Evaluating the potential of underwater television to contribute to marine litter assessments alongside bottom trawling

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Running head: Marine litter estimation from underwater tv

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Abstract

Marine litter presents a global threat to marine ecosystems, human health, and safety. Therefore, it is important to increase our knowledge about spatiotemporal trends of litter in the environment. Bottom trawl surveys provide a practical method for monitoring seafloor litter on the continental shelf, but can have severe negative impacts on the environment. Here we evaluate the potential of an underwater television survey (UWTV) to collect litter density data, and develop model-based indices of litter densities integrating coastal and offshore trawl survey data using geostatistical models. We find that UWTV in its current format may be limited as an alternative to trawling in areas with relatively low densities. There are also clear spatial trends in litter, with the highest densities in near-shores areas currently only included in the national monitoring program. This illustrate the potential of combining data, but also the importance of careful sampling designing for marine litter monitoring.

Keywords: Marine litter, geostatistical models, Gaussian Markov random fields, trawl survey, underwater tv survey, simulation

Introduction

In the Manila declaration from 2012, it was recognized that marine litter poses a worldwide threat not only to marine habitats and species but also to human health and safety (UNEP/GPA 2012). Marine litter, especially plastic litter, has been documented around the world (Barnes *et al.* 2009). In European seas, marine litter has been documented from a variety of physiographic settings, with the highest density recorded in submarine canyons Pham *et al.* (2014). Throughout the years of marine litter research, several pathways have been suggested through which marine macro litter could affect marine organisms such as ingestion, entanglement, toxicity and entrapment (Le *et al.* 2024). Studies demonstrating ingestion of plastic litter by seabirds were already published in the late 1960s (Ryan 2015), and marine litter has been observed to interact with more than 900 species around the world through ingestion or entanglement (Kühn and Van Franeker 2020). Hence, there is an urgent need to monitor trends and identifying spatial hotspots of marine litter (Sandra *et al.* 2023a).

In the Marine Strategic Framework Directive (MSFD), which was established to achieve or maintain Good Environmental Status in EU marine waters, marine litter constitutes number ten out of eleven descriptors and thus mandates that marine litter on sea floor should be monitored (European Union 2008). The International Council for the Exploration of the Sea (ICES) coordinates several scientific trawl surveys gathering data on commercial fish and invertebrate species. In 2011, it was decided to also record litter on a selection of internationally coordinated scientific trawl surveys. Over time, this procedure has been introduced into several different types of trawl surveys. In Sweden, recording of litter on the sea floor is conducted in two internationally coordinated trawl surveys: International Bottom Trawl Survey (IBTS) in Skagerrak and Kattegat and Baltic International Trawl Survey (BITS) in the Baltic Sea. In addition, litter is also registered during the Swedish national Coastal Trawl Survey (CTS), which is conducted along the Swedish west coast and its fjords.

The practice of recording marine litter in trawl surveys has raised concerns due to methodological limitations. For one, the true catchability of marine litter using different fishing gears is not known and recorded litter is most probably an underestimation of the true amounts (O'Donoghue and van Hal 2018). Litter amounts may also be underestimated given that 1) these surveys are primarily conducted far from land, 2) are only performed in areas where it is possible to trawl e.g., on soft bottoms, and 3) do not provide sufficient resolution of spatial information to allow mapping of litter (Madricardo *et al.* 2020). To overcome some of these problems, acoustic and electromagnetic methods have been suggested as alternatives, and are beneficial as they are less destructive or non-destructive and may be conducted in non-trawlable areas (Sandra *et al.* 2023b, Galgani *et al.* 2024).

In Skagerrak and Kattegat, Sweden (Fig 1) monitors the density of Nephrops (*Nephrops norvegicus*) burrows in muddy sediment on a yearly basis to provide fisheries independent data for the ICES stock assessment of Nephrops in the area. Burrows are counted by filming using an underwater television survey system (UWTV) mounted on a benthic sledge that is dragged along the sea floor and video analysis is conducted on land (Dobby *et al.* 2021). If the bottom substrate is rugged, i.e., contains large boulders or coral reefs, the sledge may also be used as a drop-camera positioned above the sea floor. An example of a photo using the UWTV is shown in Figure 1. Large parts of the Skagerrak and Kattegat are covered with the UWTV and some areas are partially overlapping with the IBTS and CTS trawl surveys. This overlap enables a direct comparison of the different methods for detecting litter on the sea floor.

The main aim of this study is to evaluate the capacity of the UWTV to detect and quantify litter, as video-based methods are considered more efficient for estimating true litter densities, and have a smaller environmental footprint. The performance of UWTV is assessed through statistical simulation and with data analysis. We also for the first time integrate offshore trawl data with Swedish coastal trawl survey data to acquire model-based indices of relative density, and to quantify spatiotemporal trends in marine litter.

Methods

Sampling programs

Underwater Television Survey System (UWTV)

Underwater television Survey System (UWTV) is used to gather data for estimation of the abundance of Nephrops (*Nephrops norvegicus*) (Dobby *et al.* 2021). The film from these surveys can also be used to register benthic macrofauna on the sea floor (Sköld 2021). In 2024, during the survey of Nephrops grounds in the Skagerrak and Kattegat, the potential of UWTV to evaluate the presence of litter was tested. In total, 87 UWTV hauls were conducted (Fig 1) during eight days and nights using the Swedish research vessel Svea to evaluate the possibility to register litter in combination with the identification of megafauna. A typical UWTV-haul runs for 10 minutes at 0.8 knots per hour, thus the area covered in one transect is approximately 148 m^2. During the analysis, each litter object within a known field of view (0.80–0.85 meters, indicated by laser dots) was registered and the amount of litter per filmed transect is transformed to litter per km^2 (Fig 2). The registration of litter objects follows the manual produced by the ICES working group for marine litter, WGML (ICES 2022).

International Bottom Trawl Survey (IBTS)

The International Bottom Trawl Survey (IBTS) has been conducted by Sweden in the Skagerrak and Kattegat in the first quarter since the 1980s, and in quarter three since 1991. These surveys are primarily conducted to estimate the number of 0- and 1-year old fish of different commercial species. Surveys and sampling of catch follows the IBTS manual (ICES 2020). The fish are caught using a GOV-trawl (Chalut à Grande Ouverture Verticale), which was originally designed to catch herring *Clupea harengus*. The codend of the GOV-trawl features a 20 mm mesh and the width of the trawl (wing spread) varies somewhat with water depth but is generally between 20 and 25 m (ICES 2020). Each haul is 30 minutes with a speed of 4 knots, and between 40–50 hauls are made each quarter in the Skagerrak, Kattegat and eastern North Sea combined. In addition to measuring and recording different fish and invertebrate species, litter is also recorded since 2012 following the ICES trawling litter manual (ICES 2022). The number of IBTS hauls coinciding with the area covered by UWTV in 2024 varies by year (Fig 1). Only IBTS stations within the area covered by the UWTV in 2024 are included in this analysis. Swedish IBTS data was downloaded from DATRAS (`https://www.ices.dk/data/data-portals/Pages/DATRAS.aspx`) (International Council for the Exploration of the Sea 2024).

Coastal Trawl Survey (CTS)

The coastal trawl survey (CTS) is performed once a year with the purpose of monitoring species composition and recruitment in the benthic fish community in the fjords and along the Swedish west coast (Svensson *et al.* 2023). Since 2013, the survey is completed in quarter three using a fishing trawl called "FiskeTrål Norden" with a 16 mm mesh in the codend and a width of the trawl (wing spread) between 9–14 m depending on depth. Each haul is 30 minutes long and conducted with a speed of 2.5 knots and around 30 hauls are made each year (Fig 1). In addition to measuring and recording different fish and invertebrate species, litter is also recorded since 2015 following IBTS and BITS manuals and more recently the ICES manual from 2022 specifically regarding marine litter (ICES 2015, 2017, 2022).

Data analysis

Simulation

We used simulation testing to evaluate the performance of the UWTV to sample marine litter. The approach consists of the following steps:

1. Generate a 1000×1000 m spatial grid.
2. For each litter density scenario, randomly distribute litter objects over the grid to get values for presence or absence of litter for each m². Only one litter object is allowed per m². A hypothetical smaller grid is shown as an example in Fig 3.
3. For each replicate and litter density scenario, apply a random sample representing the UWTV-method. A single random sample is made up of 148 consecutive cells distributed horizontally

or vertically over the grid (start location determined randomly), each cell is 1 m^2 and this is intended to mimic a UWTV transect which on average is 148 m^2.

4. Repeat step 3 for each sample size scenario (we chose 50, 100, 200, 500, 1000 transects, each with a size of 148m^2). These sample size scenarios are intended to both include relevant sample sizes (in this study 87 transects were filmed) and also more unrealistic examples such as 1000 transects. For each litter density and each sample size scenario transects were distributed 1000 times.

From the simulation experiment, we calculated: 1) the proportion of replicates (across the 1000 replicates) with empty 0 litter recorded during UWTV transects, for each litter density scenario and each sample size, 2) the mean average litter density across replicates, by litter density and sample size. R functions for the simulation experiment were developed partly using the large language model Claude (Anthropic 2024).

Statistical modelling

To estimate annual trends in relative litter abundance, we used geostatistical generalized linear mixed models (GLMMs), similar to those used in species distribution modelling. Since litter density data contain zeroes and positive continuous observations, we used a delta (hurdle) model, with a binomial and a Gamma component. This was fit as a so called "Poisson-link" delta model, which has the flexibility of a classic delta model (Aitchison 1955), but avoids the assumption that the two components are statistically independent (Thorson 2018). To account for spatial structure in the data, we included spatial random effects in the form of Gaussian Markov random fields (GMRFs) using the SPDE approach (Lindgren *et al.* 2011). The full model for a given component can be written as:

$$
\begin{aligned}
\mathbb{E}[y_{\boldsymbol{s},t}] &= \mu_{\boldsymbol{s},t}, && (1)\\
\mu_{\boldsymbol{s},t} &= f^{-1}\left(\boldsymbol{X}_{\boldsymbol{s},t}\boldsymbol{\beta}\right), && (2)\\
\omega_{\boldsymbol{s}} &\sim \mathrm{MVN}(\mathbf{0}, \Sigma_{\omega}), && (3)\\
\boldsymbol{\delta}_{t=1} &\sim \mathrm{MVNormal}(\mathbf{0}, \Sigma_{\epsilon}), && (4)\\
\boldsymbol{\delta}_{t>1} &= \rho\boldsymbol{\delta}_{t-1} + \sqrt{1-\rho^2}\boldsymbol{\epsilon_t}, \boldsymbol{\epsilon_t} \sim \mathrm{MVNormal}\left(\mathbf{0}, \Sigma_{\epsilon}\right), && (5)
\end{aligned}
$$

where $y_{\boldsymbol{s},t}$ is the response variable (number of litter items per km²) in location $\boldsymbol{s}$ at time t, μ is the mean, f^{-1} is the inverse link function, $\boldsymbol{X}$ is the design matrix for fixed effects with corresponding coefficients β. We included only a categorical effect of survey to account for different catchability of the gear used in the two surveys CTS and IBTS as fixed effects. This because there is a difference in the average densities between the surveys, and we want to test if this is due to gear or sampling area (Fig S3 and S4). We also added independent intercepts for each year, following common practices in fish stock index standardization (Thorson 2019, Anderson *et al.* 2024a). This corresponds to the assumption that marine litter is being replaced and added every year. Our initial aim was to include also the UWTV data in this model, however that was not possible since no litter was detected in 2024 (see section *Results*). Since we do not know which processes and variables give rise to spatial patterns in litter data, we rely on latent variables to model spatial patterns in the data. These are included as spatial and spatiotemporal random effects ($\omega_{\boldsymbol{s}}$ and $\epsilon_{\boldsymbol{s}}$, respectively), assumed drawn from a Gaussian Markov random field (GMRFs) with covariance matrices Σ_{ω} and Σ_{ϵ} constrained by anisotropic Matérn covariances function (Rue *et al.* 2009). Spatial random effects correspond to spatially structured variables that are constant over time (e.g., currents, depth, bathymetric slope), and spatiotemporal random effects are allowed to vary each year (e.g., weather). Anisotropy means the spatial correlations can depend on direction, which is fitting in this case since we are modelling coastal data and spatial patterns likely change more going from near shore to offshore than up and down the coast (Fig S1). Initial exploration revealed strong correlation between subsequent spatiotemporal random fields. Hence we opted to model these fields as AR1 (first-order autoregressive), where ρ is the correlation coefficient between subsequent random fields. This also helps informing predictions in years when samples were scarce in place (e.g., 2012 in Fig 1), compared to if we had modelled them as independent each year. The Stochastic Partial Differential Equation (SPDE) approach (Lindgren *et al.* 2011) requires piece-wise linear basis functions defined by a triangulated mesh. We defined this mesh using triangles with a cutoff distance (minimum distance between vertices) of 3 km and kept all other arguments in the R-function `fm_rcdt_2d_inla()` in the package `fmesher` (Lindgren 2023) at their defaults (Fig S1).

Based on exploratory data analysis, we consider three alternative models: 1) only spatial random effects 2) only spatiotemporal random effects, and 3) spatial random effects for the binomial model and spatiotemporal random effects for the Gamma model. We use marginal AIC to select the more parsimonious model.

To evaluate trends in average litter densities, we made conditional predictions for each independent year. Next, fit a model to the annual estimates, using the inverse of the CV for each year as weights to incorporate the varying uncertainty in the annual estimates.

We fit the models using the R (version 4.3.2) (R Core Team 2024) package `sdmTMB` (Anderson *et al.* 2024b) (version 0.6.0.9015). The `sdmTMB` package uses automatic differentiation and the Laplace approximation from the R package `TMB` (Kristensen *et al.* 2016), along with sparse matrix structures constructed with the SPDE method (Lindgren *et al.* 2011) using the R package `fmesher` (Lindgren 2023). Parameter estimation was performed via maximum marginal likelihood using the `nlminb` (R Core Team 2024) non-linear minimizer. We ensured the models converged by verifying that the Hessian matrix was positive definite, that the maximum absolute log-likelihood gradient for the fixed effects was less than 0.001, and that no random field marginal standard deviation was larger than 0.01. To ensure that the model was consistent with the observed data we visually inspected simulated quantile residuals (Dunn and Smyth 1996, Gelman and Hill 2006), calculated using the R package `DHARMa` (Hartig 2022) (Fig S2).

Results

In the simulation experiment we find that across 1000 replicates for each combination of litter density (6 levels of known densities, ranging from 10–20000 items per km^2) and sample sizes (6 levels of sample sizes where one sample is one transect), it is evident that the UWTV with its current sampling size and area swept is inadequate to sample litter at these *relatively* low densities. For example, when the density is 10 items per km^2, the percentage of replicates of the experiment where the survey did not catch a single litter item is as high as 91% when the sample size is 50, and 84% when the sample size is 100 (the number of hauls in the 2024 UWTV survey was 87) (Fig 4A). Moreover, while the overall mean across all 1000 replicates was close to the true mean (pink points in Fig 4A), individual replicates either estimate 0 litter density or severely overestimate the true mean by a factor of >10 in some cases. That is because if a litter item is recorded (a 10% probability), the density will be very high given the small area sampled. Similarly, when the true litter density is 50 (Fig 4B) and the sample size is 100, single replicates estimate litter densities range from 0 to ≈250 per km^2, where the higher value is an overestimation by a factor 5. The simulation experiment shows that with litter densities of 50 (comparable to the trawl surveys), it would require a minimum of 500 hauls to have a 97% probability of observing a minimum of a single litter item across 1000 iterations (Fig 4C). At higher litter densities, the number of hauls needed to have similar values is lower. At litter densities of 1000 per km^2, all replicates find litter.

From the spatiotemporal models fitted to trawl survey data, we find that the marginal AIC supported the model where both components had the same random effect structure (spatiotemporal random effects for both the binomial and Gamma components), although the model with a spatial random field for the binomial model and a spatiotemporal field for the Gamma model are nearly indistinguishable in terms of marginal AIC (Table S1). This is also evident in that the spatiotemporal random fields are more similar from year to year in the binomial model than for the Gamma model (Fig 5). The correlation between consecutive spatiotemporal random fields (ρ) was very high (0.99) in the binomial model, and relatively high in the Gamma model (0.75) (Fig 5). The random effects in addition show a clear directionality in the spatial correlation, meaning the range where correlation effectively disappears is longer going along the coast (northwest to southeast) than from coastal to offshore (Figs 5 and S1). This distance is larger for the binomial model, further illustrating that the presence of litter largely depends on the distance to the coast. There is no clear statistical difference between the survey intercepts, meaning the differences in mean catch is due to the coastal trawl survey (CTS) sampling in higher density areas (Figs S3 and S4).

The same spatial pattern is also evident in the combined model predictions (Fig 6), and here it is also clear there are some fluctuations over time with the highest densities in the first year of the time series (Fig 7). Predictions from the model shows that average litter densities ranged between 5 [95% CI: 0.86–30.3]–78 [95% CI: 20.4–300] items per km², with a mean of 34 across all years (conditional predictions for year omitting the random effects). The linear effect of year from the weighted regression on annual litter densities is negative (decline in density by -2.09 per year), but the confidence interval of the slope overlaps 0 [95% CI: -4.17–0.0039] (Fig 7).

The UWTV survey did not record a single litter item in the 87 UWTV transects that were made in 2024. While we do not know the true litter density in the area sampled by the UWTV, and that the simulation study is a simplification of reality, the simulation does indicate that under probably densities (approximately 100 items per km²), there is a 22% chance of that no litter are observed in 100 transects (Fig 4C). When no successes (litter presences) are observed in a series of binomial trials, one can estimate the upper confidence interval of probabilities of occurrence using the "rule of three" (Jovanovic and Levy 1997, McCracken and Looney 2017). The rule of three is a simple method for sample sizes larger than 30 that can be used to estimate the upper confidence interval for the probability of presence by $3/n$ (99% confidence interval is given by $4.61/n$) (Jovanovic and Levy 1997), where n is the number of trials (transects in this case). With $n = 87$, we find that the upper 95% confidence interval for probability of presence of litter in a given transect is between 0 and 0.034 (or 0 and 0.053 for the 99% confidence interval) (Fig 8A). Moreover, when a litter object is recorded by the UWTV, the estimated density will be extremely high in that specific transect (as we showed also in the simulation study), because the "swept area" is small. In 87 transects, the expectation for the upper 95% confidence interval for the number of transects with litter is $0.034 \times 87 \approx 3$. The average upper 95% confidence interval of litter density across those 87 transects is 233 items per km² (84 transects recording 0 density and three a density of 6757 items per km² [1/(6757/1000000)]) (Fig 8B). However, this is a simplification, because the UWTV could in reality record more than one litter item per transect. To further provide insight into how the confidence interval behaves under different scenarios where few transects contain litter, we calculated confidence intervals for varying number of transects with litter and varying sampling sizes using the Agresti-Coull method (Brown *et al.* 2001), implemented in the R package `DescTools` (Signorell 2024) (Fig S5).

Discussion

In this study, we used data and simulation experiments to determine the ability of Underwater TV (UWTV) to replace the more destructive trawl survey methodology for collecting data. We then applied geostatistical models to the trawl data to determine levels, trends, and spatiotemporal patterns in marine litter. We conclude that the UWTV sampling is not suitable for contributing to monitoring of marine litter in its current form. This is because it did not record any litter, likely due to the UWTV's relatively small "swept area" compared to a trawl, combined with its use in offshore areas where our spatiotemporal models showed lower litter densities compared to coastal regions. While we can still calculate upper confidence intervals for probability of occurrence, we cannot provide any expected values of litter densities, which is the aim of the survey and needed for monitoring trends in estimated litter densities. Current trawl surveys also provide large amounts of data on different categories of litter found on the seafloor. With zero or few findings in the current UWTV setup this information is lost. Important to emphasize is also that the current UWTV setup has a lower geographical coverage of Skagerrak, Kattegat and the North Sea compared to the IBTS trawl survey.

For the UWTV monitoring to contribute to estimates of litter densities and potentially replace some or all of the trawling, some modifications to the design could be made. For instance, the transect length could be increased to cover larger areas in a given tow. However, this would also increase costs as more material needs to be processed. Probably the geographical coverage of the UWTV survey would need to be expanded too in order to replace the IBTS data.

Our model based on two surveys, showing similar results in the overlapping area, provides strong evidence that litter densities are higher closer to shore. This calls for an expansion of the UWTV survey towards coastal areas if one believes that filming the seafloor is better to get a true estimate of amounts of litter (recall it does not have the same issues with catchability as a trawl haul). Preferably the UWTV should be conducted in regions that have not been previously sampled in the CTS as there is a risk that yearly trawling along the same transects have removed litter. In the future, trends in marine litter may stem from multiple data sources, and in that case a model similar to the one used here could be used to integrate those different datasets and is one of the strengths of model-based trends (Yalcin *et al.* 2023). Using multiple data sources that complement each other (e.g., in terms of location of sampling) can increase accuracy and reduce uncertainty in annual indices (Thompson *et al.* 2023).

The spatiotemporal model used here is largely inspired by species distribution models and models used to create model-based indices of abundance in fisheries science (Thorson *et al.* 2015). However, there are some interesting differences. The spatial distribution of species results from the interplay between environmental and ecological processes (competition, predation) (Elith and Leathwick 2009, Ward *et al.* 2024). For instance, the strong association species may have to certain environmental variables (e.g., depth or temperatures) can be used to improve the underlying spatiotemporal model and thereby indices (Thorson *et al.* 2015, Yalcin *et al.* 2023). In contrast, unlike biological organisms, the distribution of litter is likely more stochastic. The processes determining the dynamics of litter movements are many and which are most influential are largely unknown and likely depend on the material of the litter, where plastics may be more easily transported with currents while more dense litter or larger object are not removed easily (Van Sebille *et al.* 2020, Canals *et al.* 2021). There could also be areas acting as sinks, e.g., shelfs and deep sea areas (Harris *et al.* 2021). Hence, it is difficult to *a priori* know which covariates to include in a model, and more research on this is needed to improve models. In this study, we instead of covariates used an approach based on Gaussian Markow random fields. In similar applications (Barry *et al.*

2022, HELCOM 2023), researchers have used similar models with smoothers of latitude and longitude, and different options for modelling the temporal trends (linear, smooth, independent means). Overall these are similar models, but a benefit of using our approach is that it can determine the range at which spatial correlation disappears (and the directionality of it). While we have only applied this to a case study on the Swedish west coast, we believe it could be applied in general for estimating marine litter levels.

The clear spatial trends in marine litter highlight the important question for managers about which areas to consider for monitoring and which litter density thresholds to use for status classification. For instance, currently the offshore (IBTS) survey is used for status determination and with that relatively low densities are measured. However, as we show, the densities are much higher near shore, and near shore areas may be more sensitive to litter than offshore habitats. The results in this study indicate that near shore monitoring should be included in the status classification and also that near shore monitoring data might benefit from the addition of UWTV stations.

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Data Availability Statement:

Code and data to reproduce the results are available on GitHub (`https://github.com/maxlindmark/uwtw`) and will be deposited on Zenodo upon publication.

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Figures

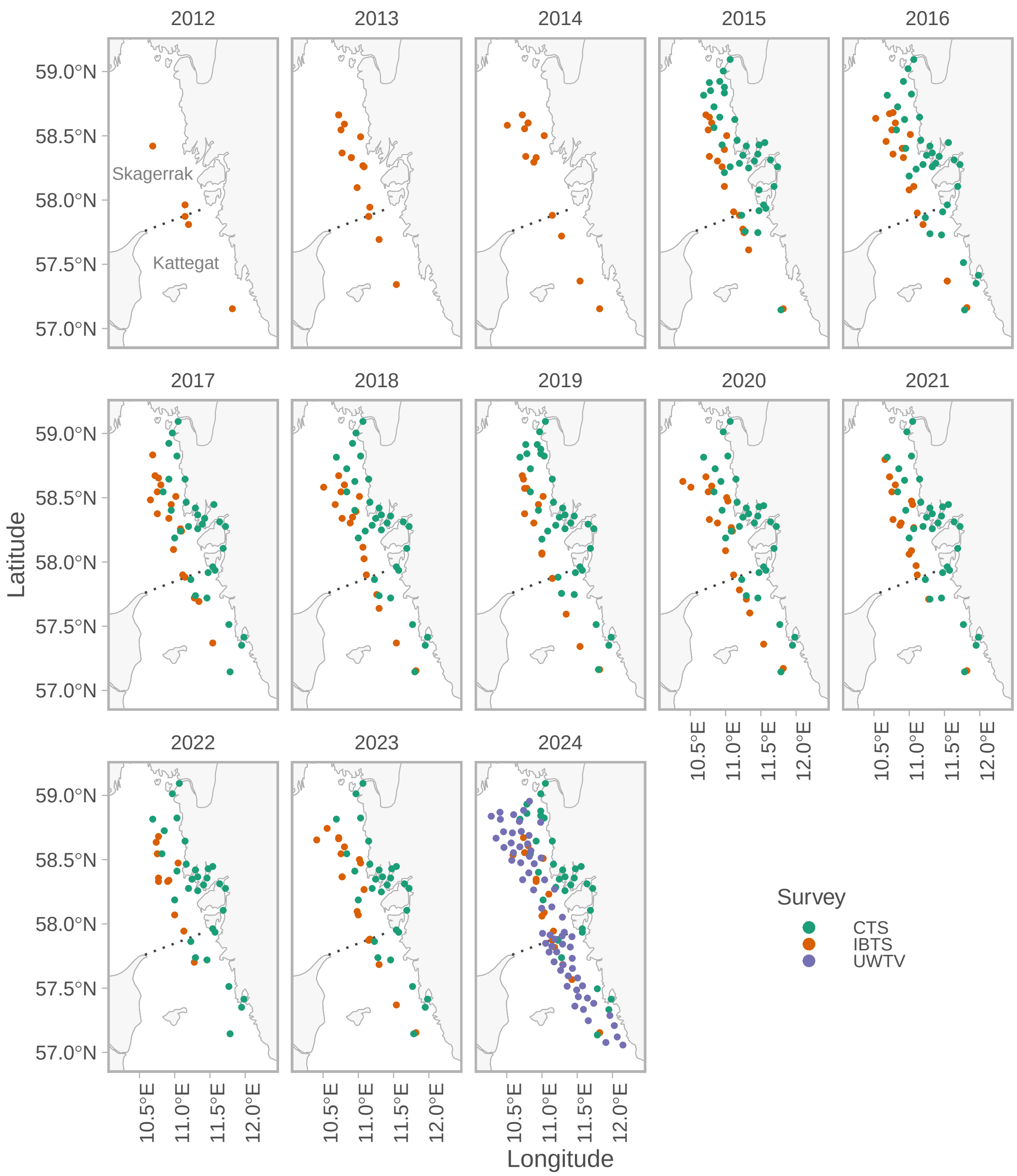

Figure 1: Sampling locations over time. The Coastal Trawl Survey (CTS) is depicted in green, the International Bottom Trawl Survey (IBTS) in orange, and the Underwater TV survey (UWTV) in purple. The IBTS is conducted in Kattegat, Skagerrak and parts of the North Sea but in this study only stations within the area covered by the UWTV survey in 2024 are included (see Fig S3). The dotted line in the topleft panel depicts the Skagerrak/Kattegat border.

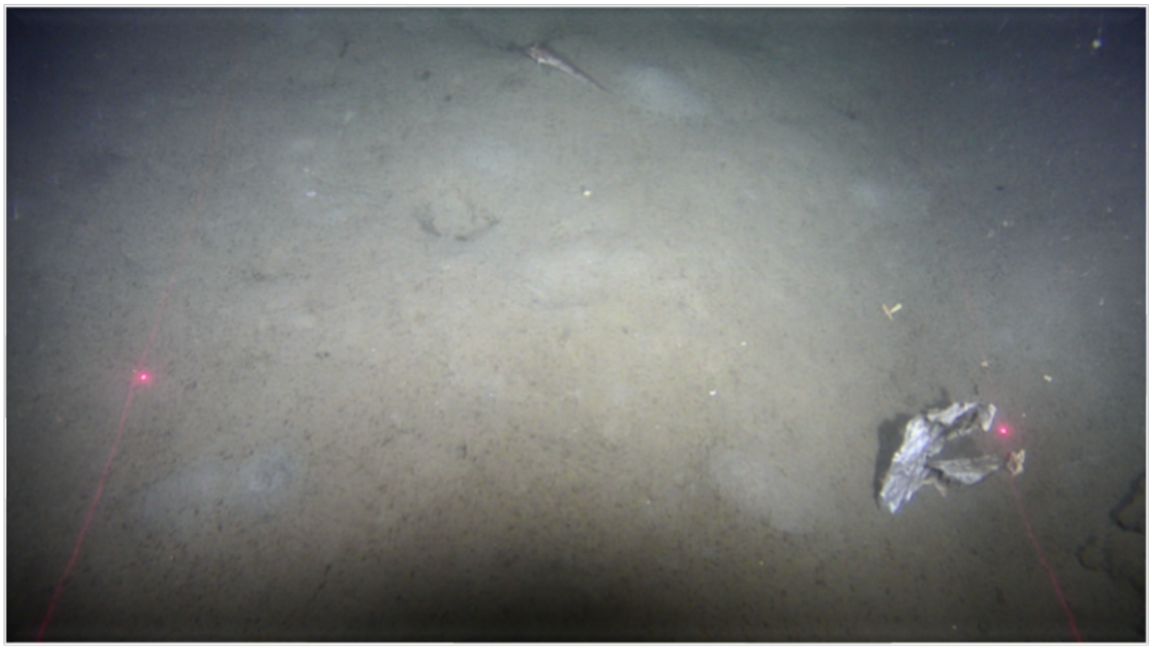

Figure 2: Image of the sea floor with a litter object taken from a transect filmed with an UWTV in 2023 in ICES subarea 4 (Kattegat). The distance between red laser dots is approximately 80 cm. Due to turbidity, it is difficult to say if the object is A2=plastic sheet or A3=plastic bag according to the Ices manual (ICES 2022). Foto SLU-Aqua, P. Jonsson.

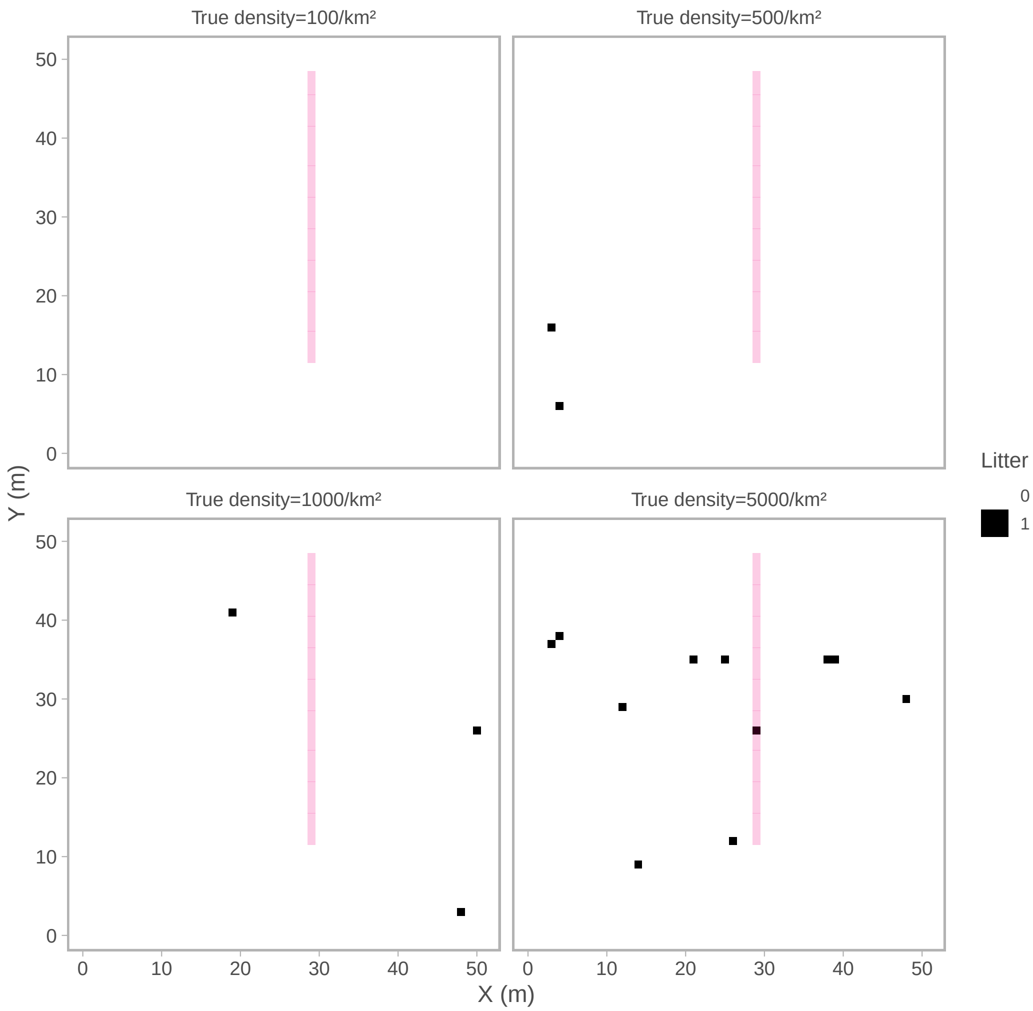

Figure 3: Example of a single replicate of a randomly filled spatial grid with known litter densities (100, 500, 1000, 5000 items per km² in this case). Black grid cells indicate presence of litter. The pink line corresponds to a randomly placed straight UWTV transect. For visualization purposes, we have used relatively high litter densities, zoomed in on a 50×50 m portion of the full grid, and divided the transect by 4 (hence, in the simulation experiment, the UWTV transect would be 4 times as long).

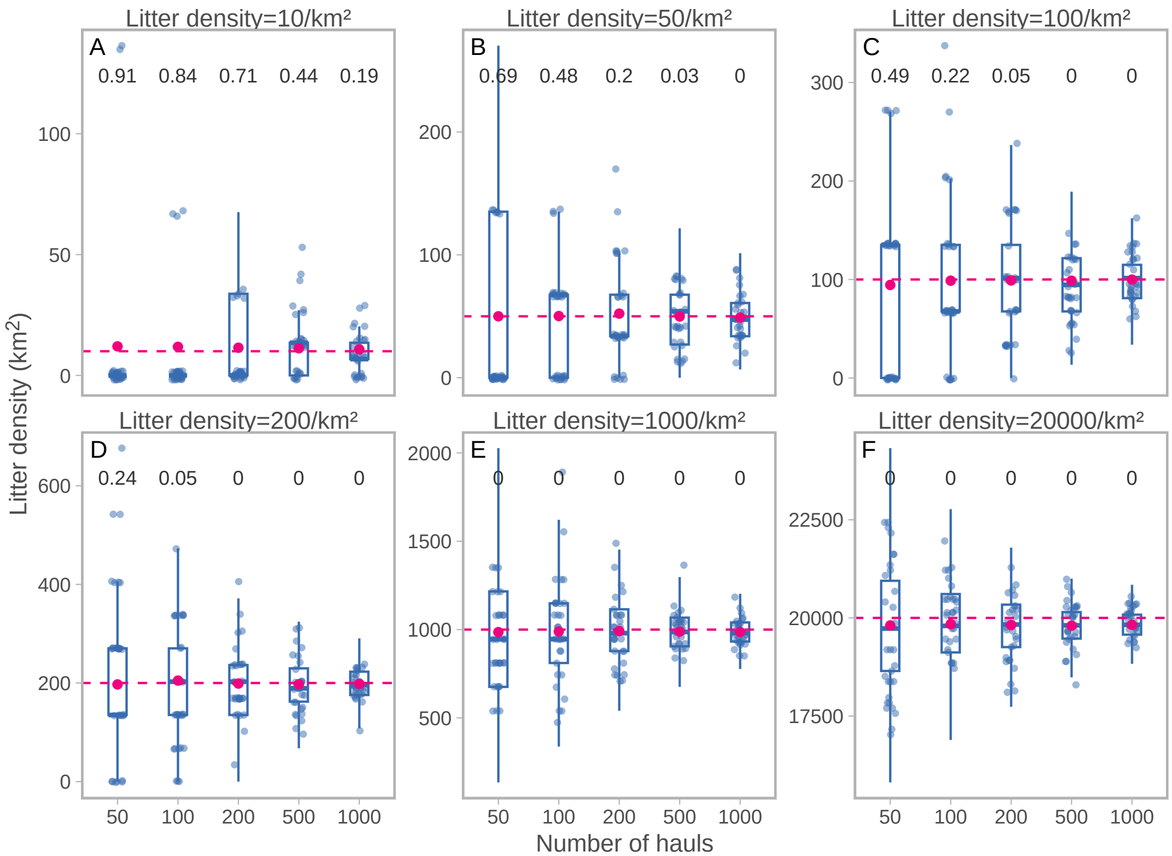

Figure 4: Results from the simulation experiment. Each panel (A–F) corresponds to a litter density scenario, and each blue point represents the estimated mean density for that sample size (number of hauls) (x-axis) and iteration. To avoid overplotting, we randomly sample 30 of the 1000 blue points and a small jitter has been added horizontally and vertically. The pink circles correspond to the mean litter density across all 1000 replicates. The horizontal pink line depicts the true litter density in the simulation (also indicated in the panel title). The number on the top corresponds to the proportion of the 1000 simulations that did not catch a single litter item in that sample size scenario.

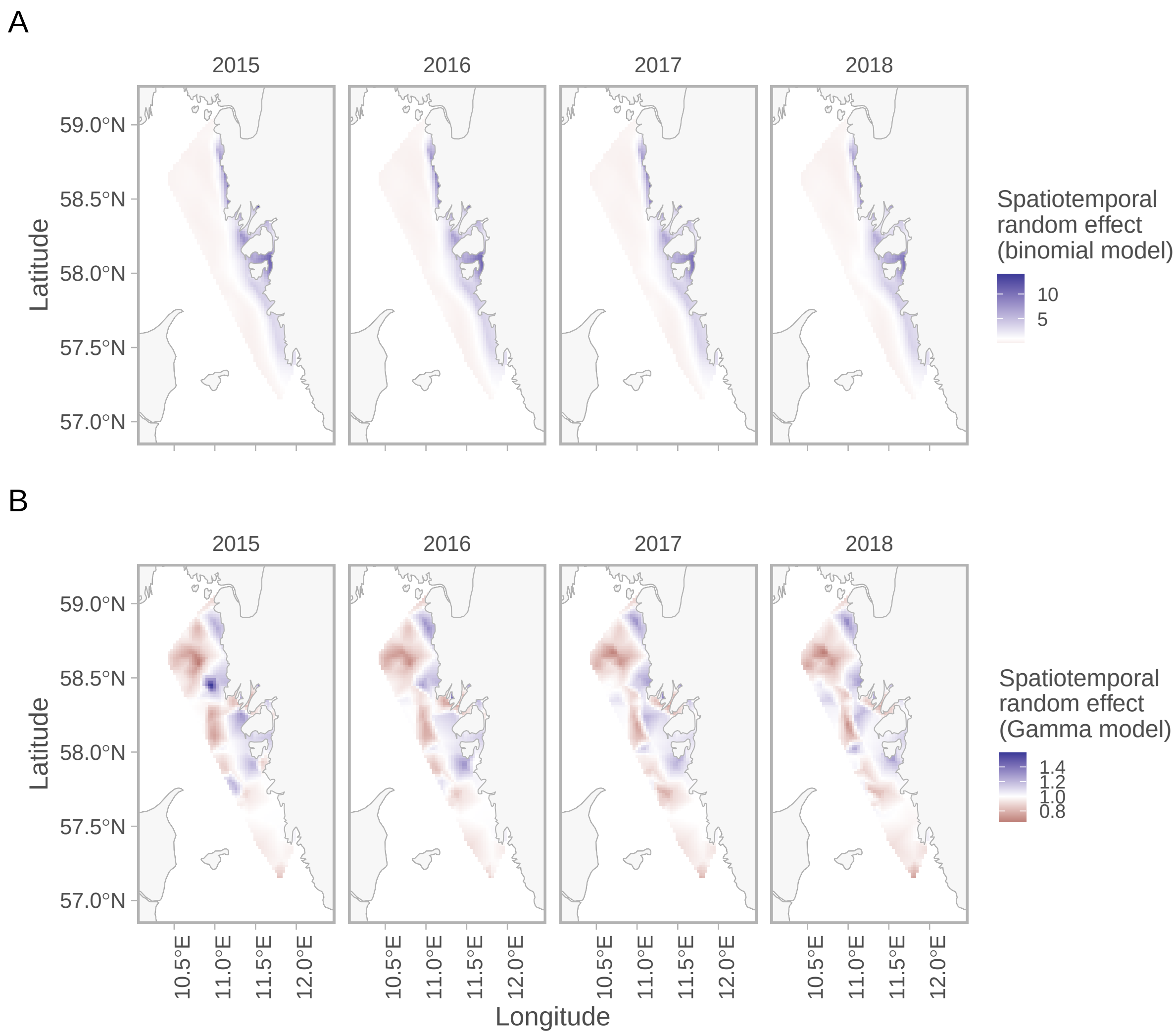

Figure 5: Spatiotemporal random effects for the binomial model (top row) and the Gamma model (bottom row) for selected years (2012, 2016, 2020, 2024).

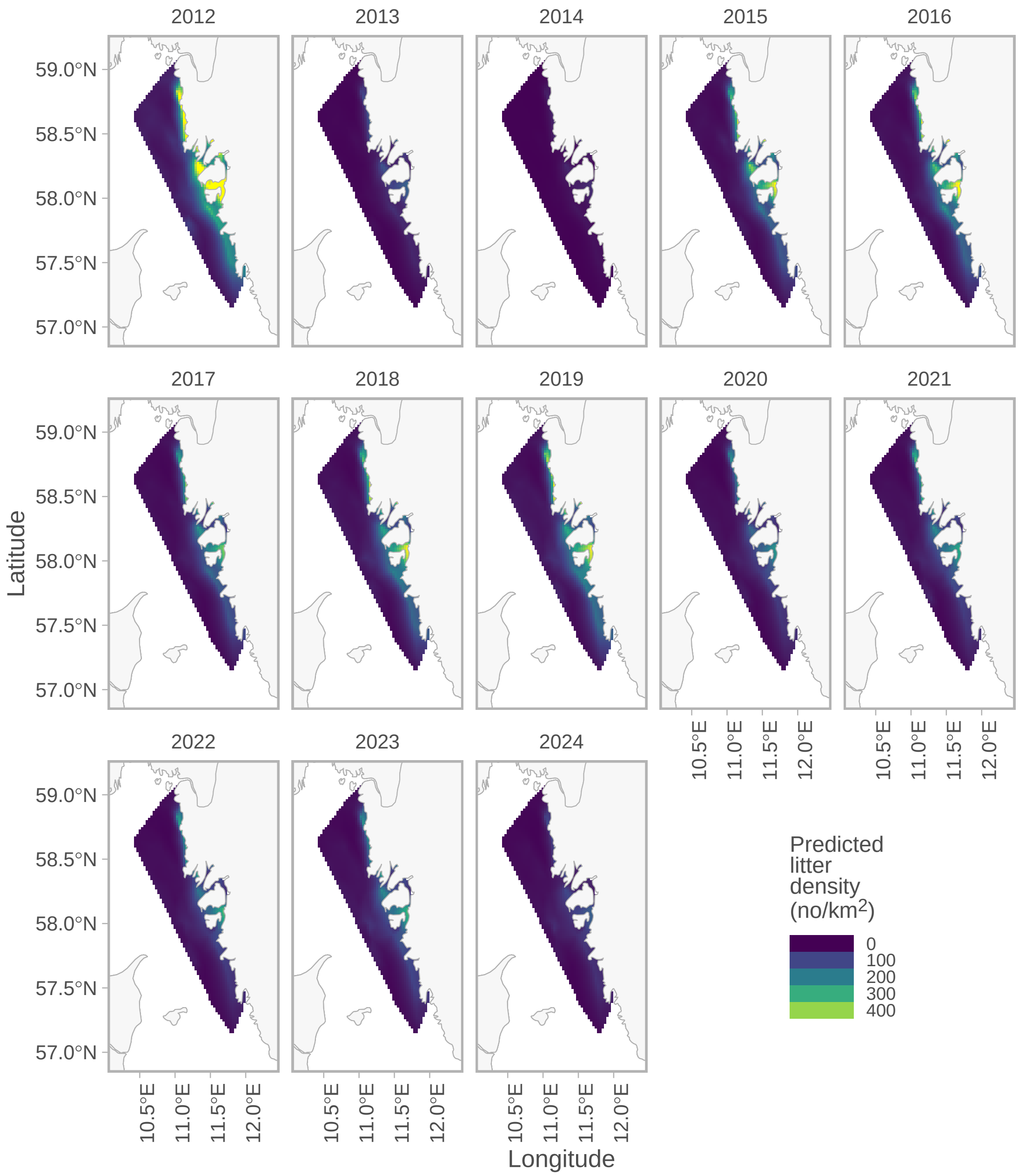

Figure 6: Predicted litter densities from the spatiotemporal model for the years 2012–2024. To better visualize the spatial patterns, values greater than the 99% quantile (479 items per km_2) are set to the highest color.

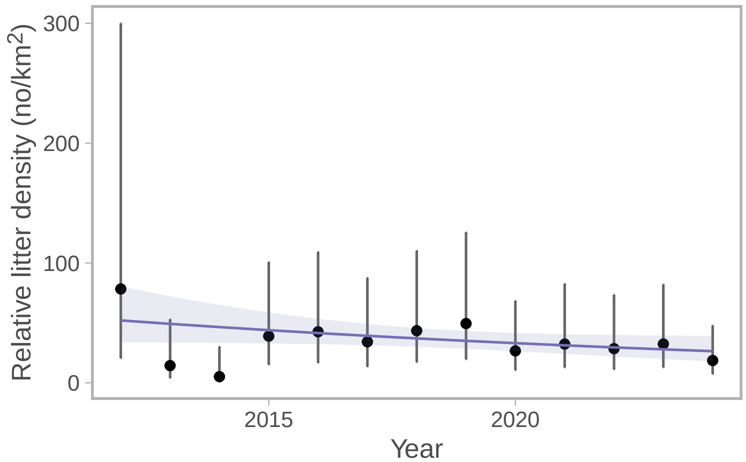

Figure 7: Conditional predictions of litter density for the IBTS level (points) and 95% confidence interval (vertical lines) without random effects. The purple line illustrates trends in annual estimates of mean litter densities and is the prediction from a GAM year modelled as a penalized spline and the inverse of the CV for annual predictions as weights.

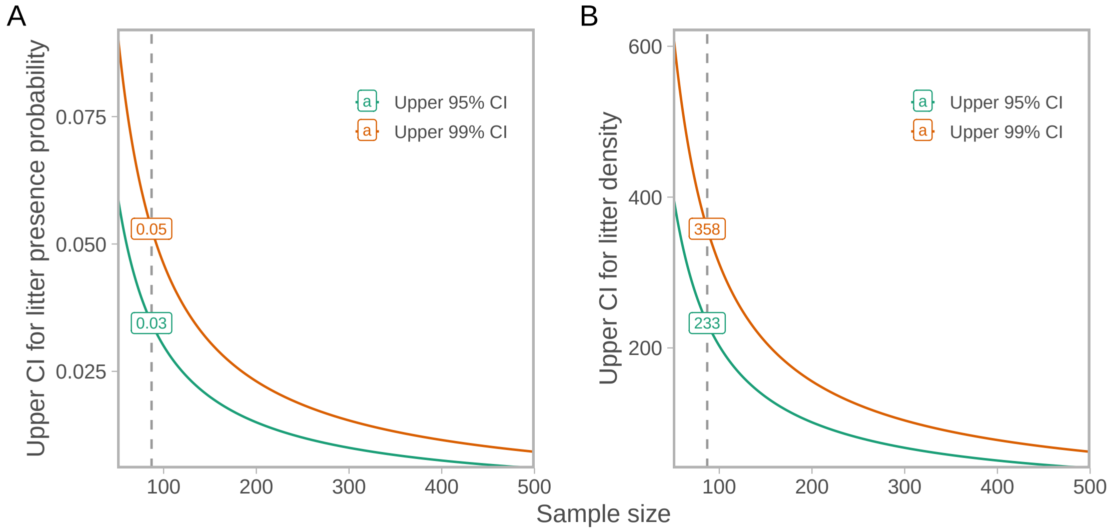

Figure 8: Illustration of how the upper confidence interval (95% in green and 99% in orange) for the probability of litter being present in a given haul (A) and the estimated density that corresponds to (B) change as a function of sample size if no hauls record any litter, using the "rule of three" and a sampled area of 148 m^2. The lower confidence interval is always zero.

Supporting Information S1

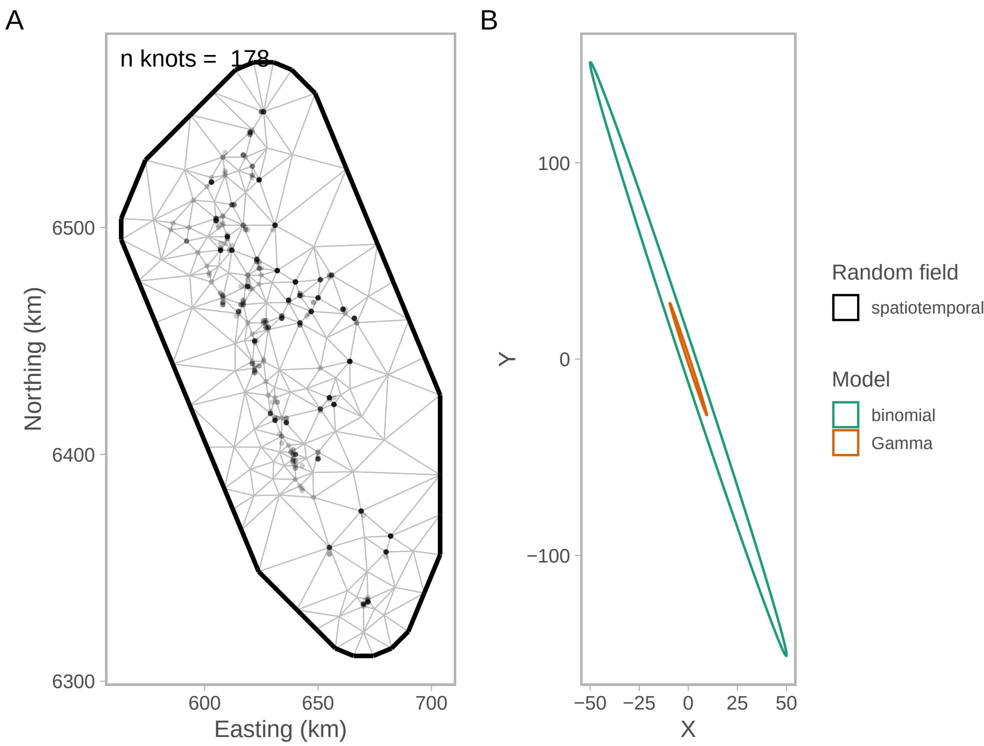

Figure S1: Panel A depicts the SPDE mesh for the litter model, and in panel B, the ellipses depict the spatiotemporal range (the distance at which correlation is effectively independent) for the two model components (green = binomial, orange = Gamma).

Table S1: AIC and ΔAIC (AIC for the model relative to the model with the lowest AIC) for all spatial and spatiotemporal GLLMs fitted to litter density data. In model 1, we use a spatial random field for the binomial and Gamma components of the delta-model, in model 2, we replace the spatial random field with a spatiotemporal AR1 random field, and in model 3 we use a spatial random field for the binomial model and a spatiotemporal AR1 random field for the Gamma model.

Model	**binomial**	**Gamma**	**AIC**	**ΔAIC**
1	Spatial	Spatial	4287	8
2	Spatiotemporal	Spatiotemporal	4279	0
3	Spatial	Spatiotemporal	4281	2

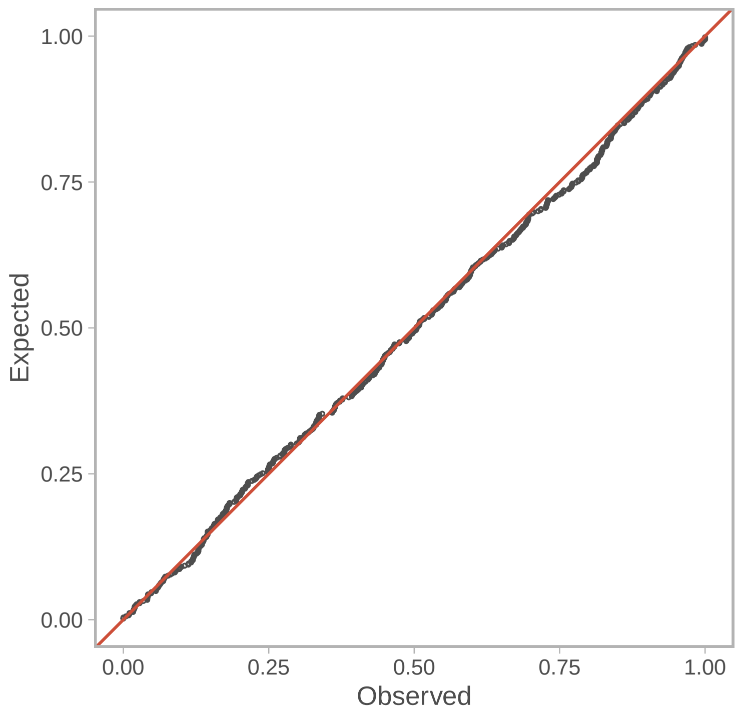

Figure S2: QQ-plots based on simulated quantile residuals for the combined predictions of the litter density models where fixed effects are held at their maximum likelihood estimate and random effects taken from a single approximate posterior sample.

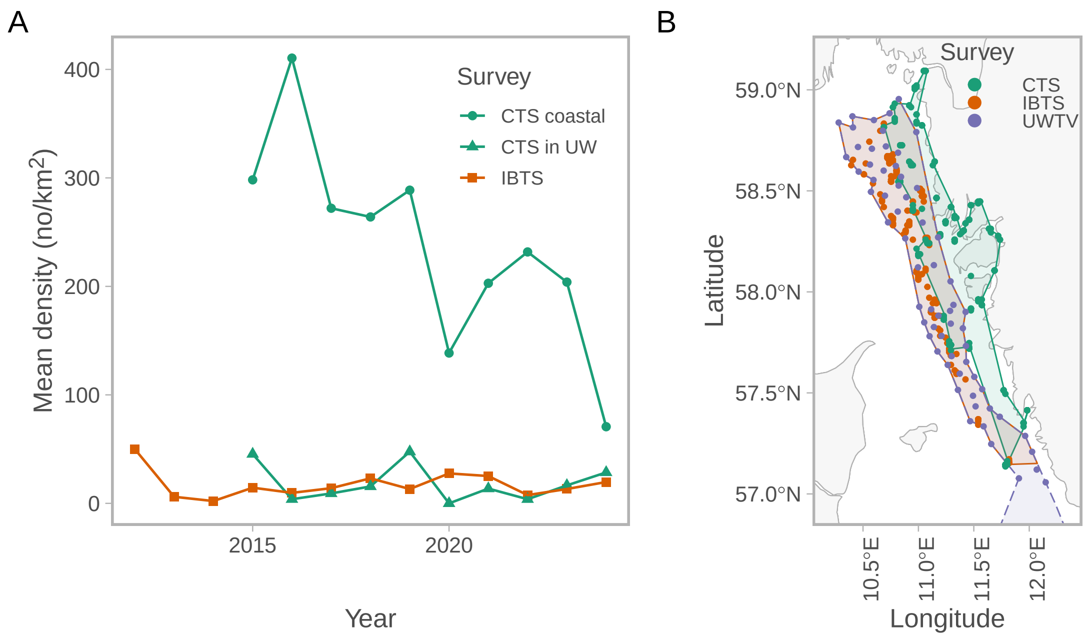

Figure S3: Mean litter densities (A) by survey (green = CTS, orange = IBTS), over time, and location of samples (B) with polygons depicting concave hulls of the survey extent. Note the CTS is split in two, where CTS in the UW/IBTS polygon is denoted CTS offshore (triangles) and coastal data are denoted CTS coastal (points), to illustrate that the differences in mean litter between CTS and IBTS is due to spatial differences in litter density and sampling area (see also Fig S4 and Fig 5).

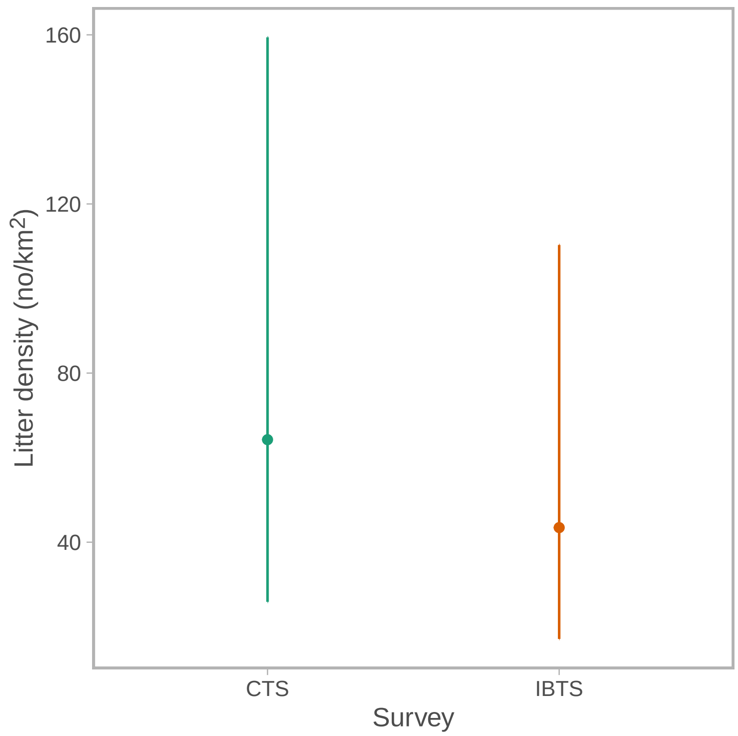

Figure S4: Effect of survey on litter density from the spatiotemporal model.

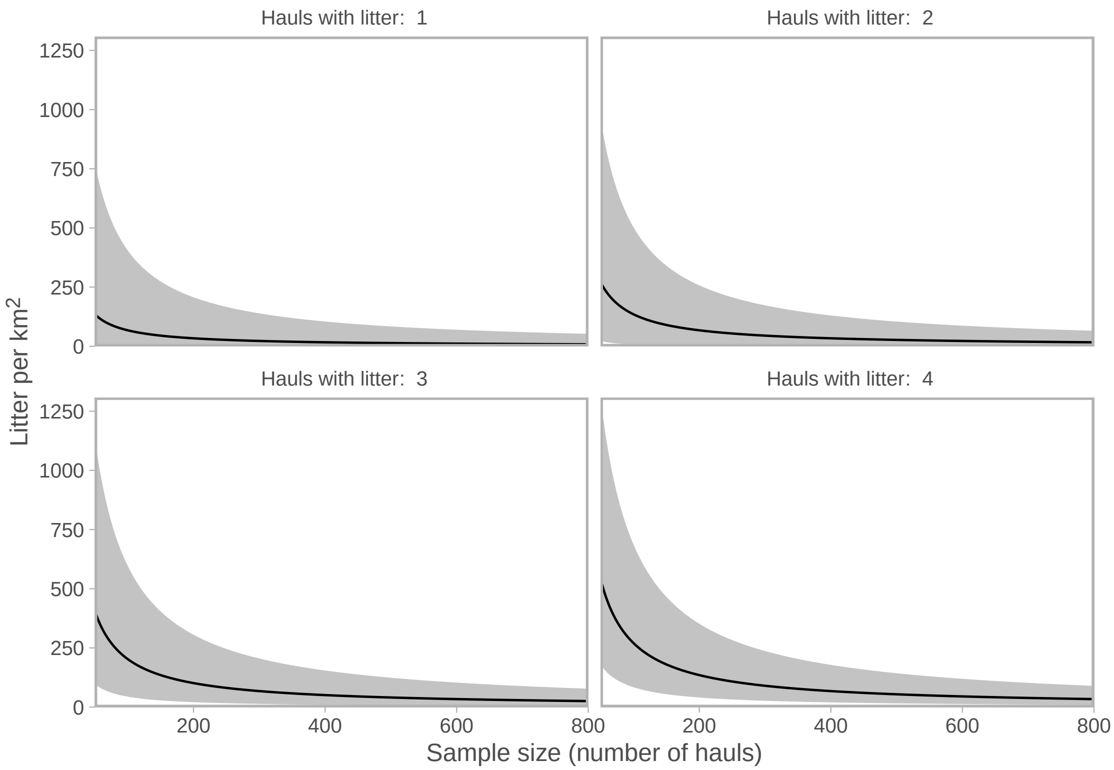

Figure S5: Litter density estimates and 95% CI for varying sample sizes (number of hauls) and number of hauls with litter per sample size using the Agresti-Coull method (note a haul with litter can only contain one litter object in this hypothetical example). Haul area: 0.000148 km². The solid line depicts the mean and the ribbon covers the 95% confidence interval.