept and the predictor variables x_i, ω_i represents the spatially correlated random effect, and ε_i is a random error term.

3.5.4 Geostatistical approach

The second method accounting for spatial correlation in INLA is the geostatistical approach. This approach was designed for geostatistical (i.e., point) observations, but can be applied to areal data in case the data is organized in a regular grid (as is the case with c-squares). The approach consists of several steps:

First, a mesh was created. In spatial statistics, a mesh is a grid or network of nodes that defines the spatial domain or area of interest. The study area was divided into smaller elements or polygons, forming a structured grid or network that allowed for spatial analysis. It's a foundational step in spatial modeling, providing the framework for spatial interpolation and analysis.

Next, the level of connectivity between different nodes, also known as the weight, was defined. The "*inla.spde.make"* function in INLA defines the weight factors for constructing a Stochastic Partial Differential Equation (SPDE) mesh. The weights determine the spatial correlations and smoothness in the spatial field modeling.

Then, an SPDE with priors was defined. SPDEs are mathematical equations used to model spatially correlated random fields. In the context of INLA, these equations are equipped with prior distributions that express our beliefs or assumptions about the behavior of the spatial process. Prior specification for parameters like range (PC priors) and sigma (standard deviation of the random field) is essential to inform the model based on available knowledge or data characteristics. For each fleet segment, three different prior specifications were tested:

1. Standard SPDE, where INLA estimates the range of sigma.
2. SPDE with informative prior ranges, where the prior range was given as the distance at which variance peaks based on the variogram (see 3.5.1). This was 150 km for large beam trawls, 200km for small beam trawls, 200km for bottom otter trawlers, 220km for flyshooters, and 200km for pulse beam trawls. This assumes the range is larger than the specified distance. For the prior of the variance (sigma), the variance in the predictor variables (absence/presence of fishing for each fleet segment) was computed and rounded up. For each fleet segment, this resulted in a value of 1.
3. SPDE with weakly informative prior ranges, where the prior range was set at 1km. This assumes the range of spatial correlation is larger than 1km. For the prior of the variance (sigma), the variance in the predictor variables (absence/presence of fishing for each fleet segment) was computed and rounded up. For each fleet segment, this resulted in a value of 1.

Once the SPDEs and their associated priors were established, spatial fields were defined using these equations. Spatial fields represent the latent (unobserved) spatial processes that are estimated or predicted within the study area. These fields often capture spatial variation or patterns in the data.

Then, the input data was stacked. INLA functions with a specific format for input data called a 'stack.' This format organizes the input data, typically in a tabular structure, making it compatible and easily interpretable within the INLA software for further analysis.

3.5.5 Variable Selection and model structure

For each of the five studied fleet segments, the relationship between the predictor variables and the response variable, fishing intensity, was explored. Based on this, some variables were transformed or excluded from the models.

3.5.5.1 Large beam trawlers

During data exploration, it became clear that the Bathymetry Position Index (BPI) exhibited a non-linear relationship with the response variable (fished or not fished by large beam trawlers), demonstrating an optimum point. Given the strong resemblance to a quadratic relationship, we incorporated BPI with a quadratic term into the model. The variable "distance to coast" posed challenges in the model due to its significant correlation with the spatial random effect introduced to address spatial dependency. Consequently, we opted to exclude this variable from the model.

The model structure was initially established with a basic Generalized Linear Model (GLM) that lacked a spatial component. The semi-variogram analysis for this model confirmed spatial correlation, extending up to approximately 200 km (Annex 2). Therefore, the model with the non-spatial approach as omitted. Then, both areal and geostatistical approaches were explored, with various priors including gamma and PC priors. These models were compared by Deviance Information Criterion (DIC) values. The model formulation is presented in equation 3. All numerical variables within the statistical model were standardized.

$$logit(\mu_i) = Mud_i + Gravel_i + Rock_i + I(BPI)_i + I(BPI^2)_i + CablesPipelines_i + OffshoreInstallations_i + Wrecks_i \quad \textbf{(eq. 3)}$$

3.5.5.2 Small beam trawlers

Contrary to the model analysing large beam trawlers, BPI showed no quadratic structure in data exploration for small beam trawlers, and therefore, only the linear term was included. The model structure was initially established with a basic Generalized Linear Model (GLM) that lacked a spatial component. The semi-variogram analysis for this model confirmed spatial correlation, extending up to approximately 180 km (Annex 3). Therefore, the model with the non-spatial approach as omitted. Both areal and geostatistical approaches were explored, with various priors including gamma and PC priors. The final model formulation is presented in equation 4. All numerical variables within the statistical model were standardized.

$$logit(\mu_i) = Mud_i + Gravel_i + Rock_i + BPI_i + CablesPipelines_i + OffshoreInstallations_i + Wrecks_i \quad \textbf{(eq. 4)}$$

3.5.5.3 Flyshooters

Contrary to the models analysing large and small beam trawlers, the variable "distance to coast" posed no challenges in the model analysing the spatial distribution of flyshooters. All other variables were consistent to the previous model. The model structure was initially established with a basic Generalized Linear Model (GLM) that lacked a spatial component. The semi-variogram analysis for this model confirmed spatial correlation, extending up to approximately 220 km (Annex 4). Therefore, the model with the non-spatial approach as omitted. Both areal and geostatistical approaches were explored, with various priors including gamma and PC priors. The final model formulation is presented in equation 5. All numerical variables within the statistical model were standardized.

$$logit(\mu_i) = Mud_i + Gravel_i + Rock_i + BPI_i + CablesPipelines_i + DistanceToCoast + OffshoreInstallations_i + Wrecks_i \quad \textbf{(eq. 5)}$$

3.5.5.4 Bottom otter trawlers

All variables were consistent to the previous model. The model structure was initially established with a basic Generalized Linear Model (GLM) that lacked a spatial component. The semi-variogram analysis for this model confirmed spatial correlation, extending up to approximately 250 km (Annex 6). Therefore, the model with the non-spatial approach as omitted. Both areal and geostatistical approaches were explored, with various priors including gamma and PC priors. The final model formulation is presented in equation 6. All numerical variables within the statistical model were standardized.

$$logit(\mu_i) = Mud_i + Gravel_i + Rock_i + BPI_i + CablesPipelines_i + DistanceToCoast + OffshoreInstallations_i + Wrecks_i \quad \textbf{(eq. 6)}$$

3.5.5.5 Pulse beam trawlers

All variables were consistent to the previous model. The model structure was initially established with a basic Generalized Linear Model (GLM) that lacked a spatial component. The semi-variogram analysis for this model confirmed spatial correlation, extending up to approximately 160 km (Annex 7). Therefore, the model with the non-spatial approach as omitted. Both areal and geostatistical approaches were explored, with various priors including gamma and PC priors. The final model formulation is presented in equation 7. All numerical variables within the statistical model were standardized.

$$logit(\mu_i) = Mud_i + Gravel_i + Rock_i + BPI_i + CablesPipelines_i + OffshoreInstallations_i + Wrecks_i \quad \textbf{(eq. 7)}$$

3.5.6 Model validation

To select which of the modelling approaches was most appropriate for each fleet segment, Deviance Information Criterion (DIC) values were computed for the areal model and the three geostatistical models. The models with the lowest combined value were assumed to be best. We abstained from further selection of significant variables as our interest lay in assessing the effects of all studied predictor variables. 95% credible intervals were used to assess which variables had a significant effect on fishing intensity, by assessing if the interval overlapped with zero. The models were validated by examining fitted values against residuals and observed values. Mapping the residuals allowed for the inspection of any remaining spatial patterns. Finally, we rechecked for spatial correlation by constructing variograms of the residuals (Annex 2 – Annex 7).

3.6 Survey for fishers

Valuable insights into why certain areas are minimally fished may also come from the fishing sector itself. Besides our statistical analysis of various variables on presence and absence of fishing, we sought input from fishers regarding their reasons for not fishing in certain areas of the Dutch EEZ. We gathered their insights regarding the spatial utilization of the North Sea through an online survey developed in Microsoft Office forms. In December 2023, we distributed an online questionnaire through *Visserijnieuws* (“Fisheries News”) and promoted it via WMR's social media channels (Twitter, Facebook, LinkedIn). The survey was aimed at fishers active in the following fleet segments:

- Large beam trawlers (> 225 kW, including pulse fishing)
- Small beam trawlers (< 225 kW, including pulse fishing)
- Flyshooters
- Bottom otter trawlers
- Pulse trawlers (aiming at fishers who were active in the pulse beam trawl fishery that was allowed in 2007-2021)
- Other

The first question directed respondents to their type of fishery, leading them to a selection of images. Each image (4-7 per fleet segment) showed a delineated unfished area identified based on the SAR maps (figure 2). Respondents were then asked about reasons for not fishing in areas with red borders. They had the option to select multiple predefined answers or give alternative reasons under 'Other.' The predefined reasons in the survey, and corresponding variables in the statistical analysis are shown in table 4.

Table 4: *Predefined options for the survey and the corresponding variable names used in the statistical analysis.*

Variable in survey	**Predictor variable in statistical analysis**
Seafloor too muddy	Mud percentage
Rocks	Rock percentage
Seafloor too rough (relief)	Bathymetry position index 5m
Too far from the coast/harbour	Distance to coast
Target species does not occur here	-
Cables and pipelines	Cables and pipelines
Shipwrecks	Shipwrecks
Too much unwanted bycatch	-
Oil platforms and other infrastructure	Offshore installations
Wind farm(s)	-
I am not familiar with the area/I am not normally active here	-
I don't know/I don't want to answer	-
Other: ...	-

Fishers were additionally queried about their involvement in pulse fisheries. If affirmative, we displayed four additional images with delineated empty fishing areas for the pulse fleet in 2018-2021, repeating the exercise. Finally, we asked the fishers about their main target species and provided the opportunity to specify their fishing gear details, such as mesh size, twinrig or quadrig, ticker chains, or other startup methods, etc.

4 Results

4.1 Statistical models of fishing intensity

4.1.1 Large beam trawlers

For large beam trawlers, the model with the geostatistical approach and default gamma priors showed the lowest Deviance Information Criterion (DIC) value (table 5). As the SPDE with PC priors of 1 had the lowest DIC value, we continued with that model.

Table 5. Model performance comparison table for using Deviance Information Criterion (DIC) values for large beam trawlers.

Modelling approach	DIC
Spatially correlated random effect, geostatistical approach	
a) SPDE default gamma priors	6346.625
b) SPDE PC prior 150	2938.487
c) SPDE PC prior 1	**2678.130**
Areal with BESAG: Spatially correlated random effect	3983.803

Among the variables incorporated into the final model for large beam trawlers, gravel and BPI had significant effects (95% C.I. does not overlap with zero) on fishing intensity (figure 9). The likelihood of an area being fished by large beam trawlers decreased with increasing gravel percentage. The significance of variable BPI, a quadratic term representing seafloor roughness and depth, indicates that cells with BPI values on the lower and higher end of the BPI range have a lower probability of being fished by large beam trawlers.

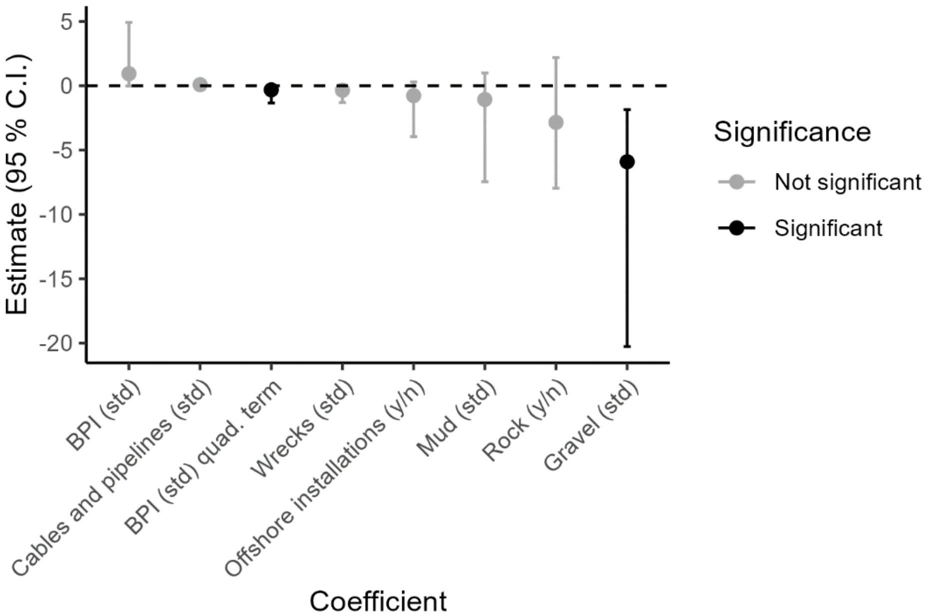


Figure 9 *Estimates for model variable coefficients and their 95% confidence intervals (C.I.) for large beam trawlers. Significant coefficients are shown in black, not significant coefficients are shown in grey. 'Std' refers to standardized variables, and 'y/n' refers to binomial variables.*

4.1.2 Small beam trawlers

For small beam trawlers, the model with the geostatistical approach and pc priors with a value of 150 showed the lowest Deviance Information Criterion (DIC) value (table 6).

Table 6. *Model performance comparison table for using Deviance Information Criterion (DIC) values for small beam trawlers.*

Modelling approach	DIC
Spatially correlated random effect, geostatistical approach	
a) SPDE default gamma priors	5143.755
b) SPDE PC prior 150	**2521.078**
c) SPDE PC prior 1	2627.988
Areal with BESAG: Spatially correlated random effect	2572.554

Among the variables incorporated into the final model, we focus on the four variables for which the credible intervals (0.025 and 0.975 quantiles) did not overlap with zero, signifying statistical significance. Mud, BPI, gravel, and cables and pipelines all had a positive effect on the chance of an area being fished, in decreasing order of effect size (figure 10). Mud had a significantly larger effect size than the other significant variables.

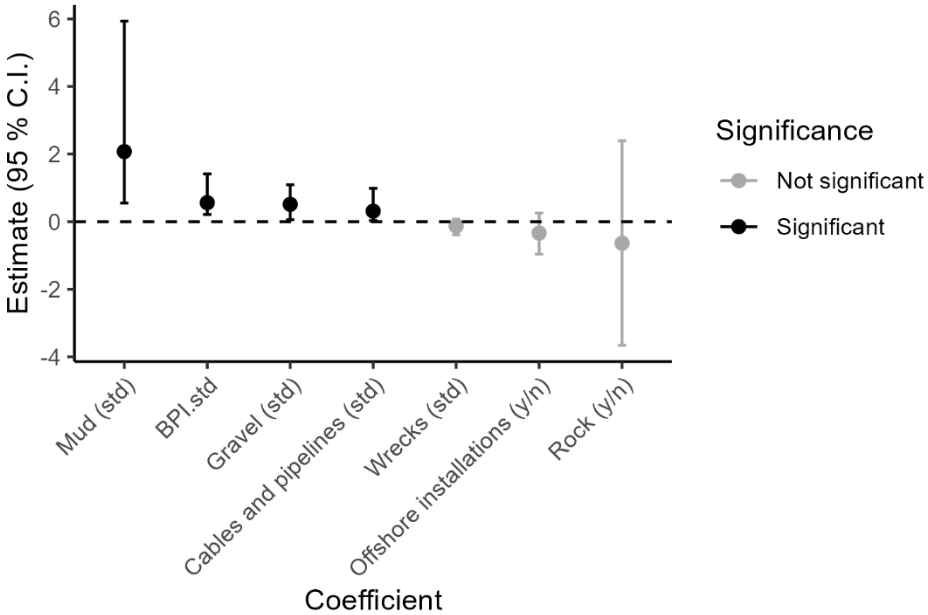


Figure 10: *Estimates for model variable coefficients and their 95% confidence intervals (C.I.) for small beam trawlers. Significant coefficients are shown in black, not significant coefficients are shown in grey. 'Std' refers to standardized variables, and 'y/n' refers to binomial variables.*

4.1.3 Flyshooters

The model with the geostatistical approach and pc priors with a value of 150 showed the lowest Deviance Information Criterion (DIC) value (table 7).

Table 7. *Model performance comparison table for using Deviance Information Criterion (DIC) values for flyshooters.*

Modelling approach	**DIC**
Spatially correlated random effect, geostatistical approach	
	1401.185
d) SPDE default gamma priors	**997.221**
e) SPDE PC prior 150	1060.628
f) SPDE PC prior 1	
Areal with BESAG: Spatially correlated random effect	1725.857

Among the variables incorporated into the final model, we focus on the three variables for which the credible intervals (0.025 and 0.975 quantiles) did not overlap with zero, signifying statistical significance. Gravel percentage and BPI, representing the roughness and depth of a terrain, showed a positive impact on the likelihood of an area being fished. Distance to coast showed a strong negative effect on the chance of an area being fished by flyshooters or not (figure 11).

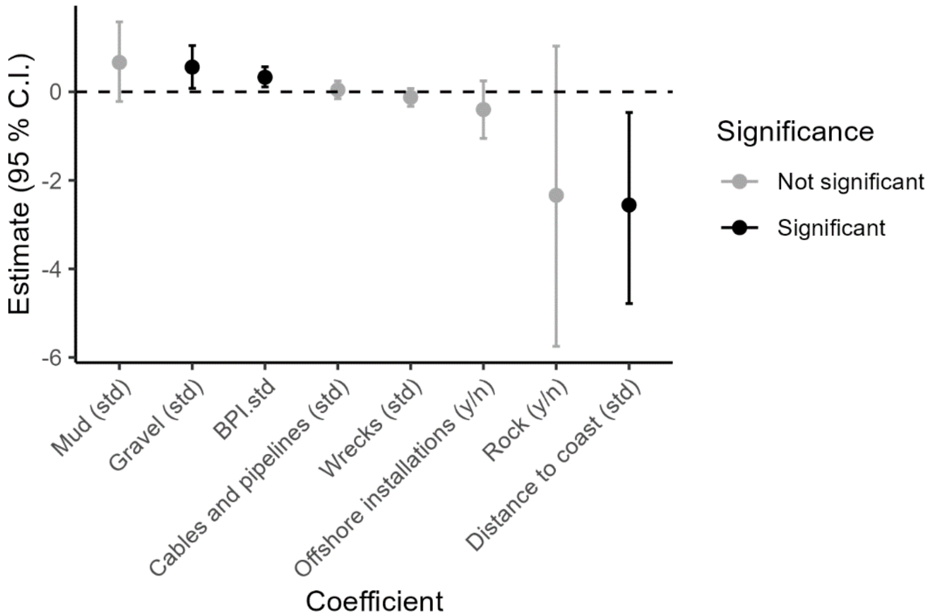


Figure 11: *Estimates for model variable coefficients and their 95% confidence intervals (C.I.) for flyshooters. Significant coefficients are shown in black, not significant coefficients are shown in grey. 'Std' refers to standardized variables, and 'y/n' refers to binomial variables.*

4.1.4 Bottom otter trawlers

For bottom otter trawlers, the model with the geostatistical approach and pc priors with a value of 150 showed the lowest Deviance Information Criterion (DIC) value (table 8).

Table 8. *Model performance comparison table for using Deviance Information Criterion (DIC) values for bottom otter trawlers.*

Modelling approach	**DIC**
Spatially correlated random effect, geostatistical approach	
	1355.295
a) SPDE default gamma priors	
b) SPDE PC prior 150	

Modelling approach	DIC
c) SPDE PC prior 1	**1349.229** 1364.764
Areal with BESAG: Spatially correlated random effect	1888.879

Among the variables incorporated into the final model, we focus on the three variables for which the credible intervals (0.025 and 0.975 quantiles) did not overlap with zero, signifying statistical significance (figure 12). Mud percentage and cables and pipelines showed a positive impact on the likelihood of an area being fished. Offshore installations showed a negative effect on the chance of an area being fished by bottom trawlers.

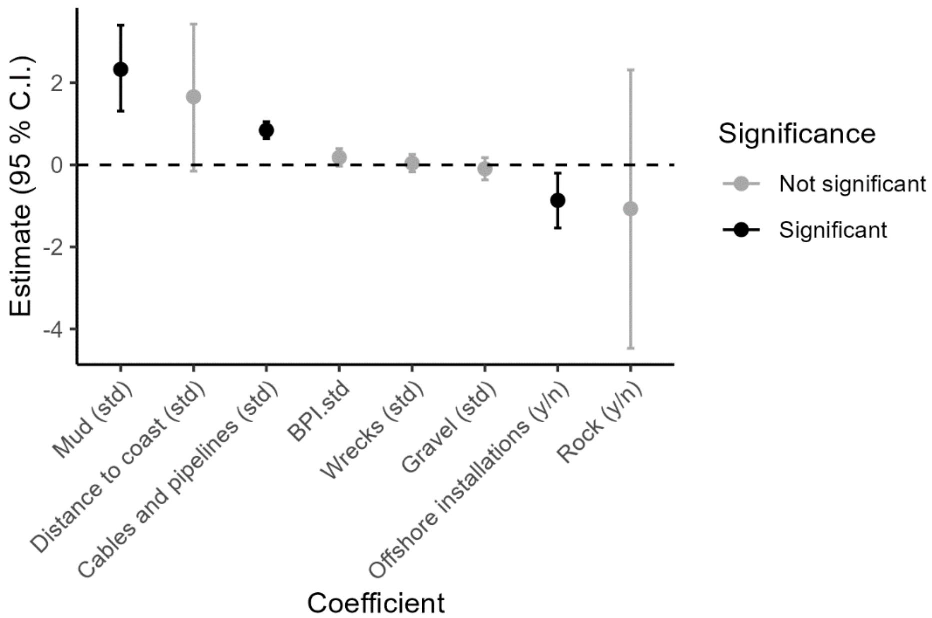


Figure 12: *Estimates for model variable coefficients and their 95% confidence intervals (C.I.) for bottom otter trawlers. Significant coefficients are shown in black, not significant coefficients are shown in grey. 'Std' refers to standardized variables, and 'y/n' refers to binomial variables.*

4.1.5 Pulse beam trawlers

For pulse beam trawlers, the model with the geostatistical approach and pc priors with a value of 150 showed the lowest Deviance Information Criterion (DIC) value (table 9).

Table 9. *Model performance comparison table for using Deviance Information Criterion (DIC) values for pulse beam trawlers.*

Modelling approach	DIC
Spatially correlated random effect, geostatistical approach	2996.936
a) SPDE default gamma priors	**1794.816**
b) SPDE PC prior 150	2276.832
c) SPDE PC prior 1	
Areal with BESAG: Spatially correlated random effect	2275.639

Among the variables incorporated into the final model, we focus on the two variables for which the credible intervals (0.025 and 0.975 quantiles) did not overlap with zero, signifying statistical significance (figure 13). There is a very small positive effect of cables and pipelines a small negative effect of gravel on the chance of an area being fished by pulse beam trawlers.

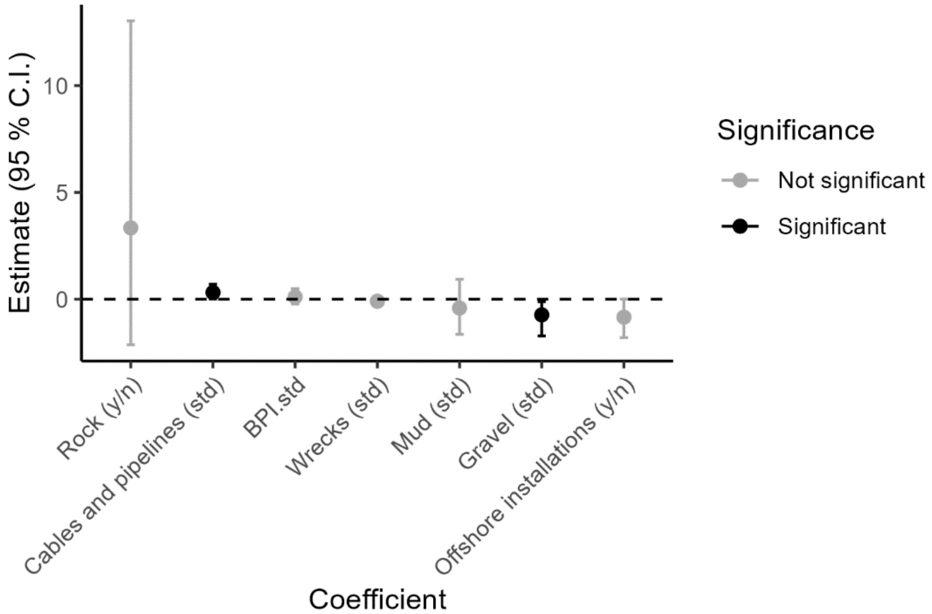


Figure 13: *Estimates for model variable coefficients and their 95% confidence intervals (C.I.) for pulse beam trawlers. Significant coefficients are shown in black, not significant coefficients are shown in grey. 'Std' refers to standardized variables, and 'y/n' refers to binomial variables.*

4.2 Survey

In total, there were twelve respondents to the survey, with at least two respondents in every fleet segment covering a variety of target species (table 10). Not all respondents filled out all questions.

Table 10. Number of respondents per fleet segment and estimated yearly number of vessels in segment in period 2018-2022 (2018-2022 for pulse beam trawlers).

Fleet segment	Respondents (n)	Fishers in segment	Target species
Large beam trawlers (>300)	4	68-97	Sole, plaice, turbot
Small beam trawlers (<300 HP)	2	5-15 (no shrimp beam trawlers)	Shrimp, sole, plaice, turbot, brill fish
Flyshooters	3	18-21	Squid, gurnard, mullet
Bottom otter trawlers	3	33-52	Norway lobster
Pulse beam trawlers	6 (Same fishers as above)	14-47	-

4.2.1 Large beam trawlers

Fishers active in the large beam trawler segment were asked to provide reasons for possibly avoiding seven areas in the Dutch EEZ (figure 14a). Four fishers active in this segment responded, while in the period 2018-2022 between 68 and 97 vessels were active in this fleet segment (excluding pulse beam trawlers). The respondents' target species were sole, plaice and turbot. For most areas, fishers gave multiple reasons for avoiding it.

Figure 14b shows the responses per unfished area. For each of the seven areas, at least one of the respondents indicated that the seabed was too muddy to fish. For all areas except area 1a, fishers indicated that they were not familiar with the area. For areas 1b, 1c, 1d and 1f, fishers give the absence of their target species as a reason for avoidance. Areas 1a, 1b, 1e and 1f were too far from the coast or harbour. Fishers indicated that areas 1a-c and 1g contained too many stones. Lastly, areas 1a and 1b were also avoided because of offshore windfarms, and area 1c because of drilling platforms and other offshore infrastructure.

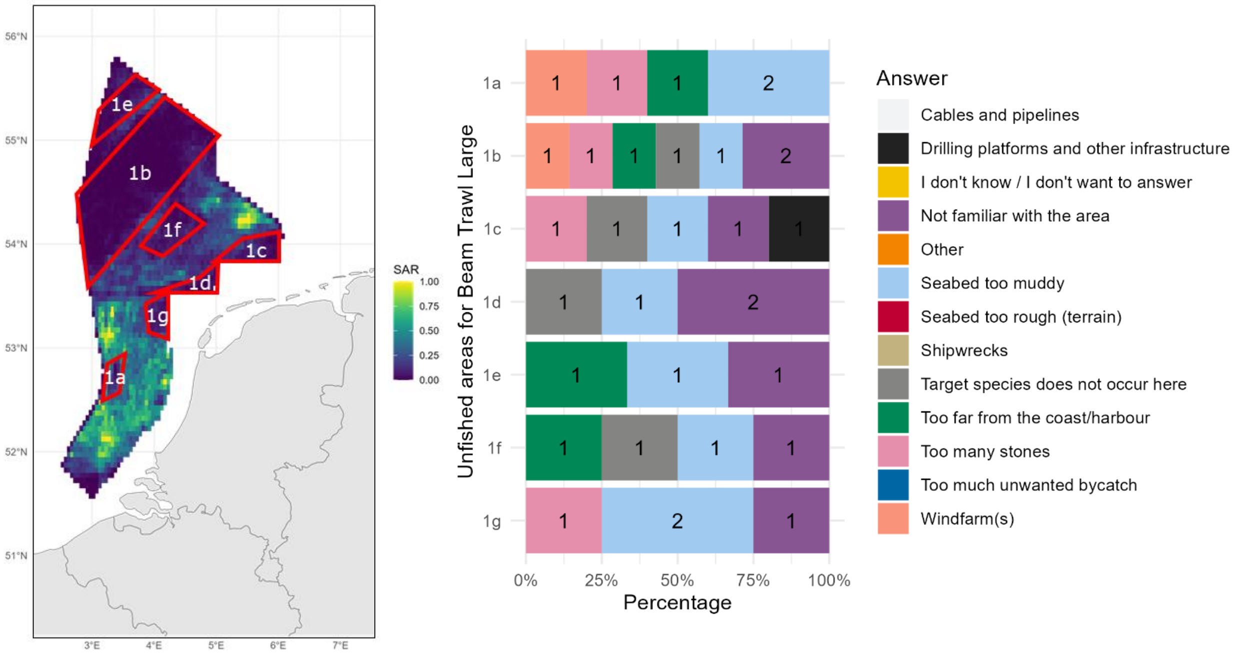


Figure 14: a) *unfished areas for the large beam trawler segment as presented to the respondents.* ***b)*** *Reasons for avoiding unfished areas as given by the respondents.*

4.2.2 Small beam trawlers

Fishers active in the small beam trawler segment were asked to provide reasons for possibly avoiding five areas in the Dutch EEZ (figure 15a). Two fishers active in this segment responded, while in the years 2018-2022 between 5 and 15 vessels were active in this fleet segment (excluding pulse beam trawlers and shrimp beam trawlers). The respondents' target species were shrimp, sole, plaice, turbot and brill. Some of the respondents in this fleet segment fished for shrimp, which often takes place within the 12 nm zone. This is often treated at as a separate fleet segment and was not studied in our analysis.

Figure 15b shows the responses per unfished area. Fishers gave multiple reasons for avoiding these areas. Fishers indicated that they were unfamiliar with areas 2a, 2c and 2e. For areas 2b, 2d and 2e, fishers responded that they were too far from the coast or harbour. Areas 2b and 2e were avoided by one fisher because the target species does not occur there. Area 2a was said to contain too many stones, while area 2e was said to be too muddy. Area 2d was avoided because of drilling platforms and other infrastructure, as well as cables and pipelines. Area 2c was avoided by one fisher because of too much unwanted bycatch. Finally, area 2a was also avoided by on fisher because of offshore windfarms.

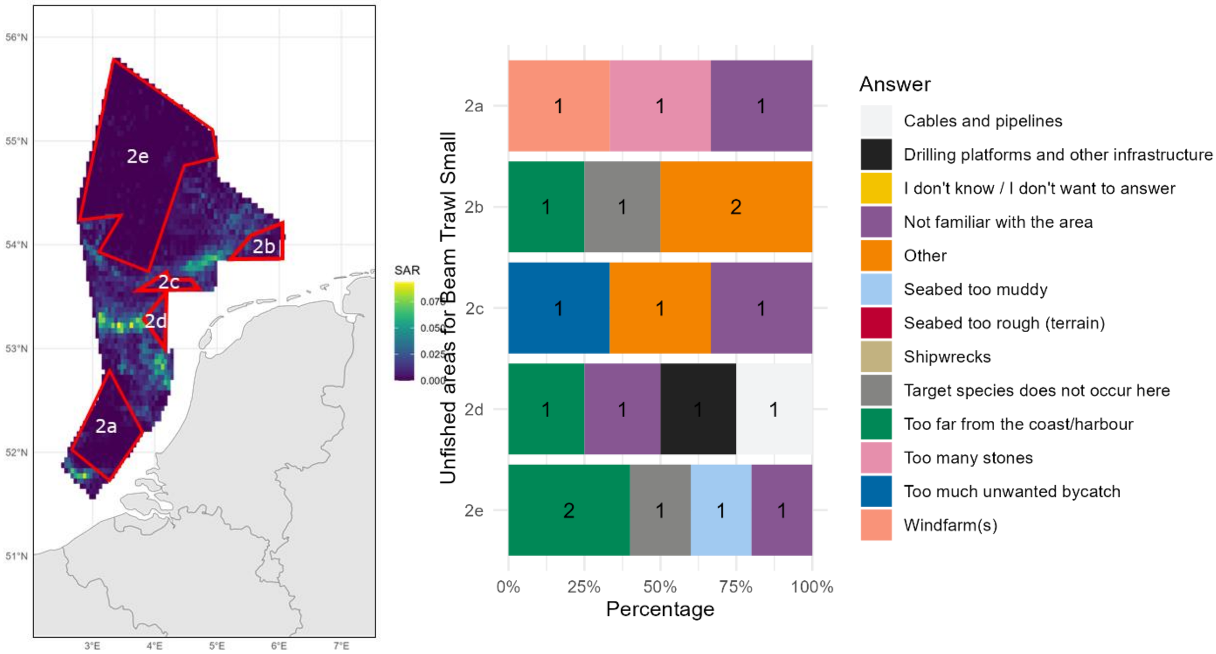


Figure 15: a) *unfished areas for the small beam trawler segment as presented to the respondents.* ***b)*** *Reasons for avoiding unfished areas as given by the respondents.*

4.2.3 Flyshooters

Fishers active in the flyshooter segment were asked to provide reasons for possibly avoiding four areas in the Dutch EEZ (figure 16a). Three fishers active in this segment responded, while in the years 2018-2022 between 18 and 21 vessels were active in this fleet segment. The respondents' target species target species were squid, gurnard and mullet.

Figure 16b shows the responses per unfished area. Fishers gave multiple reasons for avoiding these areas. The respondents indicated that they avoided all four areas because their target species do not occur there and because of drilling platforms and other infrastructure. For areas 3a, 3c and 3d, windfarms, as well as cables and pipelines were given as a reason for avoidance. Both respondents avoided area 3a because the terrain is too rough. Areas 3b and 3c were avoided because the respondents were not familiar with these areas, with area 3b also being avoided because of stones.

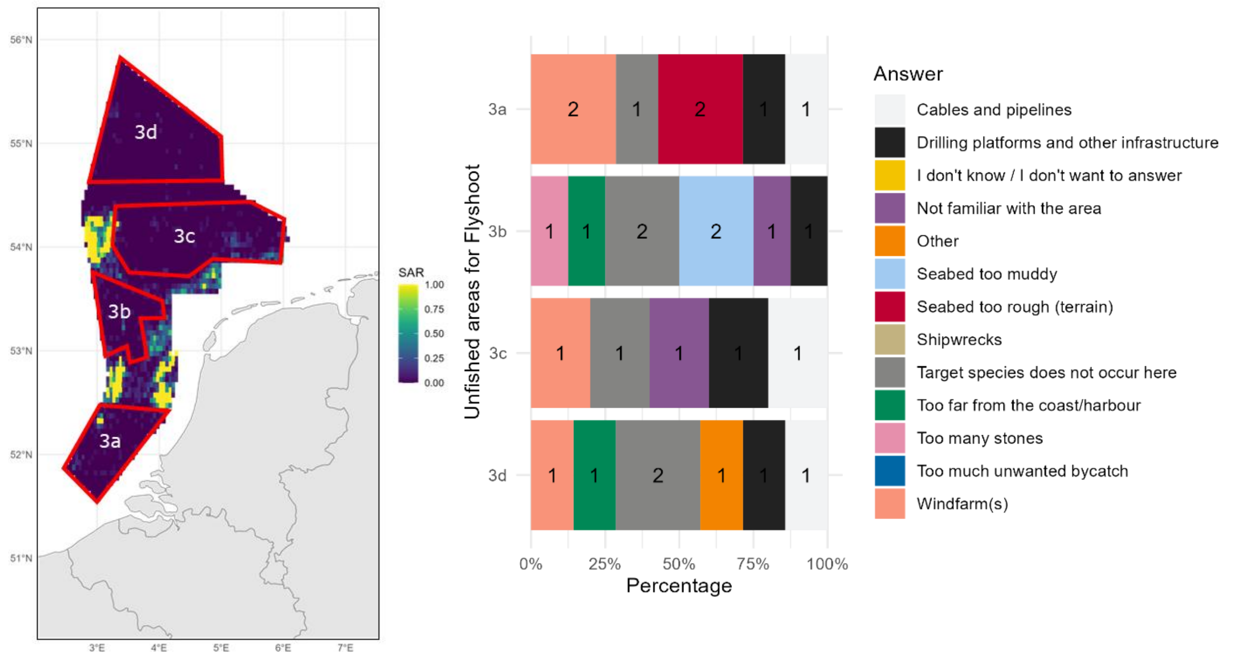


Figure 16. a) *unfished areas for the flyshooter segment as presented to the respondents.* ***b)*** *Reasons for avoiding unfished areas as given by the respondents.*

4.2.4 Bottom otter trawlers

Fishers active in the bottom otter trawlers segment were asked to provide reasons for possibly avoiding five areas in the Dutch EEZ (figure 17a). Three fishers active in this segment responded, while in the years 2018-2020 between 33 and 52 vessels were active in this fleet segment. The respondents' target species were Norway lobster.

Figure 17b shows the responses per unfished area. Fishers gave multiple reasons for avoiding these areas. The main reason for avoidance for all areas and by most fishers in this segment was the absence of target species. Areas 4b-d were avoided because they are too muddy. Areas 4a, 4d and 4e were avoided because of the roughness of the seabed. Areas 4b and 4d were avoided because of drilling platforms. Fishers also avoided 4d because of windfarms and cables. The presence of stones was given as a reason to avoid areas 4a and 4d. Area 4e, in the far north of the Dutch EEZ, was avoided because of the distance to the coast or harbour.

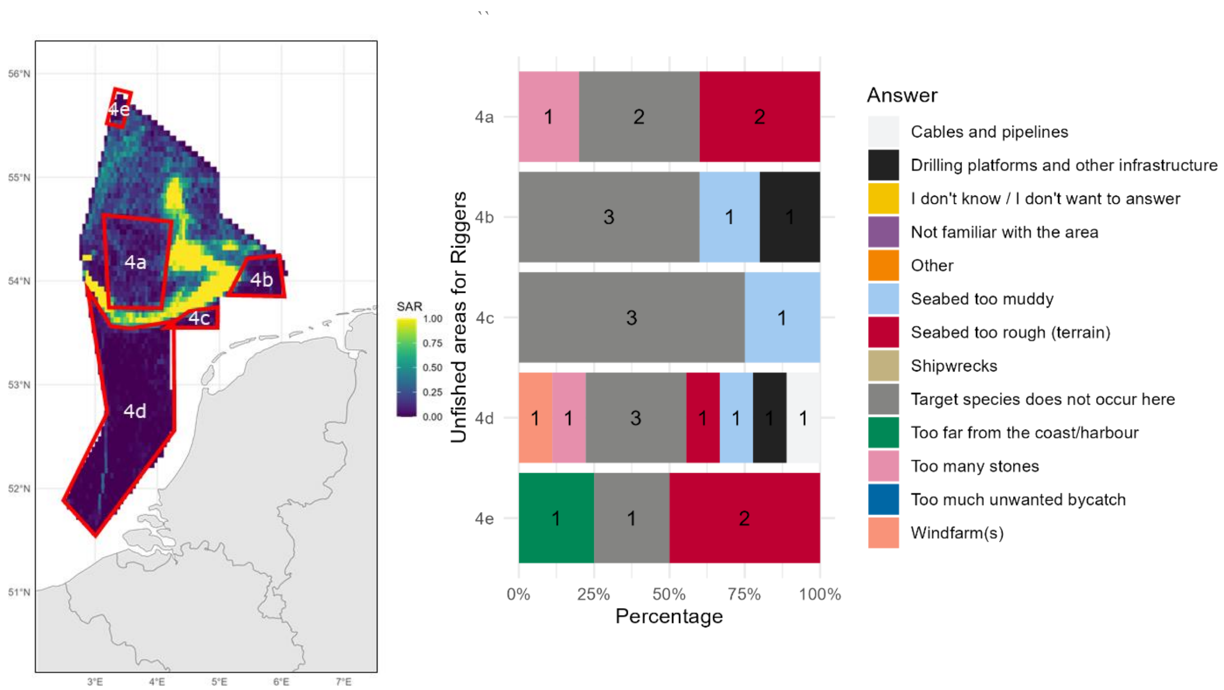


Figure 17: a) *unfished areas for the bottom otter trawlers segment as presented to the respondents.* ***b)*** *Reasons for avoiding unfished areas as given by the respondents.*

4.2.5 Pulse beam trawlers

Fishers who used to be active in the pulse beam trawl segment were asked to provide reasons for possibly avoiding five areas in the Dutch EEZ (figure 18a). Three fishers who used to fish with this gear, all of whom are currently active in the large beam trawl segment. In the years 2018-2022 between 14 and 47 vessels were active in this fleet segment.

Figure 18b shows the responses per unfished area. Fishers gave multiple reasons for avoiding these areas. For each of the areas, unfamiliarity is given as a reason for avoidance by at least one respondent. The more northern areas, 5b-d, were avoided because the seabed was too muddy, and the target species does not occur there. Area 5a-c were avoided due to windfarms, with area 5a also being avoided because of drilling platforms, cables and pipelines, and the rough terrain. The area farthest north, 5d, was also avoided because of the distance to the coast or harbour.

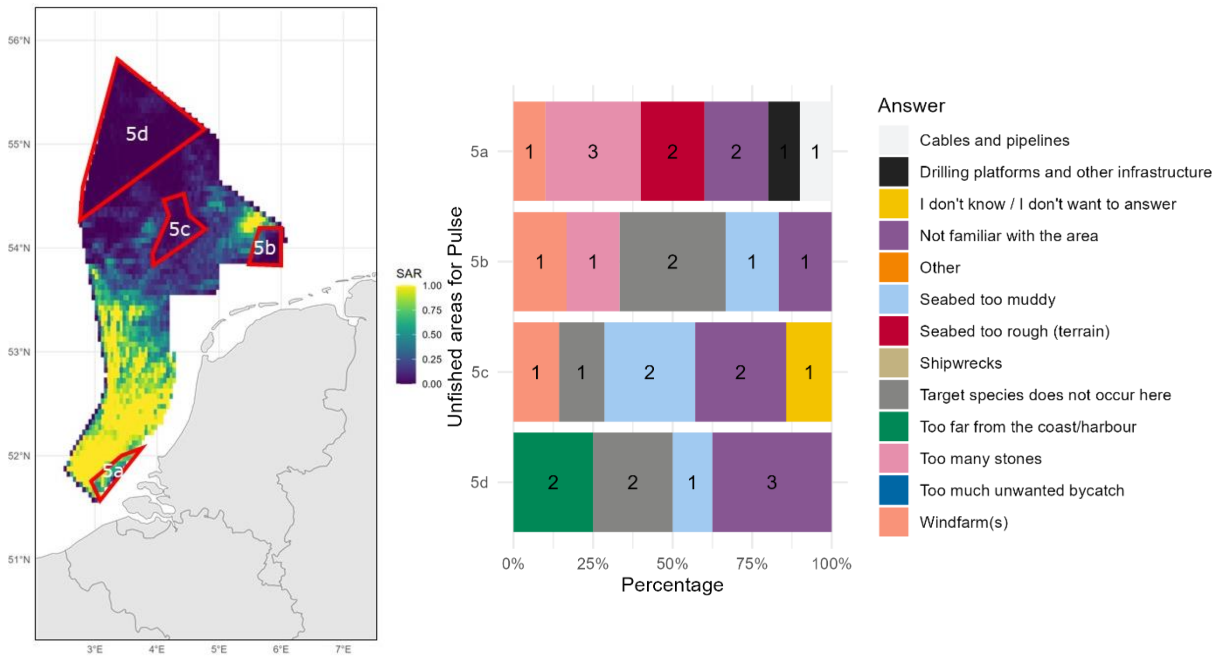


Figure 18: a) *unfished areas for the pulse beam trawl segment as presented to the respondents.* ***b)*** *Reasons for avoiding unfished areas as given by the respondents.*

5 Discussion

This research aimed to identify regions with minimal fishing activity among the primary large-scale fleet segment groups in the Dutch fishing fleet and investigate the main variables contributing to low fishing activity in these regions. Visualization of fishing intensity, expressed as swept area ratio, revealed clear differences in fishing intensity across different areas. We employed both quantitative and qualitative approaches to further examine why fishing intensity is low in certain areas.

5.1 Limitations

The selection of a binomial model involved several trade-offs. Our model results revealed significant spatial effects that were not accounted for by the variables, indicating a considerable degree of spatial correlation (similar likelihood of an area being fished or not due to proximity). This can partly be attributed to our use of a binomial model, where the response variable was whether an area was "fished" or "unfished." This makes it challenging to discern linear relationships between fishing effort and environmental and technical variables. However, since this study aimed to identify reasons for the absence of fishing in large areas rather than the preferences of different fleet segments, this approach is justified. Additionally, determining which areas were unfished required setting an arbitrary threshold per fleet segment. The goal was to achieve a balanced dataset of fished and unfished cells. Although the threshold values were carefully considered, choosing different thresholds might yield new insights. For future studies, a sensitivity analysis varying this threshold is recommended.

The distance to the coast could not be included in some of the models due to its resemblance to spatial correlation, which is the variable an INLA model compensated for. This heavily constrained the model's performance, leading us to exclude it as a predictor variable in those cases. However, it is likely that distance to the coast does play a role in the distribution of fishing effort, as it was frequently cited as an important variable by fishers. So, although it might not be explicitly included in our model, it is likely to have a significant effect. Another predictor variable that could not be included was sand contents, as the variable had high collinearity with mud content. Therefore, if a relationship with mud is identified, it may actually reflect a correlation with sand content instead, underscoring the complexity of the analysis.

The pulse ban above 55 degrees latitude was not taken into account in our analysis. Consequently, this restricted area was treated as if it were an empty area and tested against various predictor variables. This means that the lack of fishing activity above 55 degrees cannot be accurately attributed to the analysed predictor variables, potentially skewing the statistical model. Therefore, the results should be interpreted with extreme caution.

Similarly, we excluded the 0-12 mile coastal zone a priori from the analysis, as most fishing activities are not allowed here. However, small beam trawlers are permitted to fish in this region. For greater precision, this area should have been included in the analysis. Unlike the issue with pulse fisheries, this exclusion is not expected to have major consequences for the analysis of small beam trawlers; it simply limits the amount of data used for the analysis.

An important consideration in the analysis on the distribution of fishing effort is scale. Fishers may prefer or avoid certain areas on a very small scale, which cannot be adequately studied using conventional VMS data analysis. This micro-scale distribution results in significant differences in trawl frequency between areas that are very close to each other (Rijnsdorp et al., 1998). However, since this study aimed to identify reasons for avoiding large parts of the Dutch EEZ, this difference in micro-scale distribution does not need to be taken into account for the purposes of this study.

Lastly, social factors may influence fishers' choices on if, where, and when to fish (Schadeberg et al., 2021). Our results also indicate that there may be many variables, beyond variables tested here, that influence why fishers avoid certain areas. The greatest potential for future fisheries may lie in unfished areas that fishers do not exploit because they are unfamiliar with them, and where biotic and abiotic variables do not seem to limit fishing. It is important to note that the presence of target species is a crucial variable that was not fully explored in this research, as there is limited information on the spatial presence of all target species at the spatial and temporal scale used in this study.

5.2 Implications per fleet segment

We assessed relationships between the chance of an area being fished and various predictor variables. As we expected, the data showed a strong degree of spatial correlation. After incorporating this spatial effect in our statistical models, we found that the variables that influence the chance of an area being fished or not differ between the fleet segments studied. Therefore, the following section provides a discussion of the results for each fleet segment.

In addition to statistical analysis, input was sought from fishers regarding their reasons for avoiding specific areas, resulting in low fishing intensity. Through an online survey, fishers provided direct insights into variables such as the presence of target species, bycatch risks, and familiarity with the area, which are challenging to assess through statistical methods. To see the congruence between modelling results and survey results, the survey outcomes are discussed in the context of the modelling results per fleet segment .

5.2.1 Large beam trawlers

Large beam trawlers were present in a large part of the Dutch EEZ, with larger clusters of non-fished areas towards the edges of the EEZ. Statistically, the absence of fishing for large beam trawlers was significantly negatively influenced by the quadratic BPI term and the gravel cover. The quadratic BPI term implies that areas with intermediate elevation (compared to the surroundings) were most likely to be fished and areas with lower and higher elevations are less likely to be fished. The preference of large beam trawlers for slightly elevated areas is confirmed by Hintzen et al. (2021), who compared the habitat preference of conventional Dutch beam trawlers to that of Dutch pulse beam trawlers. Van der Reijden et al. (2018) studied the habitat preference of beam trawlers targeting plaice, beam trawlers targeting sole, and otter trawlers and found that the target species had an effect on the preferred topography, with beam trawlers targeting sole preferring depressions between sand ridges and those targeting plaice preferring the exposed ridges of sand banks. The negative relationship with gravel cover indicates that areas with high gravel content were avoided. This was also found by Hintzen et al. (2021) and is confirmed by the fishers in the survey, as they give stones/gravel as a reason for avoidance. Van der Reijden et al. (2018) do not find a significant (negative) effect of gravel cover. Fishers also indicated that a common reason for avoidance is that the seabed is too muddy. This is not in line with the results from our analysis and is also not found by Hintzen et al. (2021), although it is confirmed by Van der Reijden et al. (2018). Furthermore, fishers give the absence of the target species as a reason for avoidance. The fishers who participated mainly targeted common sole (*Solea solea*), which is often found farther south than the unfished areas in the northern part of the Dutch EEZ. The distance to the coast was also indicated as a reason for avoidance of the areas furthest away from the coast. Due to modelling constraints, this variable could not be included in the statistical analysis, so it was not possible to validate this survey outcome. Van der Reijden et al. (2018) confirm that beam trawlers fishing for sole prefer nearshore habitats. For most of the unfished areas, fishers also indicate that they are unfamiliar with that area, which leads to avoidance. Although this could indicate these areas are potentially interesting as future fishing grounds for the large beam trawler fleet segment, fishers also report technical limitations to fishing in these areas, such as the high mud content. Van der Reijden et al. (2018) conclude that large beam trawlers prefer specific, uncommon habitats depending on the target species, which implies that habitat and target species restrict the possibility of expanding fishing activity into unfished areas.

5.2.2 Small beam trawlers

Small beam trawlers displayed a very scattered fishing pattern, with both larger and smaller unfished areas. The fishers fished less in the northern and southern parts of the Dutch EEZ. Their spatial distribution showed close resemblance to the spatial pattern of mud contents. It is important to note that these vessels are allowed to fish within the 12-mile zone and the plaice box, but these areas were excluded from the analysis. A significant positive relation was found between fishing intensity by small beam trawlers and mud content, BPI, and the presence of cables and wrecks. Where we initially expected avoidance of areas with harder structures, it is interesting to find fishing activity near cables and pipelines, and close to wrecks. It could be that in these areas, biomass of the target species is higher, as these fish tend to school in places with harder structures. The results of the survey do not confirm the outcomes of the modelling. Fishers in this fleet segment gave varying reasons for avoiding parts of the Dutch EEZ. The areas in the northern part of the Dutch EEZ were avoided because of their distance to the coast. The survey answers were non-uniform. Other than being too far from the coast, none of the options was answered more than once. However, for area 2b and 2c, fishers indicated that the target species hasn't been caught there for years, or that if caught, they are undersized.

5.2.3 Flyshooters

Flyshooters show scattered fishing patterns with some concentrated areas of activity. They tend to concentrate their activity in the central and southern EEZ, leaving large unfished areas mainly in the north. The statistical analysis showed that they are often found around gravel and elevations, and they seem to prefer areas farther from the coast. This preference for areas farther from the coast may be caused by the presence of target species in those areas, which was reported by the fishers as a reason for avoidance of all unfished areas. The presence of wind farms, cables, pipelines, and other infrastructure were also reported by fishers as reasons for avoidance. The avoidance of offshore infrastructure is likely due to the fact that flyshoot fishing uses cables that cover several square kilometres of seabed. Interestingly, offshore installations and cables and pipelines were not found to significantly affect fishing intensity in the model. Fishers note that the southern part of the Dutch EEZ (3a) is avoided due to rough terrain, which is not in line with the model finding that areas with rougher terrain are more likely to be fished. Additionally, several fishers mentioned avoiding certain areas (3b and 3c) because these were unfamiliar to them. This could indicate these areas are potentially interesting as future fishing grounds for the flyshoot fleet segment, though other reasons for avoidance, such as the absence of target species, are also given for these areas. To our knowledge, this is the first study into the habitat preferences of flyshoot fishing in the North Sea.

5.2.4 Bottom otter trawlers

Bottom otter trawlers were nearly absent from the southern part of the EEZ. Statistical analysis revealed that the likelihood of an area being fished was positively influenced by mud content. It is possible that this is caused by the distribution of the fleet segment's target species: Norway lobster (*Nephrops norvegicus*) is known to prefer muddy sediments with intermediate grain sizes for burrowing (Campbell et al., 2009). The survey results reveal that the main reason for avoiding the unfished areas was the absence of target species. Given the association of Norway lobster with muddy sediments, this is in line with our model outcomes. This is also in line with the findings of Van der Reijden et al. (2018). The presence of cables and pipelines also increased the likelihood of an area being fished. The reasons for this are unclear, but it could be due to aggregations of target species near cables and pipelines. The presence of offshore installations reduced the likelihood of an area being fished by bottom otter trawlers. This avoidance of offshore installations is confirmed by the fishers in the survey, as this is given as a reason for avoiding two areas (4b and 4d). For two areas (4a and 4e), the roughness of the seabed was given as a reason for avoidance. This implies that rough seabeds are unsuitable for this fleet segment and that these unfished areas are not interesting as potential future fishing grounds for bottom otter trawlers. The model results do not confirm this, as BPI did not have a significant effect on fishing intensity. For the other areas, the seabed was too muddy. This contradicts the findings from our models, which suggest that this type of fishing prefers muddy sediments, though it could be that the mud particles in these areas are smaller than the preferred grain size of Norway lobster. Van der Reijden et al. (2018) conclude that bottom otter trawlers prefer specific uncommon habitats with low bed shear stress and are situated in deeper areas with high mud contents. This is in line with our findings that habitat type and target species together limit the possibility of expanding fishing activity into unfished areas.

5.2.5 Pulse beam trawlers

Pulse beam trawling was an alternative method to the traditional beam trawling technique and was practiced by a portion of the Dutch beam trawler fleet from around 2009 until 2021, when it was outlawed. Pulse beam trawlers were heavily concentrated in the southern and western parts of the EEZ, smoothly transitioning to a total absence in the North, due to a ban on pulse fishing above a latitude of 55°N.

In our analysis, we did not take into account the pulse ban north of 55 degrees latitude, and the restricted area was treated like other empty areas and tested against many predictor variables (but not the restriction). This discrepancy, where the lack of fishing activity above 55 degrees cannot be attributed to any of the predictor variables analysed, can significantly influence the statistical model. Therefore, the statistical results should be interpreted with extreme caution.

The statistical analysis revealed that pulse trawlers fished more in areas with cables and pipelines and less in areas with gravel. The positive relation with cables and pipelines could be due to the target species, which is mainly sole, aggregating near these structures on the seabed or being influenced by magnetic fields produced by underwater cables. Evidence for these effects on fish is limited, and it is generally accepted that these magnetic fields do not significantly affect fish (Copping et al., 2021). The avoidance of gravel was also observed in Hintzen et al. (2021). Fishers indicated that the presence of wind farms and gravel/stones were reasons for avoiding the areas, which shows the model is consistent with the survey. Also, fishers indicated an absence of their target species in the northern areas, which is consistent with the distribution of sole. Lastly, all unfished areas (5a-d) were said to be avoided because fishers were unfamiliar with them. Although this could indicate these areas are suitable as future fishing grounds for pulse beam trawlers, other technical limitations as well as absence of the target species were also given as reasons for avoidance.

5.3 Conclusion

Throughout this study, every identified unfished area revealed a distinct reason for the absence of fishing activity. The statistical analysis, conducted separately for the main fleet segments, but considering all unfished areas per fleet segment in one analysis, revealed one or more significant predictor variables contributing to the absence of fisheries in the unfished areas in these segments. Consistently, in the survey, no individual unfished area was solely attributed to 'being unfamiliar with the area,' testifying that fishers were able to indicate reasons for not visiting specific areas. This study highlights the complexity of the variables contributing to the spatial distribution of fishing activity and serves as reminder to approach marine spatial planning for fleet segments separately. Considering the distributions of various fleet segments is essential when formulating spatial planning for the Dutch North Sea, it is important to ensure that spatial closures due to nature protection or energy production do not disproportionately affect specific fleet segments.

6 Quality Assurance

Wageningen Marine Research utilises an ISO 9001:2015 certified quality management system. The organisation has been certified since 27 February 2001. The certification was issued by DNV.

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CBS, PBL, RIVM, WUR (2024). Bodemfauna Noordzee en bodemvisserij, 2016 - 2019 (indicator 1251, version 06, 18 November 2021) www.clo.nl. Centraal Bureau voor de Statistiek (CBS), Den Haag; PBL Planbureau voor de Leefomgeving, Den Haag; RIVM Rijksinstituut voor Volksgezondheid en Milieu, Bilthoven; en Wageningen University and Research, Wageningen.

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Justification

Report: C051/24

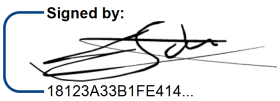
Project Number: 4318100252

The scientific quality of this report has been peer reviewed by a colleague scientist and a member of the Management Team of Wageningen Marine Research

Approved: dr.ir. E Schram PhD MSc

Researcher

Signature:

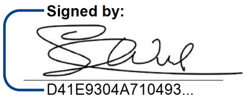


Date: 26 August 2024

Approved: C.J. Wiebinga

Business Manager Projects

Signature:



Date: 26 August 2024

Annex 1 Spatial modelling framework

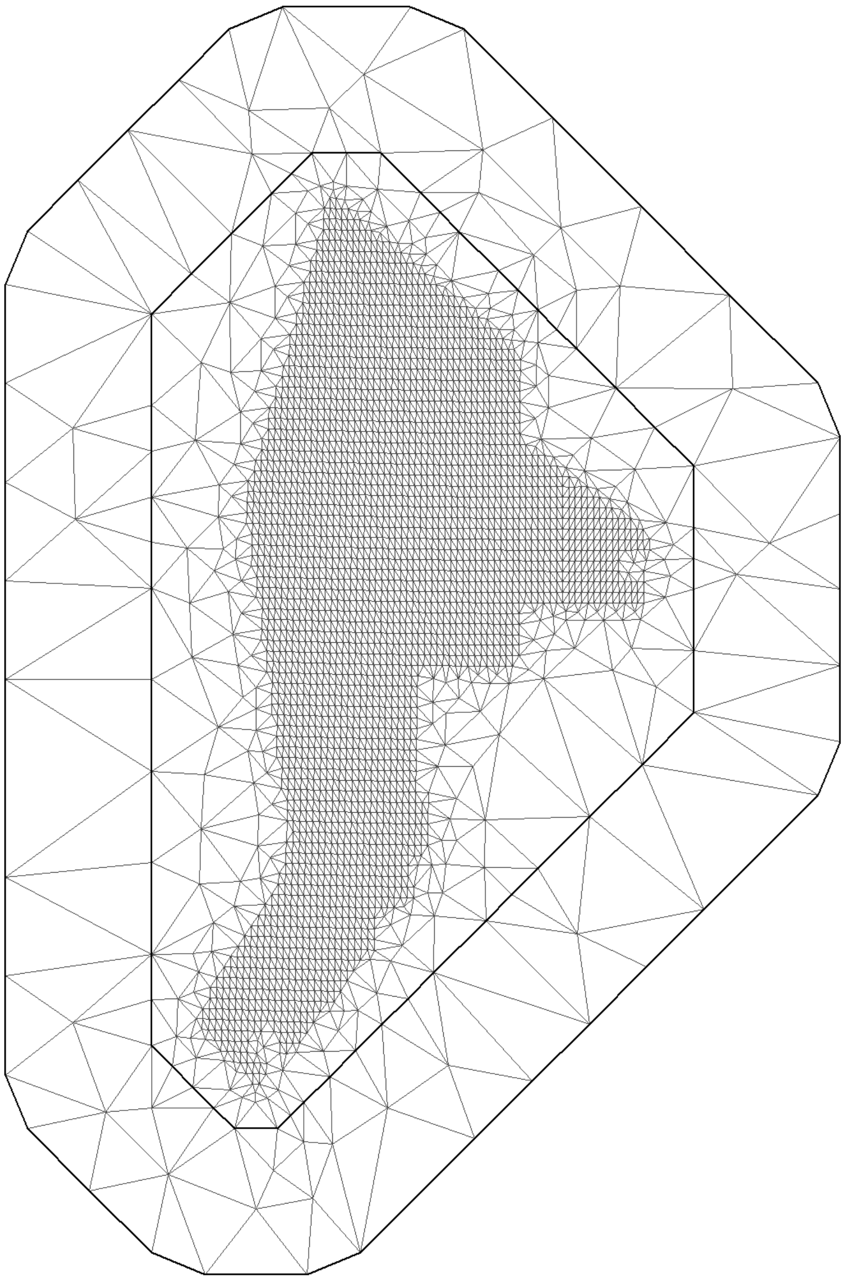


Figure 19: *Mesh used for INLA-models accounting for spatial correlation using a geostatistical approach, based on c-squares. Cells that are (partly) in an OWF were excluded.*

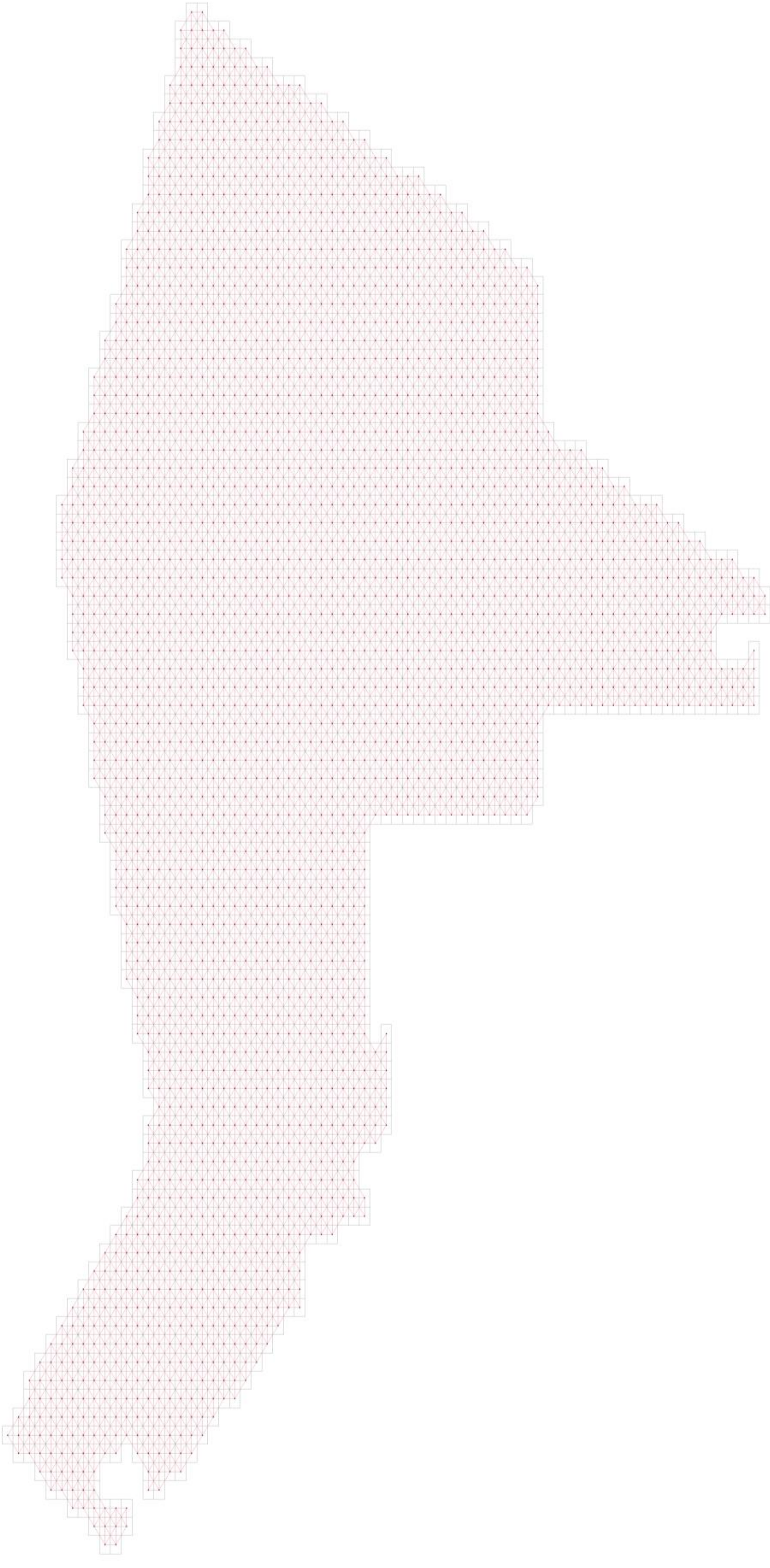
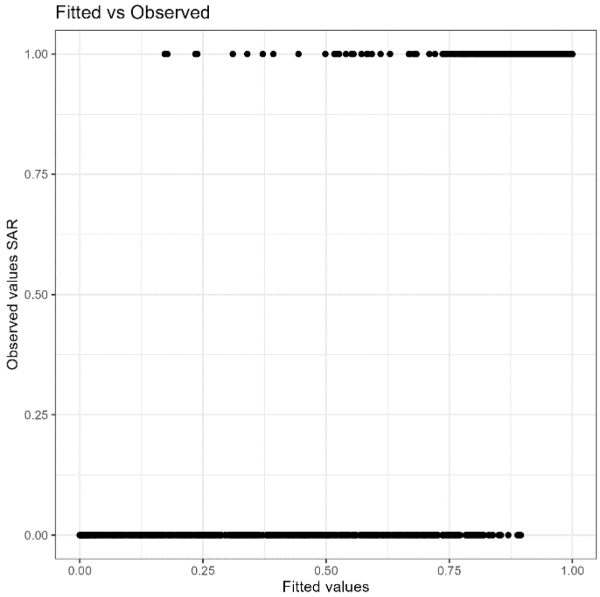
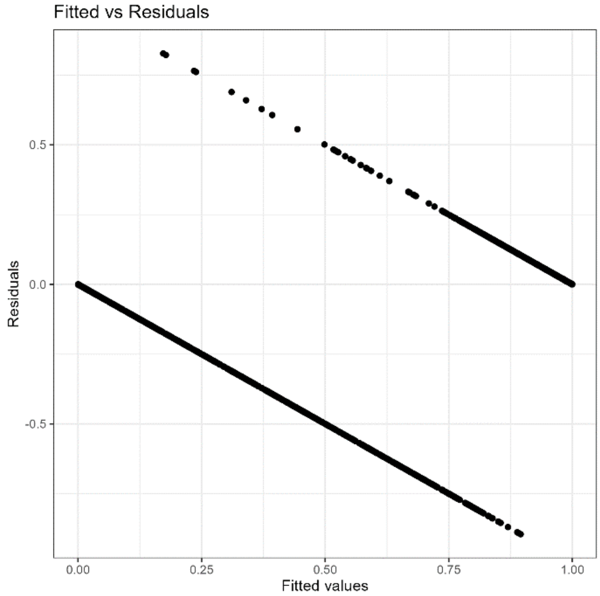
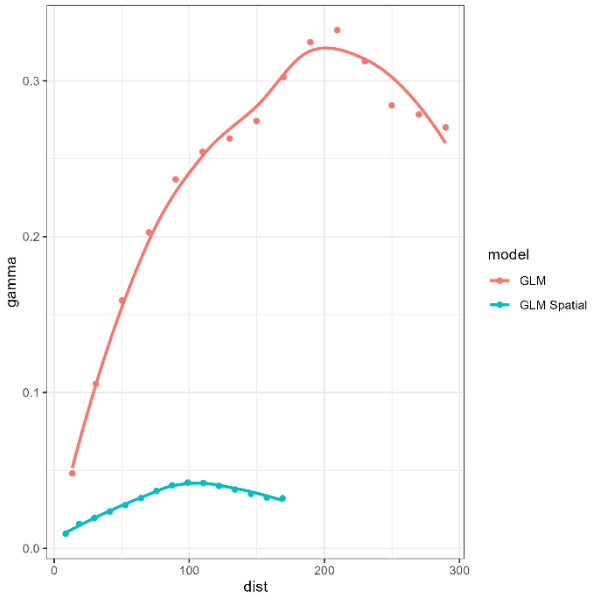


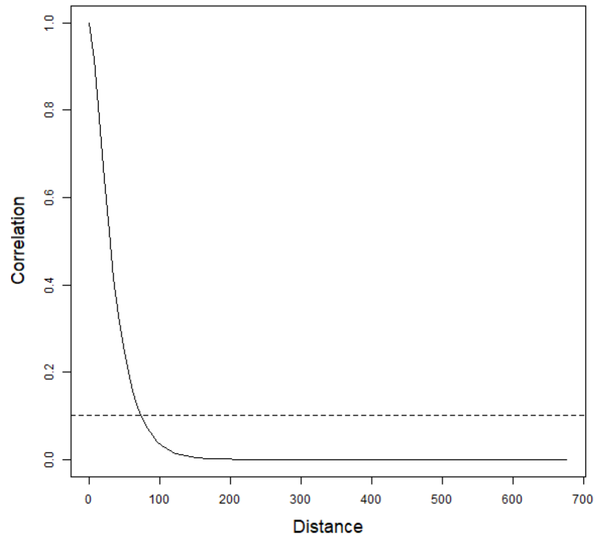
Figure 20: *Nearest neighbours grid based on queen adjacency used for INLA-models accounting for spatial correlation using an areal approach. Cells that are partly in an OWF were excluded.*

Annex 2 Model validation: Large beam trawlers









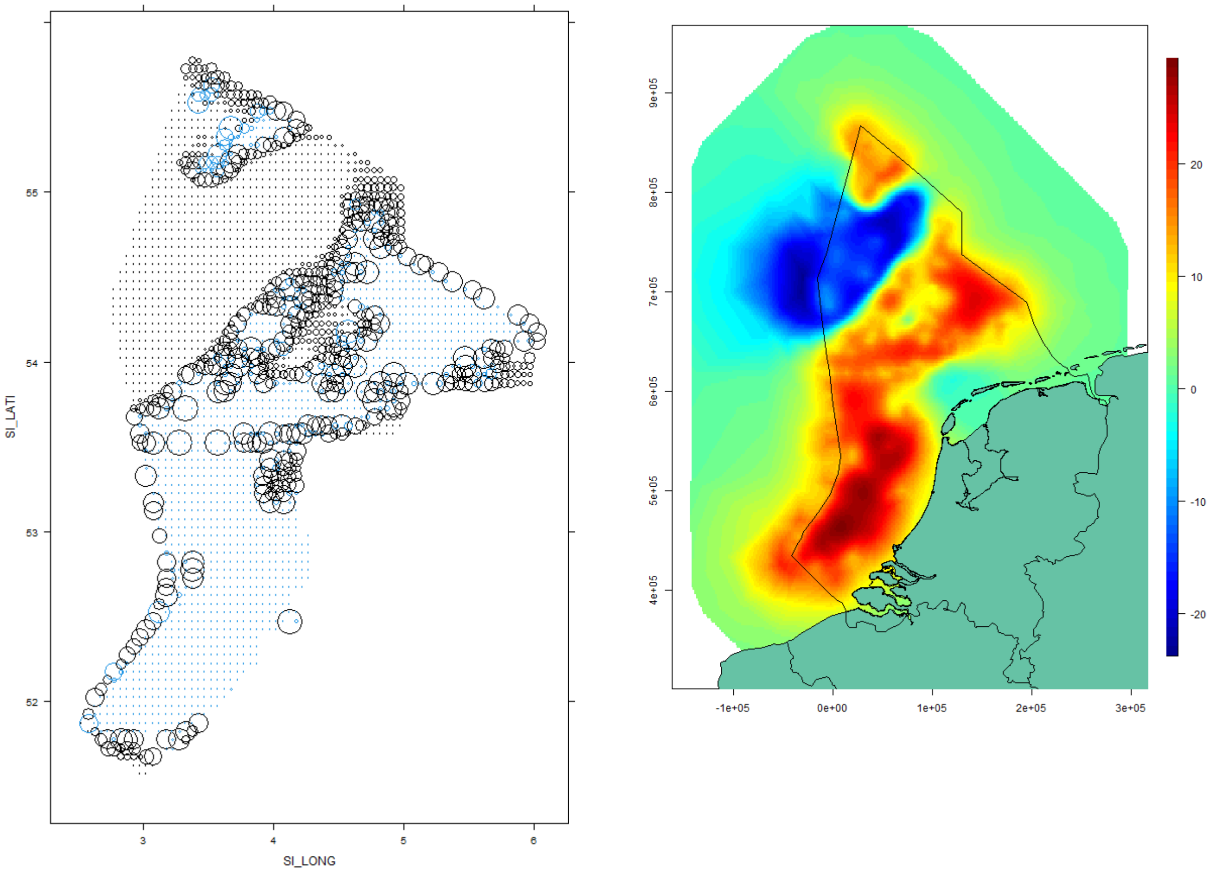
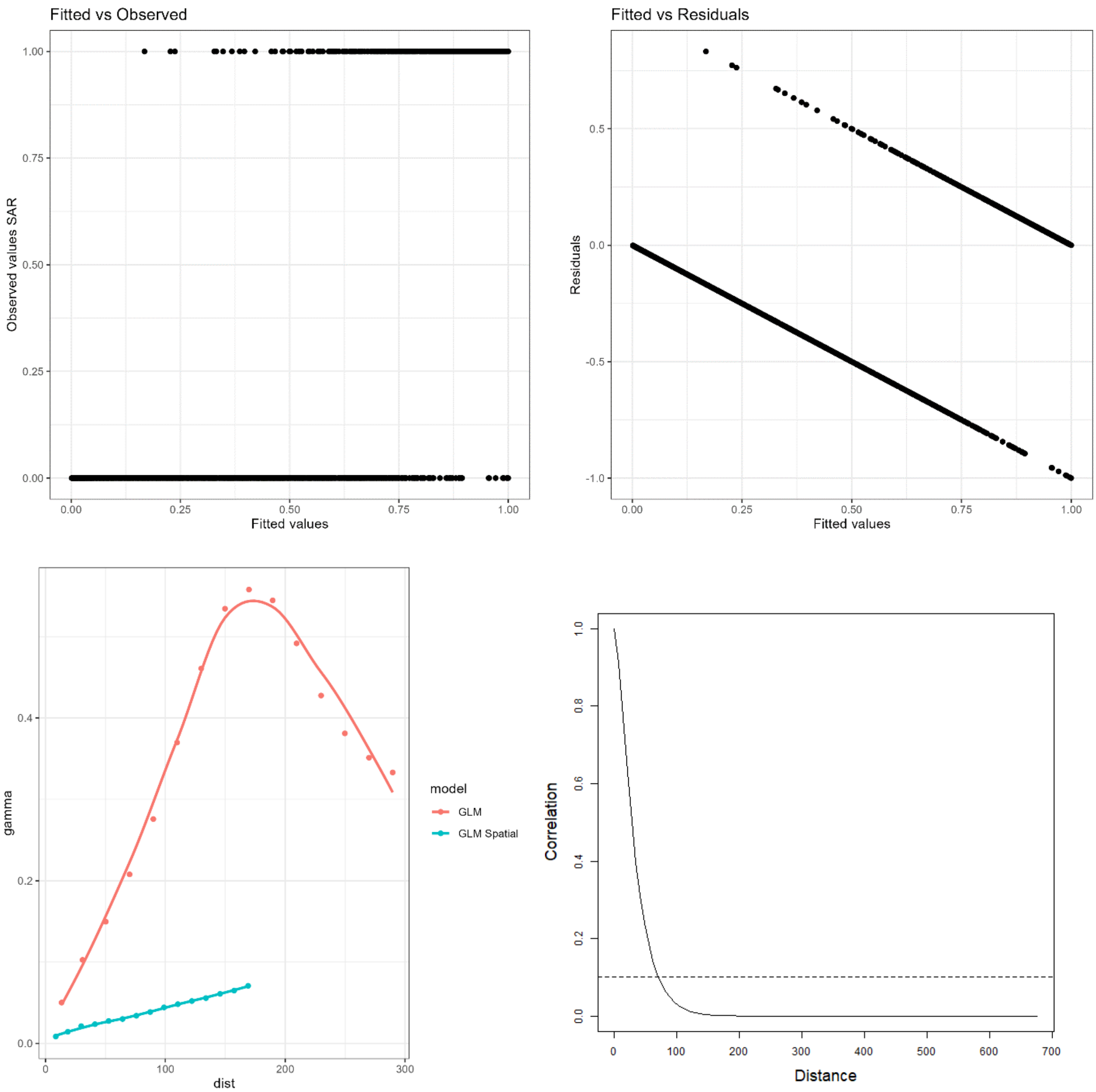
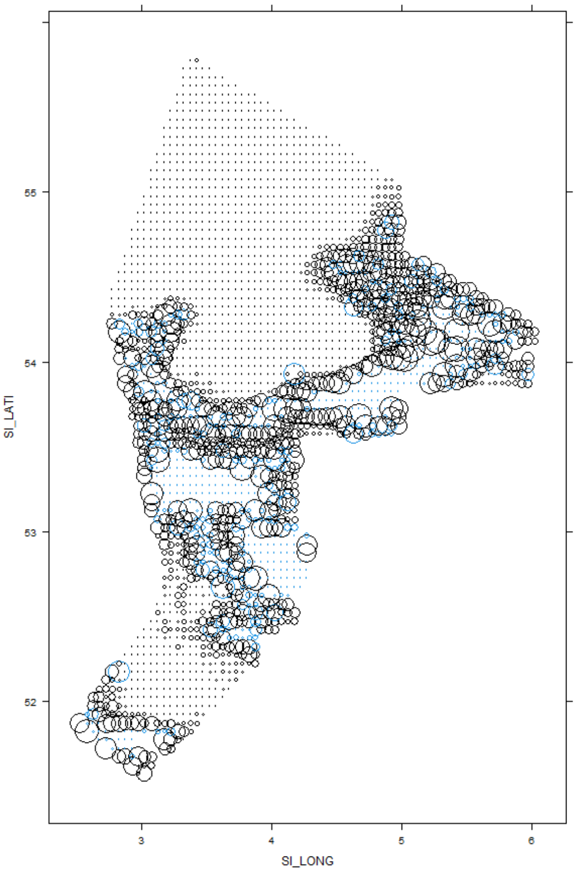


Figure 21: *For large beam trawlers* ***a)*** *Fitted vs. observed.* ***b)*** *Fitted vs. residuals.* ***c)*** *Variograms of the models with and without spatial terms.* ***d)*** *Strength of the spatial correlation across distance.* ***e)*** *Spatial residuals.* ***f)*** *Strength of the spatial effect.*

Annex 4 Model validation: Small beam trawlers





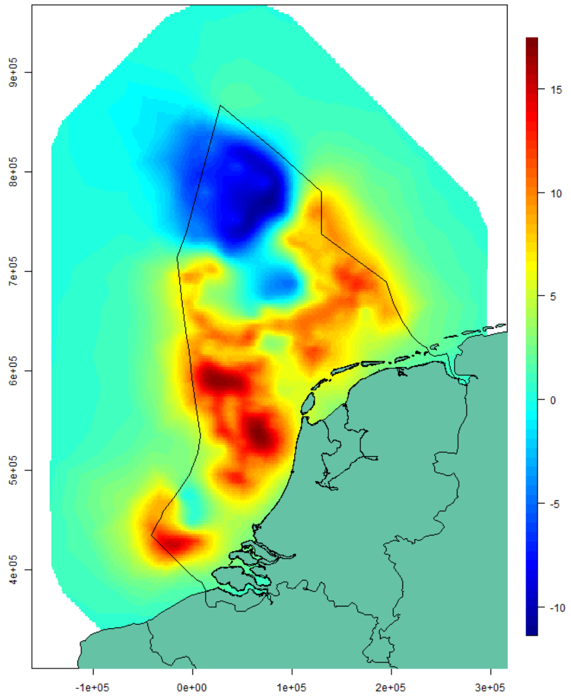
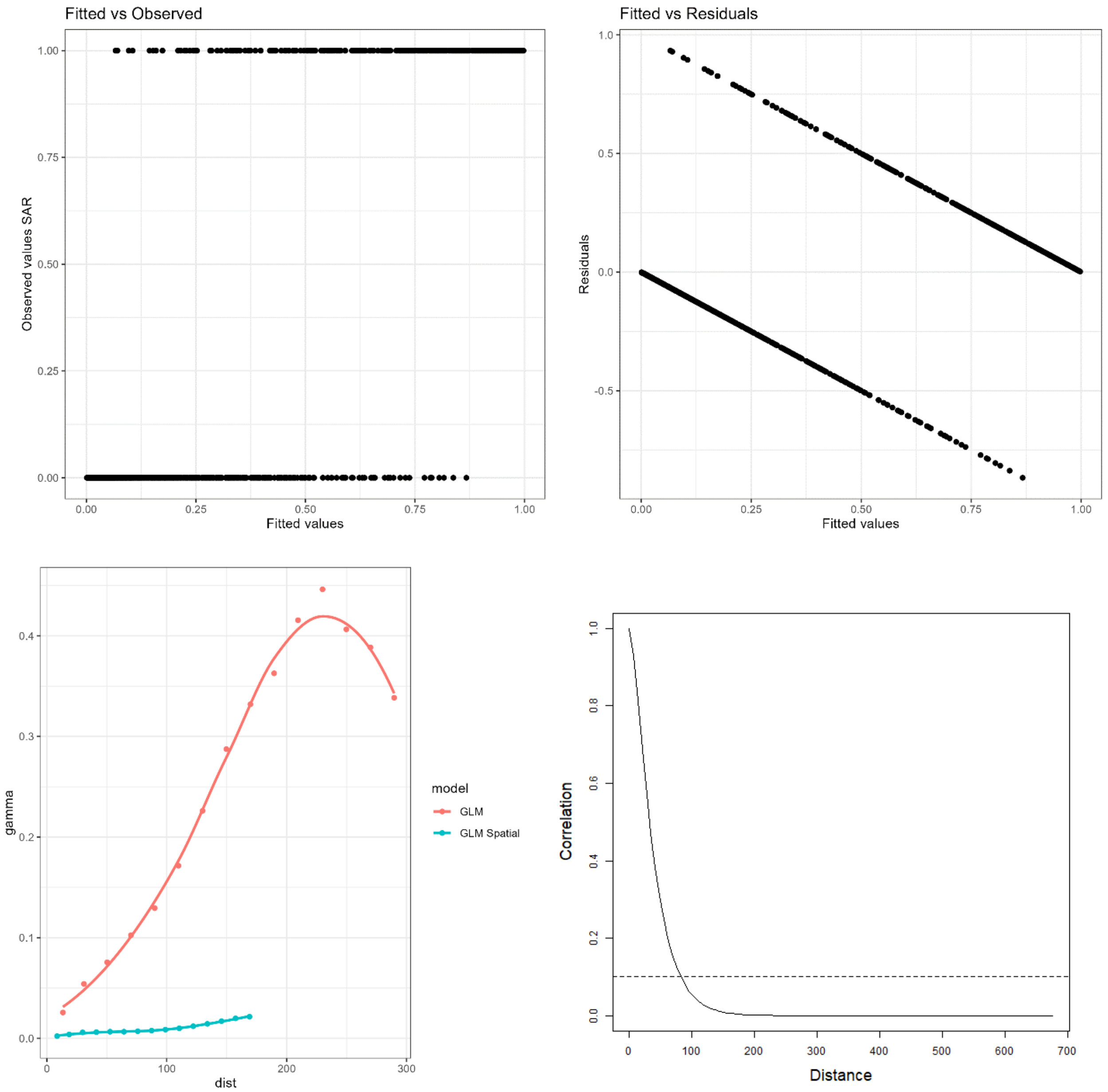


Figure 22: *For small beam trawlers* ***a)*** *Fitted vs. observed.* ***b)*** *Fitted vs. residuals.* ***c)*** *Variograms of the models with and without spatial terms.* ***d)*** *Strength of the spatial correlation across distance.* ***e)*** *Spatial residuals.* ***f)*** *Strength of the spatial effect.*

Annex 5 Model validation: Flyshooters



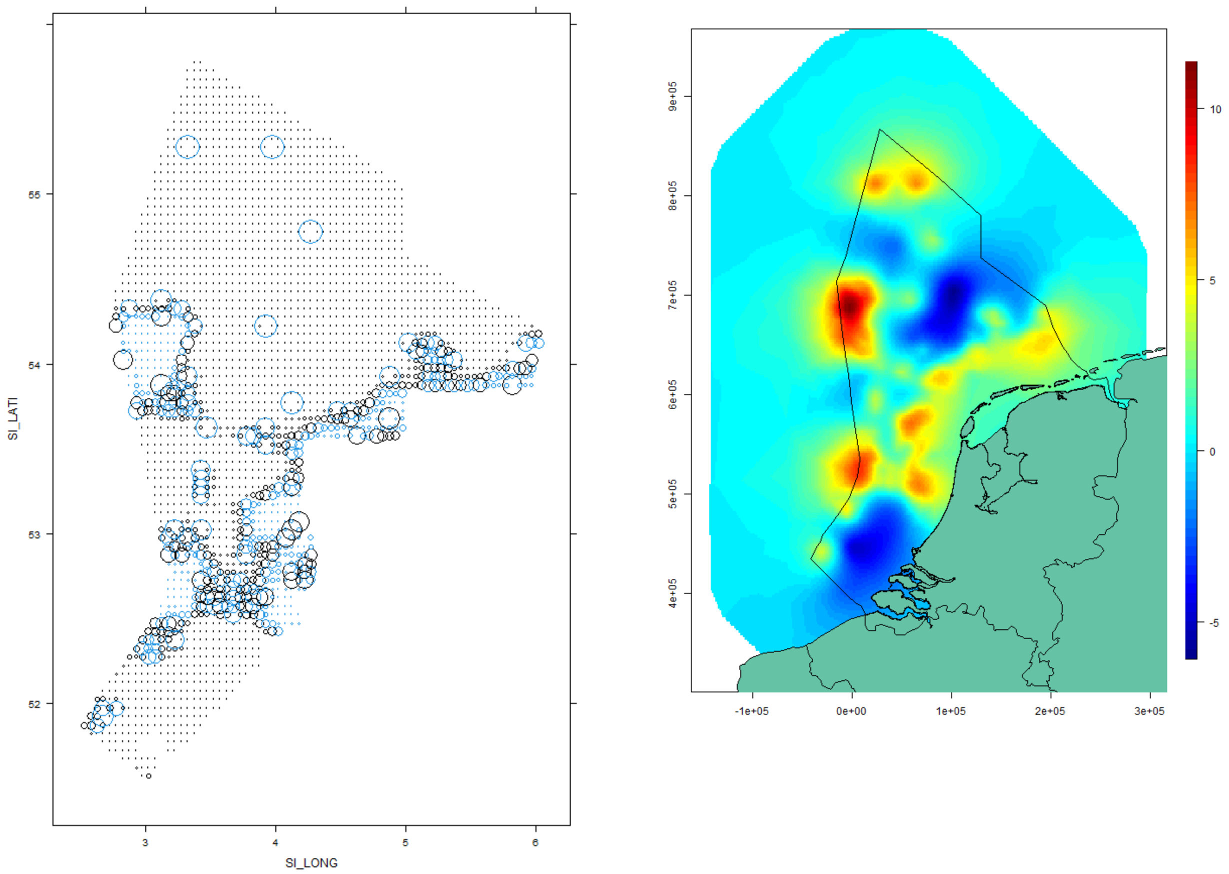
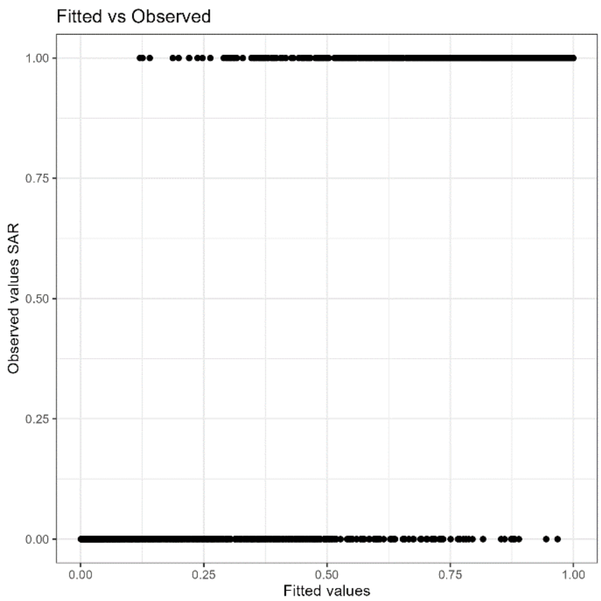
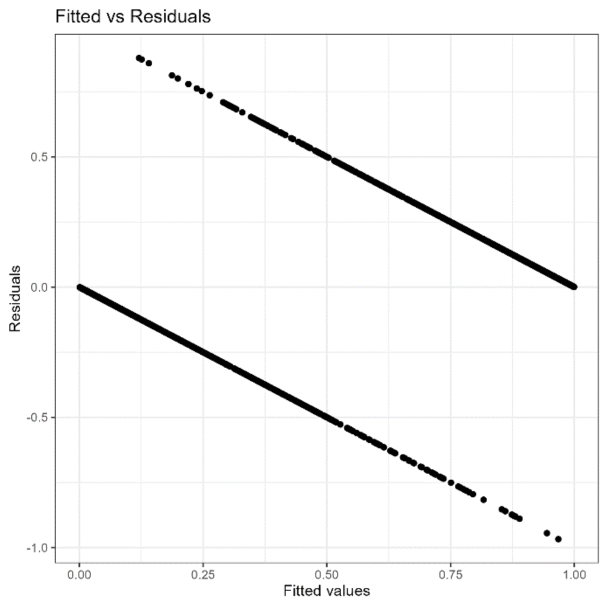
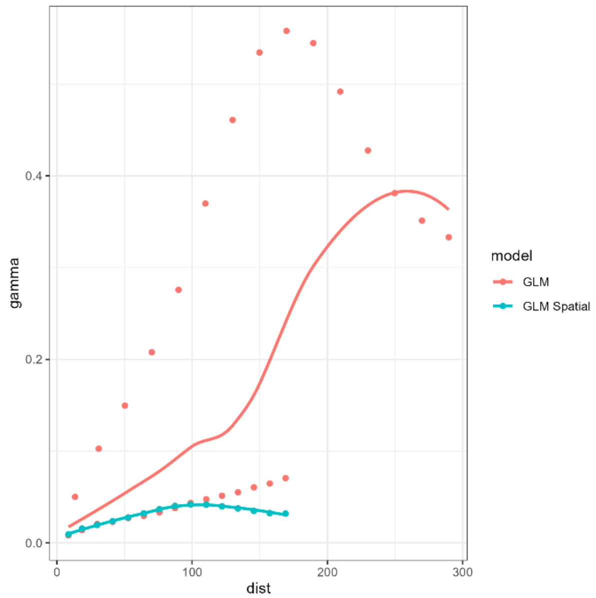


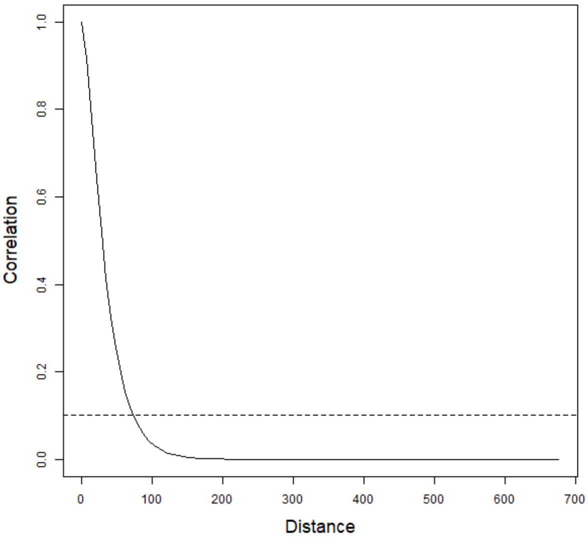
Figure 23: *For flyshooters **a)** Fitted vs. observed. **b)** Fitted vs. residuals. **c)** Variograms of the models with and without spatial terms. **d)** Strength of the spatial correlation across distance. **e)** Spatial residuals. **f)** Strength of the spatial effect.*

Annex 6 Model validation: Bottom otter trawlers









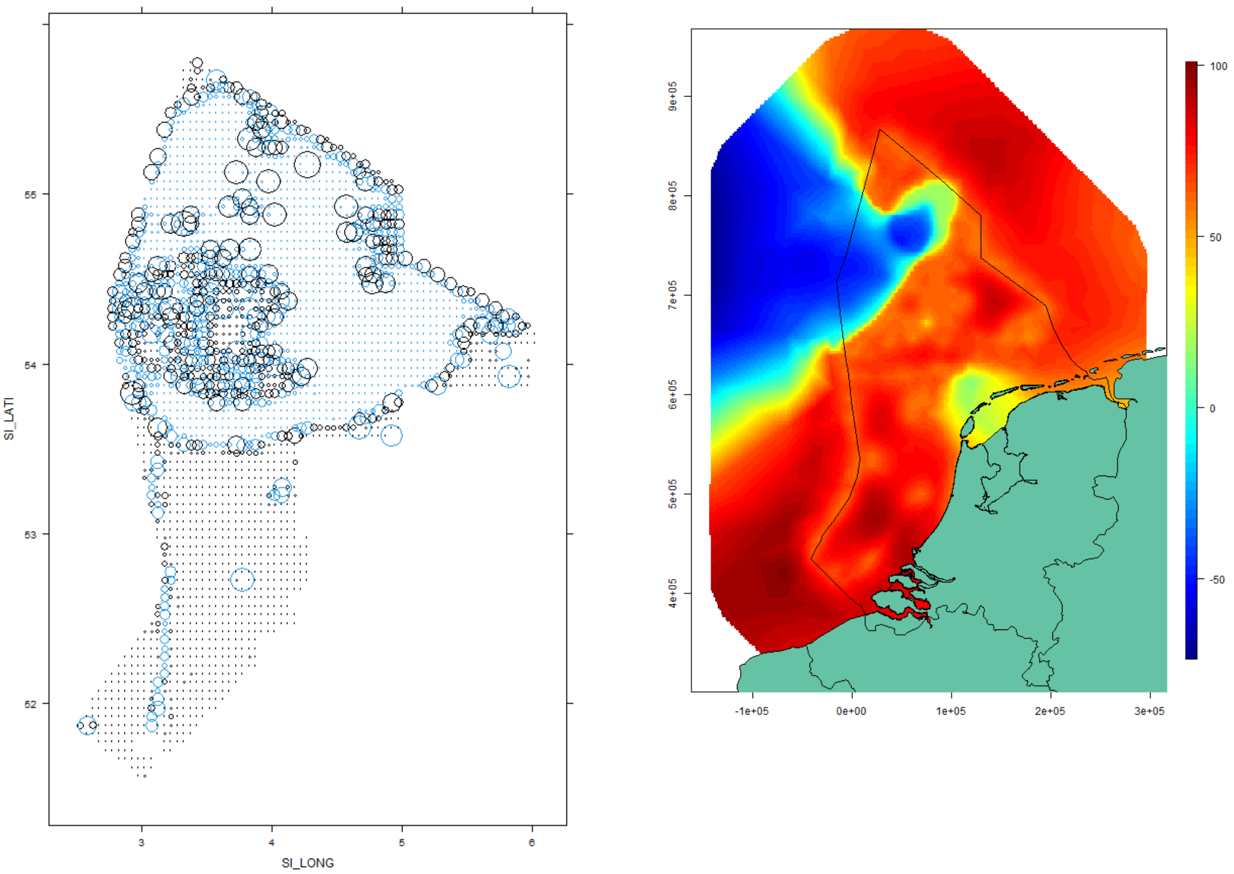
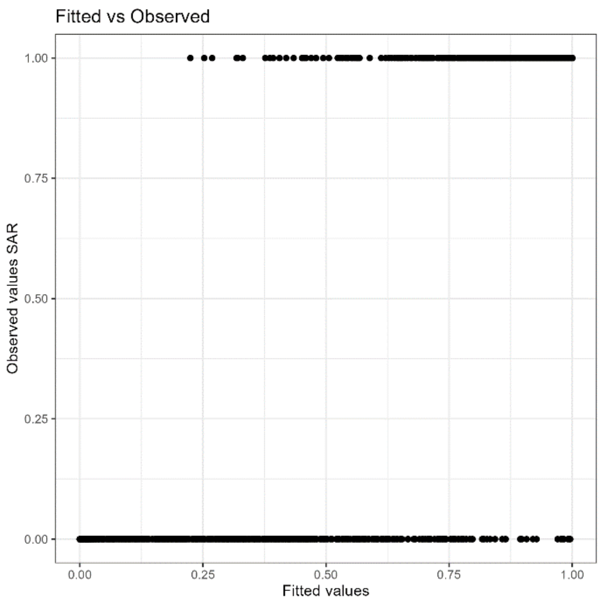
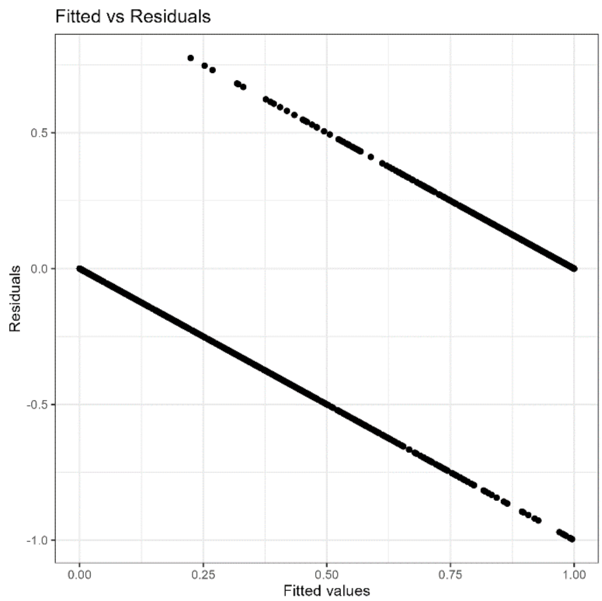
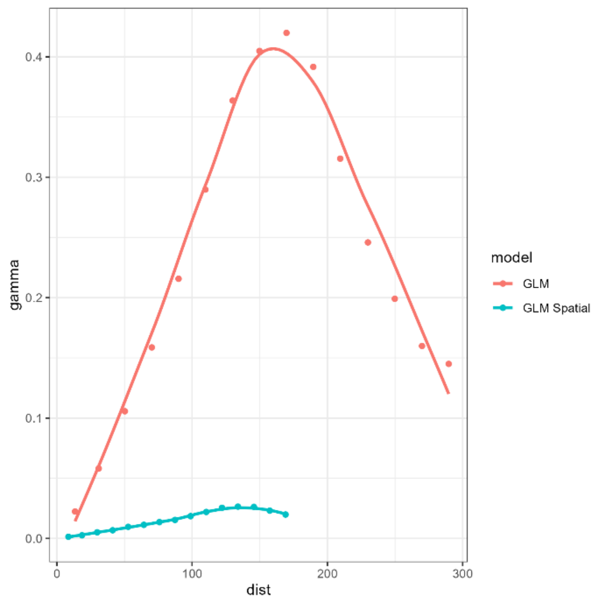


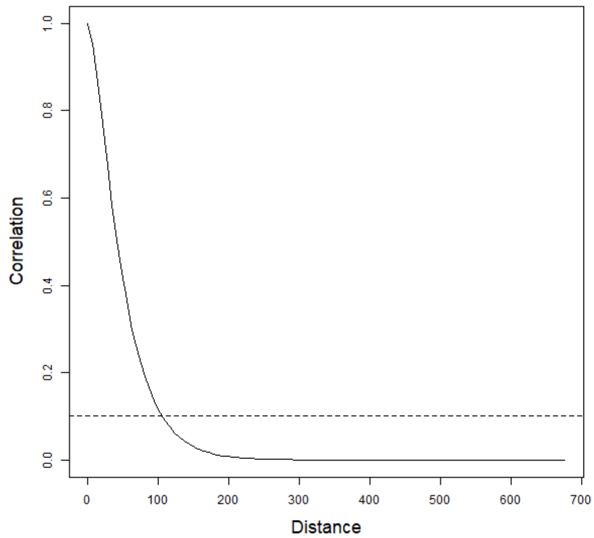
Figure 24: *For bottom otter trawlers* ***a)*** *Fitted vs. observed.* ***b)*** *Fitted vs. residuals.* ***c)*** *Variograms of the models with and without spatial terms.* ***d)*** *Strength of the spatial correlation across distance.* ***e)*** *Spatial residuals.* ***f)*** *Strength of the spatial effect.*

Annex 7 Model validation: Pulse beam trawlers









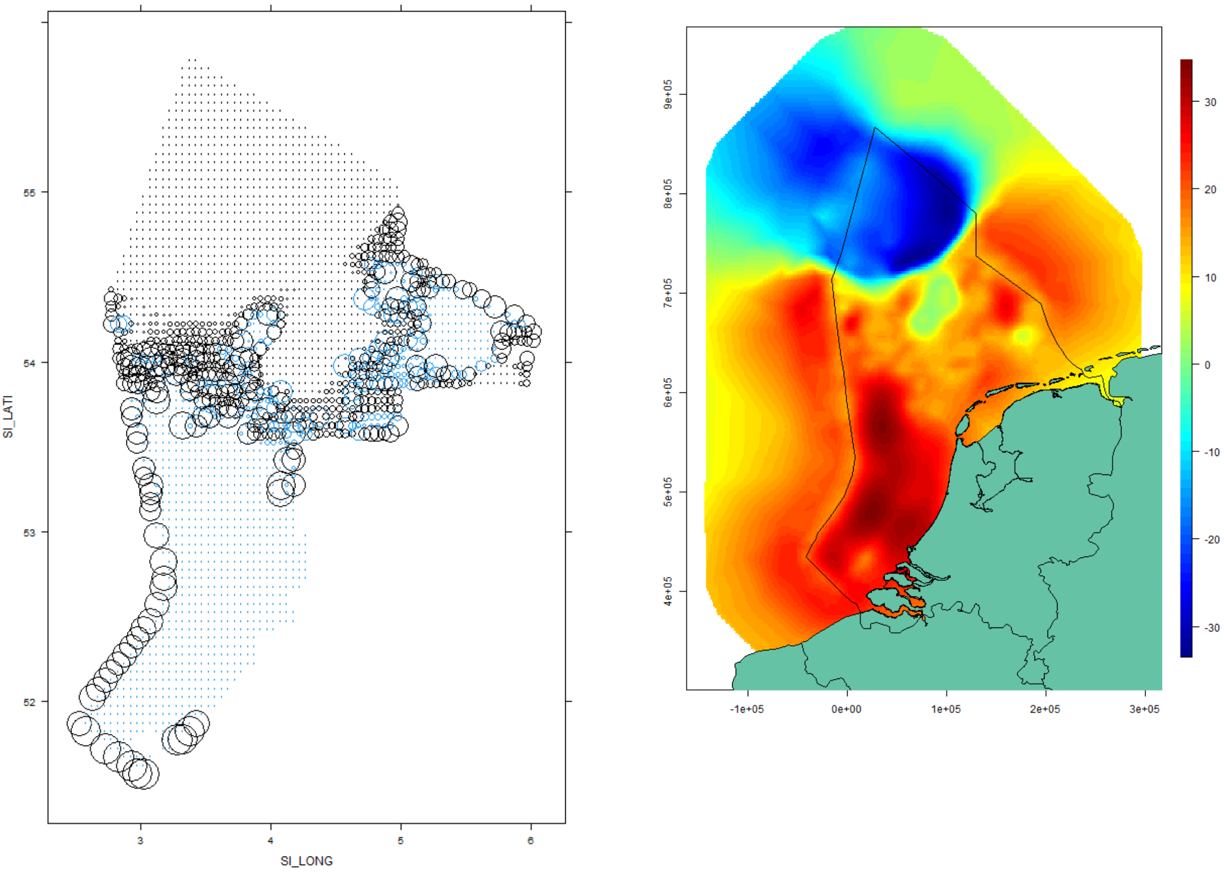


Figure 25: *For pulse beam trawlers* ***a)*** *Fitted vs. observed.* ***b)*** *Fitted vs. residuals.* ***c)*** *Variograms of the models with and without spatial terms.* ***d)*** *Strength of the spatial correlation across distance.* ***e)*** *Spatial residuals.* ***f)*** *Strength of the spatial effect.*

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