Modelling and forecasting of beach litter assessment values

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Abstract NL Een model is ontwikkeld voor het voorspellen van de hoeveelheid strandafval op Europese stranden. We selecteerden een negatief binomiaal gegeneraliseerd lineair model (NB-GLM) omdat deze geschikt is voor het modelleren van asymptotisch dalende trends en een natuurlijke keuze is voor telgegevens met overdispersie. NB-GLMs werden gefit voor vier Nederlandse en vier Duitse stranden aan de Noorzee. Uit de voorspellingen bleek dat de Europese drempelwaarde voor strandafval (Threshold Value) naar verwachting in 2026 wordt bereikt voor Duitsland (90% betrouwbaarheidsinterval tussen 2023 en 2031) en in 2047 voor Nederland (90% betrouwbaarheidsinterval 2037 en later dan 2050). De resultaten kunnen worden gebruikt om te evalueren of de huidige reductiesnelheden voldoende zijn, of dat er aanvullende nationale of regionale maatregelen nodig zijn.

Abstract UK A model has been developed for forecasting total counts of beach macrolitter on European beaches. A negative binomial generalized linear model (NB-GLM) was used, because this model is suitable to model asymptotic trends and is a natural choice for count data with overdispersion. NB-GLMs were fitted for the Dutch-North Sea and German-North Sea beach litter. The model predicts that the threshold value (TV) could be reached in Germany in 2026 (90% confidence interval: 2023-2031) and in the Netherlands in 2047 (90% confidence interval: 2037 and later than 2050). The forecasts can be used to evaluate whether the current reduction rate is sufficient, or if increased national and regional reduction measures may be needed.

Keywords: beach litter, forecasting, negative binomial generalized linear model, OSPAR, EU

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Contents

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Preface

In this research, a simple model has been developed for forecasting macrolitter counts on European beaches. This research was funded by Rijkswaterstaat, The Netherlands.

Jon Barry (Centre for Environment, Fisheries and Aquaculture Science, United Kingdom), Martin Knotters (Wageningen University & Research, The Netherlands), Camille Lacroix (Centre de documentation, de recherche et d’expérimentations sur les pollutions accidentelles des eaux, France), and Jakob Strand (Aarhus University, Denmark) are acknowledged for their valuable comments on an earlier draft of this report.

Dennis Walvoort, Willem van Loon, Marcus Schulz & Silvère André

Summary

A model has been developed for forecasting total counts of beach macrolitter from OSPAR and EU beach litter surveys, based on available survey data which are aggregated within country-MSFD subregions. This model has been developed in view of a European need for forecasting when Intermediate Measurable Targets (IMTs), and ultimately the European Threshold value (TV) for beach litter, could be reached.

A negative binomial generalized linear model (NB-GLM) was used, because this model is suitable to model asymptotic trends and is a natural choice for count data with overdispersion. An additional method using annual median values was developed to detect the start of a decreasing trend period to be modeled. NB-GLM models were fitted for the Dutch-North Sea and German-North Sea beach litter monitoring data for the most recent period where a decreasing trend is visible (for the Netherlands: 2011-2019; for Germany: 2013-2019). The model predicts that the threshold value (TV) could be reached in Germany-North Sea in 2026 (90% confidence interval: 2023-2031), and in the Netherlands-North Sea in 2047 (90% confidence interval: 2037 - later than 2050).

A model assumption is that the current asymptotically decreasing reduction rate will be maintained. We propose that the use of this model and assumption is preferable to expert judgement. In addition, the model forecasts can be updated regularly when new data become available. An implicit assumption when modelling is that reduction measures, like those induced by the new EU Single Use Plastics (SUP) directive, are sustained. The model forecasts can also be used to evaluate whether the current reduction rate is sufficient, or if increased national and regional reduction measures may be needed. The possible contribution of transboundary pollution can also be considered in specific country-subregions. It is proposed to only apply this NB-GLM model to litter groups with sufficient non-zero litter counts to keep the signal-to-noise ratio high and modelling feasible. These litter groups can be *e.g.* Total Count (TC), Single Use Plastics (SUP) and Maritime related types (SEA).

1. Introduction

1.1. Problem statement

The Technical Group on Marine Litter (TGML), which functions within the context of the EU Marine Strategy Framework Directive (MSFD), has defined marine litter as:

. . . any persistent, manufactured or processed solid material discarded, disposed of or abandoned in the marine and coastal environment. Litter consists of items that have been made or used by people and deliberately discarded or unintentionally lost into the sea or on beaches, including such materials transported into the marine environment from land by rivers, draining or sewage systems, or winds (Galgani et al., 2013a)

This is a refinement of the definition given by The United Nations Environment Programme (UNEP, Cheshire et al. (2009)).

Marine litter has considerable environmental, social, and economic impacts (Galgani et al., 2013a; Werner et al., 2016):

- environmental impacts are: harm due to entanglement, smothering and ingestion by marine animals (Kühn and Van Franeker, 2020), as well as triggering invasions of non-native species;
- economic impacts affect sectors like aquaculture, fisheries and recreation;
- social impacts include reduced recreational and aesthetic values of beaches and coastal waters.

Litter occurs in all compartments of the marine environment. It is monitored on the coast, on the seafloor and in the surface layer of the water column. Marine litter is considered in three size classes: macro (>2.5 cm), meso (0.5-2.5 cm) and micro (<0.5 cm) (Galgani et al., 2013b). This report focusses on macrolitter deposited on the coastline, hereafter called beach litter.

Hanke et al. (2019) compiled an extensive database with pan-European beach litter data. Based on these data, they derived baselines for beach litter for the years 2015 and 2016. They define baselines as:

. . . litter abundance information that can be used as a reference point in time in order to test the achievement of quantitative litter reduction goals.

As beach litter reduction goal, Van Loon et al. (2020) proposed a single threshold value (TV) for the European Union. Although threshold values are defined as *the lowest observed adverse effect level of beach litter on species or humans* (Schulz et al., 2019), Van Loon et al. (2020) took a more pragmatic approach due to the lack of data on harm caused by beach litter. The threshold value they propose equals 20 litter items per 100 m of coastline and is based on the 15th-percentile of the total count (TC) of the 2015-2016 EU beach litter data set provided by Hanke et al. (2019). The total count is the total number of litter items found during a survey, along a 100 metre section of coastline. This TV was adopted by the EU Marine Strategy Coordination Group in 2020, and has the legal status of an EU recommendation.

In addition to a threshold value, Van Loon et al. (2020) also provided a method for calculating the assessment value (AV). The assessment value gives the current state of the total count that should be used for compliance checking against the threshold value. It was agreed in the EU to use the median total count of at least 40 most recent surveys within a country-MSFD subregion (*e.g.* France-Bay of Biscay) as an assessment value. These surveys should all occur within one MSFD-cycle of six years, and preferably within a three-year period in order to get a more up-to-date assessment. The assessment value is calculated for each country-subregion. For example, the Netherlands only has a single subregion, *i.e.*, the Greater North Sea, whereas France has four marine subregions, *i.e.*, the Greater North Sea, Celtic Seas, the Bay of Biscay and the Mediterranean Sea. A notional example of a baseline value, the threshold value, an intermediate measurable target, and annual assessment values is given in Figure 1.1.

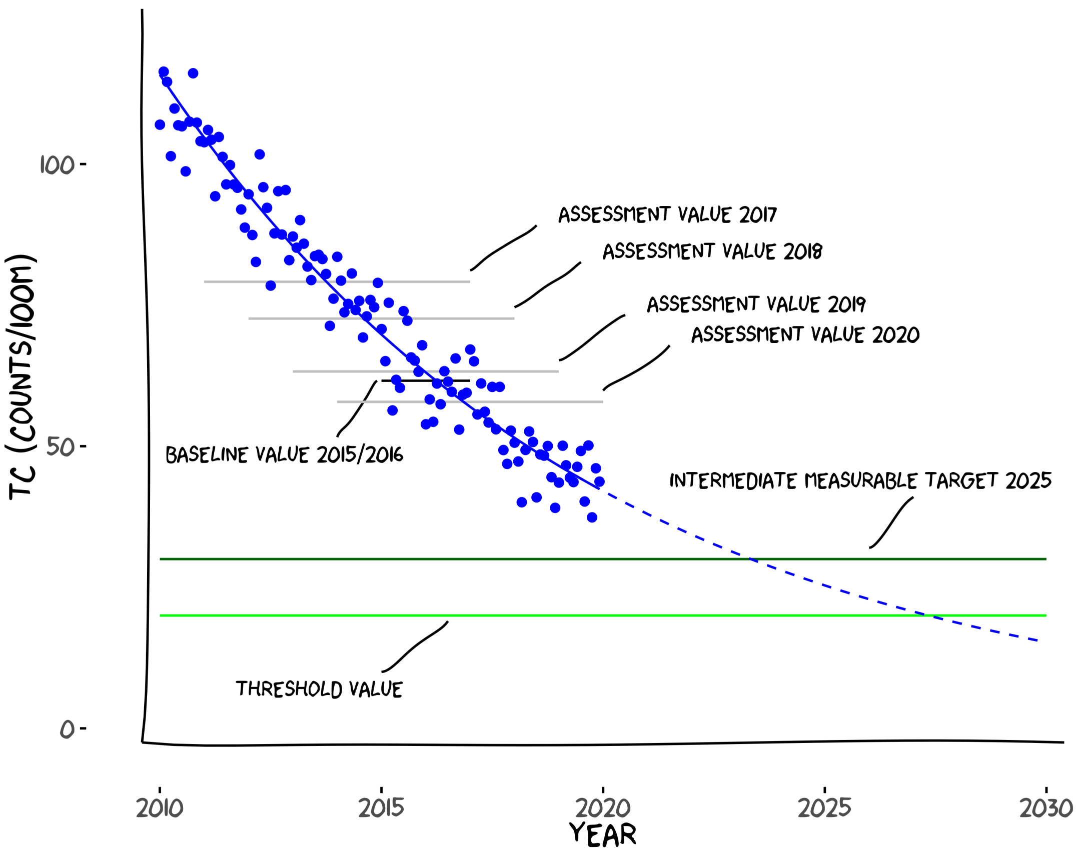

Figure 1.1 *Notional example of total counts (TC) as function of time. The survey data (blue dots), the baseline value (black line), assessment values for specific years (grey lines), the intermediate measurable target for 2025 (dark green line), and the threshold value (light green line) are given in this figure. The lengths of the horizontal black and grey lines correspond to the periods that have been used to calculate the baseline and assessment values respectively. The solid blue line is the fitted total count and the dashed line the forecasted total count. Note that in this example, a clear asymptotically declining trend is visible that is expected to drop below the threshold value in 2027.*

A significant part of beach litter consists of single use plastics (SUPs). For the European Union, Hanke et al. (2019) estimated the contribution of SUP for the years 2015 and 2016 to be almost 40% of the TC. SUPs are of particular interest as in 2019, the European Parliament has voted to ban the following SUPs by 2021 (EP 2019): single-use plastic cutlery (forks, knives, spoons and chopsticks), single-use plastic plates, plastic straws, cotton bud sticks made of plastic, plastic balloon sticks, oxo-degradable plastics and food containers and expanded polystyrene cups. Earlier, the EU had issued a plastic bag directive, which bans the free distribution of single use plastic bags (EC, 2015). Consequently, several member states banned the handing out of plastic bags free of charge in shops and supermarkets (*e.g.*, the United Kingdom in 2015 and the Netherlands in 2016). It is therefore expected that the numbers of SUPs recorded on beaches in Europe will decrease the coming years.

After litter reducing directives come into force, member states need to implement litter reducing measures. An obvious parameter to evaluate the efficacy and efficiency of these measures is the time needed for the assessment value to reach intermediate measurable targets (IMTs) and ultimately the threshold value (TV). To estimate this time, a model with a linear structure appears to be inappropriate, because its response is unbounded and will eventually lead to forecasts of negative assessment values in case of a negative slope, or to forecasts of ever increasing assessment values in case of a positive slope. Van Loon et al. (2020) already mentioned the limitations of this approach. In addition, they argue that a more appropriate model should have an asymptotically declining trend until the pristine state of nearly zero litter count per 100 m has been reached.

1.2. Aim

The aim of this study is to derive models that are suitable for forecasting beach litter assessment values of total counts and other litter groups such as SUP and SEA. Member states can annually update these models to re-estimate the time needed to reach the intermediate measurable targets and the threshold value, and to quantify the effectiveness of their litter-reducing measures. We demonstrate these models for beach litter data of the Netherlands and Germany.

1.3. Outline

We start with the derivation of the models in Chapter 2. In Chapter 3, we apply the models to Dutch and German beach litter data. After a discussion of the models in Chapter 4 we finalize with some concluding remarks in Chapter 5. The annexes contain the R-source code (R Core Team, 2020), that has been used for the calculations in this report including a concise user manual. They also contain figures and tables with numerical model results for total counts, and figures with SUP and SEA models.

2. Data and Methods

2.1. Data preparation

Beach litter data for the Netherlands and Germany were obtained from the OSPAR data originator portal. These data were cleaned using the guidelines of Hanke et al. (2019), by removing mesoplastic fragments (<2.5 cm), paraffin/wax types and other pollutants from the dataset. This data cleanup was automatically performed by using the R-package litteR (Walvoort and van Loon, 2020). This package uses a litter type file to exclude these types. The litteR-package was also used to validate the beach litter data and to calculate total litter counts per 100 m of beach.

For Germany and the Netherlands we selected the beaches with the most complete survey time series. For Germany, these monitoring beaches are Juist, Minsener Oog, Scharhörn, and Sylt. For the Netherlands, these monitoring beaches are Bergen, Noordwijk, Terschelling, and Veere.

We followed the criteria in Section 2.4 to select data periods for Germany and The Netherlands.

2.2. Model derivation

We need a model that satisfies the following requirements:

1. the model should be able to capture an existing asymptotically declining trend (Van Loon et al., 2020). We assume that this trend will be maintained by the current and additional future litter-reduction measures;
2. the model should not allow for unrealistic extrapolations. This rules out, for instance, the use of polynomial regression models;
3. the model is preferably linear in its parameters, so that linear algebra can be used for inference. This greatly facilitates estimation of model parameters and the estimation of confidence intervals;
4. the model should take into account that litter data are counts and should be robust against extreme values.

With regard to criterion 4, natural data distributions that fit count data are the Poisson distribution and the negative Binomial distribution. The latter is the more flexible of the two because it can model overdispersion. The Poisson distribution is more restricted as its variance is always equal to its mean (Hanke et al., 2019).

Given the criteria listed above, we propose to use a negative binomial generalized linear model with the log-link function (NB-GLM). This GLM models the asymptotically declining trend as an exponentially declining function with a lower bound of zero. To shed some light on how this model looks like, suppose that Y is a random variable denoting the response or dependent variable. In our case Y is the amount of beach litter. Furthermore, it is assumed that Y follows a negative binomial distribution. This assumption seems to be justified by the results in Hanke et al. (2019). The expectation of Y, given survey date t, is (the vertical bar means "given"):

$$E(Y|t) = g^{-1}(\eta) = \log^{-1}(\beta_0 + \beta_1 t)$$

where t is the survey date (expressed as a real number), $\eta = \beta_0 + \beta_1 t$ is a linear predictor, g is the link function, in this case the log-link function, and β_0 and β_1 are unknown regression coefficients that need to be estimated. Therefore, a prediction or forecast $\hat{y}$ at time t is given by:

$$\hat{y}(t) = \exp(\beta_0 + \beta_1 t) \tag{2.1}$$

2.3. Modelling

We fitted an NB-GLM to survey data by means of the `glm.nb` function in the MASS package of R (Venables and Ripley, 2002). The MASS-package is one of the default packages of R (R Core Team, 2020). This approach uses all available total count data to estimate the model parameters by maximum likelihood.

After fitting the linear predictor η given in Section 2.2, the back-transformation given by Eq.2.1 results in the median count on the original scale of the count data. The median is consistent with the use of median assessment values in OSPAR and EU beach litter assessments (CEMP 2021; Hanke et al. (2019); Van Loon et al. (2020)). The implementation of the `predict`-function for `glm.nb` in the MASS-package does not provide confidence intervals. Therefore, we used stochastic simulation to estimate median litter counts and the 90% confidence interval. We followed the procedure below:

1. estimate the model parameters (β_0, β_1) by means of the `glm.nb` function of the MASS-package of R (Venables and Ripley, 2002);
2. estimate the corresponding variance-covariance matrix of these parameters by means of the `vcov`-function of the stats-package of R (R Core Team, 2020);
3. draw N sets of model parameters by using the function `mvrnorm` in the MASS-package of R (Venables and Ripley, 2002);
4. use these N sets of model parameters to estimate N corresponding curves by means of Equation 2.1. Each curve can be seen as a single realization of our trend model, given the uncertainty in the parameters;
5. estimate the 5%, 50% and 95%-percentiles of these curves for each date. This gives the lower bound of the 90% confidence interval, the median, and the upper bound of the 90% confidence interval respectively.

The number of simulations N should be high. In practice, it is usually a tradeoff between precision and computation time. As our simulations are fast, we took N large ($N = 100000$).

In addition, for each country the data of the three or four beaches are pooled together in agreement with the TV and IMT assessments (Van Loon et al., 2020). It should be kept in mind that these aggregated results may mask opposite trends at individual beaches (Schulz et al., 2017). It is therefore recommended to also calculate the trends for individual beaches as background information for the nationally aggregated results.

2.4. Practical use of the model

A so called Rmd-file containing the source code that implements the model in Section 2.2 is distributed as part of this report. The code is also given in Annex 2. This section provides some guidelines to run the model in the Rmd-file. See also Annex 1.

First a directory is created, in which the Rmd-file (*e.g.*, litter-forecast-nl.Rmd), the selected data file (*e.g.*, beach-litter-data-nl.csv), and the litteR type file (*e.g.*, types-ospar.csv) are placed. The Rmd-file opens automatically in RStudio after double clicking with the left-mouse button.

In the beginning of the Rmd-file, the following parameters need to be adjusted: `FILENAME_LITTER`, `FILENAME_GROUPS`, `SPATIAL_CODE`, `GROUP_CODE`, `DATE_FROM` and `DATE_TO`. Perform a first run by clicking on the Knit-button in RStudio. Evaluate the annual median litter counts plot in the resulting report (HTML-file), and use the following criteria to select the modelling period by eye:

1. the annual median plot should show a decreasing trend in the *most recent* years;
2. we recommend a minimum of at least five *most recent* years for confirming that the decline is structural and that it reflects recent litter reducing measures;
3. we recommend that the modelling period should consist of at least approximately 50 surveys (see motivation below);
4. The surveys are preferably distributed evenly in time to be able to confirm an exponentially declining model structure;
5. The first year of the modelling period is the year where the annual median count is relatively high.

Our recommendation for a minimum number of 50 surveys has both statistical and practical reasons. From a statistical point of view, the number of surveys should not be too small for estimating model parameters. The more practical reason is the limited number of surveys that is usually available in a period of five years. Given a minimum of three beaches per country-subregion and four surveys per beach per year, the number of surveys is 60. However, in Arctic regions only three surveys per year may be feasible since the winter survey usually cannot be performed. This would lead to 45 surveys for Arctic regions. Furthermore, Schulz et al. (2017) indicate that a data availability of three out of four surveys per beach is still acceptable for beach data aggregation, which also leads to a minimum number of surveys of 45. Our recommendation of 50 surveys is between 45 and 60, but this number may be smaller for Arctic regions or for individual beaches. But irrespective of this number, one should always be critical with respect to model forecasts. In addition, one should not only focus on the median forecast, but also report the confidence intervals.

Edit the Rmd-file to set the first date of the modelling period (`DATE_FROM`). Run the Rmd-file again to obtain the final results. The resulting report (HTML) contains:

- the user settings;
- a data quality control section;
- a bar chart and table with median annual count data;
- a time-series plot and corresponding table of the fitted NB-GLM including its 90% confidence interval;
- the model diagnostics.

Note that the second run overwrites the results from the first run. If you want to keep the report from the first run, copy the report to a separate subdirectory or rename it.

3. Results

3.1. Start of the declining trend

Our prime interest is in modelling the expected asymptotically declining trend (Figure 1.1) of beach litter at lower levels. Therefore, we first need to decide where the decreasing trend approximately starts. This is an important step because the inclusion of data from a period of increasing total counts, which occurred before the start of the decreasing trend, would blur the trend model. As the starting date, we selected the year 2011 for the Dutch data and 2013 for the German data based on visual inspection of the time-series of annual median TCs (Figure 3.1) and by using the criteria described in Section 2.4.

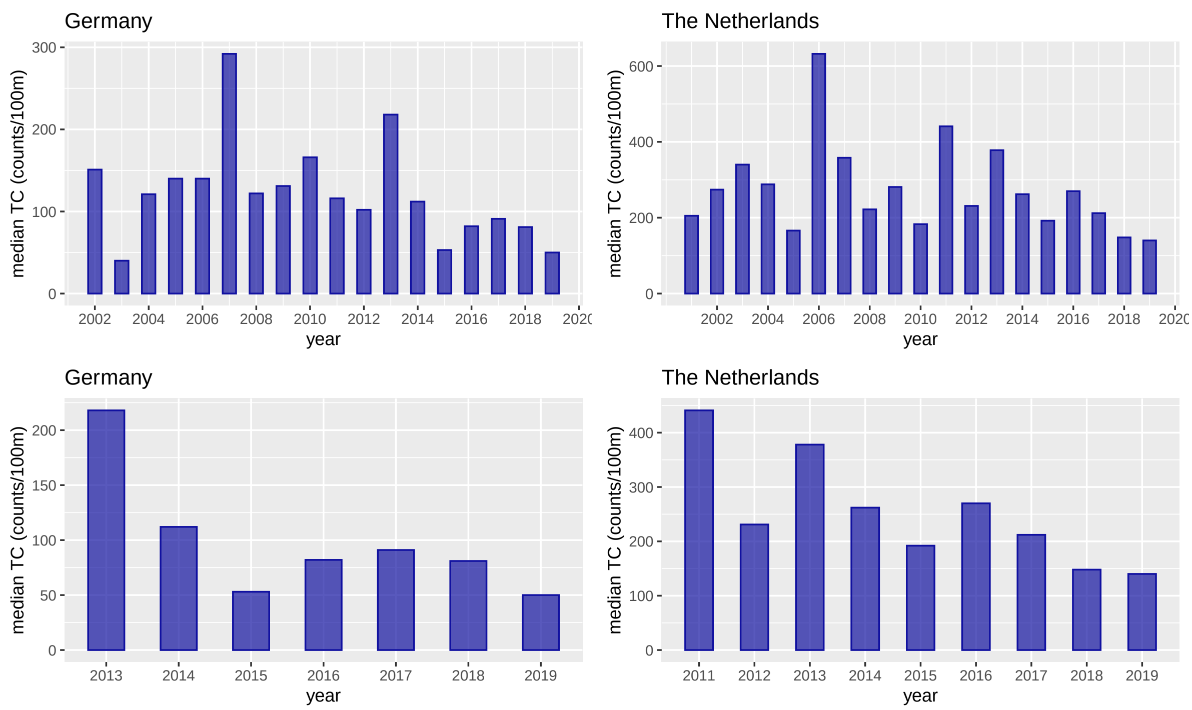

Figure 3.1 *Annual median total counts (TC) for the German (left column) and the Dutch (right column) monitoring beaches. The top row gives all available years, whereas the bottom row gives the selected years where a declining trend is visible.*

3.2. Modelling survey total counts

We fitted NB-GLMs to the total counts of each country-subregion. Figure 3.2 gives the results for Germany and the Netherlands. The dots are the survey data, the red line is the fit, and the blue ribbon represents the 90% confidence interval of the fit.

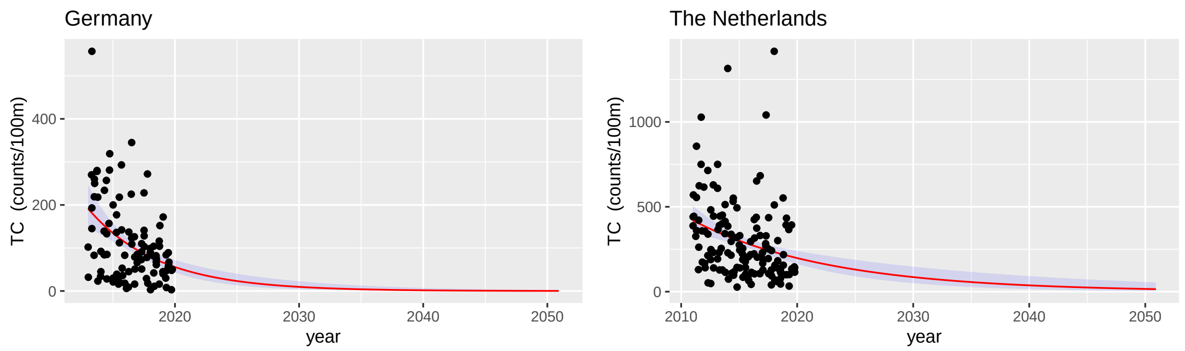

Figure 3.2 *Fitted NB-GLM for Germany (left) and the Netherlands (right). The dots are the survey data, the red line is the model fit, and the blue ribbon represents the 90% confidence interval of the fit. The parameters for Germany are* $\beta_0 = 5.25$ *and* $\beta_1 = -6.68$ *and for the Netherlands* $\beta_0 = 6.04$ *and* $\beta_1 = -3.34$*. Model parameters have* $p < 0.001$*.*

The left part of each figure, up to and including the year 2019, is the interpolation period. Here total litter counts are predicted by interpolation. The right part is the extrapolation period. Here litter counts are based on forecasting as no survey data are available for this period. The models show that for Germany, the threshold value will be reached between 2023 and 2031 and for the Netherlands after 2037 (based on the 90% confidence intervals). The expected years that the TV will be reached (based on the models) are 2026 and 2047, respectively. Note that the confidence intervals are relatively wide. In case of the aggregation of beaches with opposite trends, the aggregated trend may be less clear (Schulz et al., 2017). It is therefore in general recommended to also analyze the individual beach trends as background information for the interpretation of the aggregated country-subregion trend. This has been done in Figure 3.3, which shows that the decreasing trend in Figure 3.2 is caused by the decreasing trends of the monitoring beaches Noordwijk, Terschelling and Veere. For Bergen, a slight increase is observed.

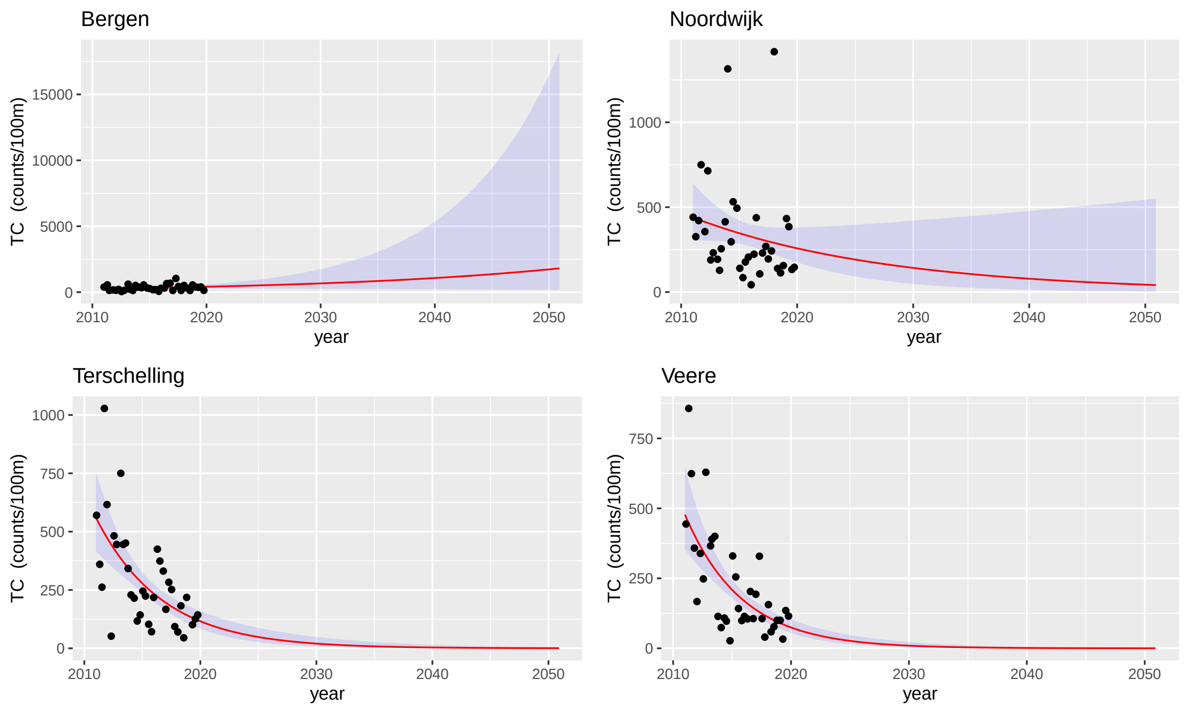

Figure 3.3 *Fitted NB-GLMs for the individual monitoring beaches of the Netherlands. Only the beaches at Noordwijk, Terschelling and Veere show decreasing beach litter trends.*

The R-script in Annex 2, also available as a downloadable Rmd-file, can be used to update the models annually in the future when new data become available. These new data can be used to check the assumption that the conditions that cause the asymptotically declining trend still hold. It is expected that the confidence intervals will get smaller as more data become available, when litter counts decrease, and when most or all beaches within a country-subregion show a similar trend.

3.3. Modelling SUP and SEA groups

The presented NB-GLM model is also suitable to model groups other than total count (TC), such as single use plastics (SUP) and maritime related types (SEA). Two examples of the resulting GLM models are shown in Annex 5. As for total count, tables with detailed results are produced by the code in Annex 2 for these models. These SUP and SEA models are currently used for the OSPAR beach litter assessment 2021 (OSPAR, 2021, in prep.).

4. Discussion

Modelling survey data at individual beaches is an informative and theoretically sound way to analyze data. Apart from predictions and forecasts, it also provides uncertainty information (confidence intervals) which will facilitate and refine the interpretation. An NB-GLM is suitable for modelling count data with overdispersion, and relatively robust for extreme values.

For the extrapolation period it is assumed that the asymptotic reduction rate is the same as for the interpolation period. Indeed, the model may not be valid anymore when external conditions change, *e.g.* when additional litter reduction measures are taken. Therefore, it is recommended to regularly update the model when new survey data become available. We propose that the use of this model and its assumptions is preferable to expert judgement as the results are reproducible, data-driven, and have quantified uncertainty information (confidence intervals).

We do not recommend to use this model for forecasting increasing trends. Due to the exponential nature of the model, long-term forecasts may then lead to extremely high and unrealistic litter counts. In addition, we should always be critical about the results when forecasting (extrapolating) many years ahead.

It is proposed to only apply this NB-GLM model to litter groups with sufficient litter counts to make maximum likelihood estimation of the model parameters possible. These litter groups can *e.g.* be total count, single use plastics, fisheries related types and more abundant material groups such as plastics. The application of this method to single litter types is *a priori* not recommended, but may be possible if specific litter types are sufficiently abundant.

Furthermore, if one wants to model several beaches in a single country-subregion together, then these beaches should preferably show similar trend behaviour. For the Netherlands, for example, that is not always the case. In the Dutch situation, three beaches have decreasing trends, and the beach of Bergen shows a slight increase. The overall Dutch trend at the four monitoring beaches is however decreasing. If, however, within a country-subregion a mixture of decreasing and increasing beach litter trends occurs, the aggregated trend for the country-subregion will become less clear (Schulz et al., 2017).

Model performance is usually quantified by validation. That is, the data are split in two mutually exclusive sets: one for calibration (fitting) and one for validation (testing). To validate a model for forecasting purposes, the data are usually split in time. The older data are used for calibration, the more recent data for validation. However, in our situation this type of validation is not possible yet, due to a limited amount of data/years. Cross-validation is not useful either, as it only validates predictions in the data period (the past) and does not validate forecasts (the future). Therefore, split-in-time validation is recommended in the future when more data have become available.

5. Conclusions

We propose a negative binomial generalized linear model with log-link function (NB-GLM) for forecasting total counts of beach litter. This model does not only comply with the special nature of the data (counts), but is also able to model asymptotically declining trends. This kind of trends are the expected future behaviour of beach litter total counts after litter reducing measures are sustained and further implemented by the member states of the European Union.

The NB-GLM model is based on total count beach litter data from individual surveys.

The source code of this model is given in Annex 2 of this report. When new data become available, data analysts can refit the model, re-estimate the year when assessment values for total count could reach intermediate measurable targets and the threshold value, and validate forecasts, respectively. In addition, this model is also applicable to the forecasting of counts of other litter groups such as single use plastics, fisheries and maritime related types.

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Annex 1 User manual of the NB-GLM script

Introduction

Annex 2 contains the R-script that can be used for modelling your data. This annex briefly explains how to use the scripts.

The script requires a recent installation of the R-environment and RStudio, an integrated development environment (IDE) for R. Although this manual primarily focuses on MS-Windows users, users of other operating systems may also find these instructions useful.

Installation of R

The latest version of R can be downloaded from the Comprehensive R Archive Network CRAN website as follows:

1. Navigate in a web-browser to https://cran.r-project.org;
2. Select the R-version for your operating system, *e.g.*, `Download R for Windows`;
3. Select 'base';
4. Select `Download R x.y.z` (where x.y.z. is the version number);
5. Double click on the downloaded file and follow the installation instructions on the screen. In case of doubt, simply select the default/recommended settings.

Installation of RStudio

The latest version of RStudio can be downloaded from the RStudio website: click products and follow the instructions.

Installation of required packages

The following packages need toe be installed: `tidyverse` and `litteR`. The easiest way to install these packages is by means of the package manager of RStudio. The package manager is located at the lower right panel of RStudio. The installation instructions are as follows:

1. click on the `Packages` tab in the lower right panel;
2. click on the `Install` button on the upper left of this tab. The `Install Packages dialogue` will appear;
3. type `tidyverse` and `litteR` in the `Packages` text box;
4. click the `Install` button. RStudio will now install these packages.

Running the script

The script and some sample data are distributed together with this report. To use it:

1. create a directory on your computer;
2. store the script (extension .Rmd) and the data files in this directory;
3. open the script in RStudio (File | Open File. . .);
4. click the `Knit`-button to run the script. The demo data will be analysed and an HTML report will be produced;
5. add your own data to this directory. These data should comply with the `litteR`-format;
6. modify the filenames in the R-script and click the `Knit`-button.

Annex 2 Script for modelling survey total counts

The R-code below has been used for the calculations in this report. The code is provided as (digital) supplementary material as part of this report.

````
---
title: "R-script 'Forecasting litter counts based on survey data'"
date: "`r format(Sys.time())`"
output:
    html_document
editor_options:
  chunk_output_type: console
---

```{r user-specified-settings}
FILENAME_LITTER <- "./data/beach-litter-data-nl-agg.csv"
FILENAME_GROUPS <- "./data/types-ospar.csv"
SPATIAL_CODE <- "Netherlands"
GROUP_CODE <- "TC"
DATE_FROM <- "2011-01-01"
DATE_TO <- "2050-12-31"
```

```{r setup, include=FALSE}
knitr::opts_chunk$set(echo=FALSE, message=FALSE, comment = "", dpi=300)
```

```{r}
# load packages (available from CRAN)
library(tidyverse)
library(litteR)
```

# Introduction

This report gives the fit of a negative binomial generalized linear model (NB-GLM) with
    log-link function to litter counts of individual surveys.

This script is part of Walvoort et al (2021, Annex 2, doi: 10.18174/546866):

- version: 1.0.0
- date: 2021-05-31

# Settings

User-specified settings:

- litter data: `r FILENAME_LITTER`
- group data: `r FILENAME_GROUPS`
- group code: `r GROUP_CODE`
- period: `r DATE_FROM` - `r DATE_TO`
````

```
# Data input and validation
```{r}
# initialize pseudo random number generator
set.seed(314)

# preprocessing
DATE_FROM <- as.Date(DATE_FROM)
DATE_TO <- as.Date(DATE_TO)

# read permissible litter types and litter groups
d_typ <- read_litter_types(FILENAME_GROUPS) %>%
    filter(group_code == GROUP_CODE)
type_names <- d_typ %>%
    pull("type_name") %>%
    unique

# read litter data
# - keep only permissible litter types
# - keep only records starting at DATE_FROM
d_ltr <- suppressWarnings(read_litter(FILENAME_LITTER, type_names = type_names)) %>%
    filter(
        date >= DATE_FROM,
        spatial_code == SPATIAL_CODE) %>%
    select(-spatial_code)

# compute group counts
d_ltr <- d_ltr %>%
    group_by(.RECORD_ID, date) %>%
    summarise(y = as.integer(round(sum(count))), .groups = "drop") %>%
    select(-.RECORD_ID)
```

Where does the trend start?

The bar plot below gives the annual median values of `r GROUP_CODE`. It can be used to
    select the starting date (see `DATE_FROM` above) for trend modelling. This is an
    important step, because an increasing trend that precedes the monotonically
    decreasing trend would hamper the model.

Note that one should select a sufficient number of data (e.g., at least the 5 most
    recent years) to accurately estimate the model parameters. The time-series should
    not be too long either, as old data may not properly reflect current litter reducing
     measures.

```{r fig.width=5, fig.height=3.5, out.width=700}
d <- d_ltr %>%
    mutate(year = as.integer(format(date, format = "%Y"))) %>%
    group_by(year) %>%
    summarise(n = sum(!is.na(y)), y = round(median(y)), .groups = "drop")

ggplot(
    data = d,
    mapping = aes(x = year, y = y)) +
    geom_col(na.rm = TRUE, width = 0.5, colour = "#1111A0", fill = "#1111A0", alpha =
    0.7) +
    scale_x_continuous(name = "year",
                       breaks = 2000 + 1:25*2, minor_breaks = 2000:2050) +
    scale_y_continuous(name = str_c("median ", GROUP_CODE, " (counts/100m)")) +
    ggtitle(SPATIAL_CODE)
```
```

```
<br><br><br>
The table below gives the total number of surveys per year (n) and the annual median
    values of `r GROUP_CODE`.
```{r}
names(d) <- c("year", "n", str_c("median ", GROUP_CODE))
d %>%
  knitr::kable()
```

Modelling

In this section, we will fit a NB-GLM to the data. It has the general formula:

_y_ = exp(_b_₀ + _b_₁ _x_₁)

where _y_ are litter counts, _x_₁ is the year, and _b_₀ and _b_<
    sub>1</sub> are coefficients.

Model diagnostics are given in the final section of this report. Here, `(Intercept)`
    corresponds with _b_₀ and `year` with _b_₁.

```{r}
minimum_years <- 5
n_years <- length(unique(d$year))
if (n_years < minimum_years) {
    warning(str_glue(str_c(
        "Your data period is less than {minimum_years} years (i.e., {n_years})\n",
        "It is advised to use at least the {minimum_years} most recent years.")),
        call. = FALSE)
}

minimum_surveys <- 50
n_surveys <- sum(d$n)
if (n_surveys < minimum_surveys) {
    warning(str_glue(str_c(
        "Note that the number of surveys is only {n_surveys}\n")),
        call. = FALSE)
}
```

```{r}
# add forecasting period
d_ltr <- d_ltr %>%
    bind_rows(
        tibble(
            date = seq(from = DATE_FROM, to = DATE_TO, by = "month"),
            y = NA_integer_) %>%
            filter(!(date %in% d_ltr$date))
    ) %>%
    arrange(date) %>%
    mutate(
        i = as.numeric(date),
        date_norm = (i - min(i)) / (max(i) - min(i))) %>%
    select(-i)

# modelling
m <- MASS::glm.nb(y ~ date_norm, data = d_ltr)
```
```

````
# Results

The plot below gives the predictions (black dots), the model response (red line) and
    corresponding 90%-confidence interval (blue band). The table gives the numeric
    results (lower and upper are the lower and upper bounds of the 90%-confidence
    interval respectively).


```{r}
# simulation
n_sim <- 100000
b <- MASS::mvrnorm(n = n_sim, mu = coef(m), Sigma = vcov(m))
d_ltr$upper <- d_ltr$lower <- d_ltr$median <- NA_real_
for (i in 1:nrow(d_ltr)) {
  r <- exp(b[, 1] + b[, 2] * d_ltr$date_norm[i])
  q <- quantile(r, probs = c(0.05, 0.50, 0.95))
  d_ltr$lower[i]  <- q[1]
  d_ltr$median[i] <- q[2]
  d_ltr$upper[i]  <- q[3]
}

# plot results
ggplot(data = d_ltr) +
    geom_ribbon(
        mapping = aes(x = date, ymin = lower, ymax = upper),
        fill = "blue", alpha = 0.1) +
    geom_path(
        mapping = aes(x = date, y = median),
        colour = "red", na.rm = TRUE) +
    geom_point(mapping = aes(x = date, y = y), na.rm = TRUE) +
    scale_x_date(name = "year") +
    scale_y_continuous(name = str_c(GROUP_CODE, " (counts/100m)")) +
    ggtitle(SPATIAL_CODE)
```

```{r}
# print table
d_ltr %>%
  mutate(year = as.integer(format(date, "%Y"))) %>%
  group_by(year) %>%
  summarise(
    observed = median(y, na.rm = TRUE),
    modelled = median(median),
    lower = median(lower),
    upper = median(upper),
    .groups = "drop") %>%
  mutate_all(round) %>%
  (knitr::kable)
```


# Model diagnostics

Model diagnostics are given below:

```{r}
summary(m)
```
````

```
```{css, echo=FALSE}
body{
    font-size: medium;
}
h1 {
    margin-top: 1.5em;
    font-size: xx-large;
    color: #1111A0;
}
pre code, pre, code {
  white-space: pre-wrap !important;
  overflow-x: hidden !important;
  word-wrap: break-word !important;
  word-break: keep-all !important;
}
```
```

Annex 3 Model results for Total Counts for Germany

The table below gives observed and modelled total counts based on survey dates for the four monitoring beaches of Germany. In addition, the lower and upper bounds of the 90% confidence interval are given.

year	observed	modelled	lower	upper
2013	218	176	140	221
2014	112	148	124	178
2015	53	123	107	142
2016	82	103	91	117
2017	91	87	75	100
2018	81	73	61	87
2019	50	61	49	77
2020	NA	51	39	68
2021	NA	43	31	61
2022	NA	36	24	54
2023	NA	30	19	48
2024	NA	25	15	43
2025	NA	21	12	38
2026	NA	18	9	34
2027	NA	15	7	30
2028	NA	13	6	27
2029	NA	11	5	24
2030	NA	9	4	22
2031	NA	7	3	19
2032	NA	6	2	17
2033	NA	5	2	15
2034	NA	4	1	14
2035	NA	4	1	12
2036	NA	3	1	11
2037	NA	3	1	10
2038	NA	2	1	9
2039	NA	2	0	8
2040	NA	2	0	7
2041	NA	1	0	6
2042	NA	1	0	6
2043	NA	1	0	5
2044	NA	1	0	4
2045	NA	1	0	4
2046	NA	1	0	3
2047	NA	0	0	3
2048	NA	0	0	3
2049	NA	0	0	2
2050	NA	0	0	2

Annex 4 Model results for Total Counts for Netherlands

The table below gives observed and modelled total counts based on survey dates for the four monitoring beaches of the Netherlands. In addition, the lower and upper bounds of the 90% confidence interval are given.

year	observed	modelled	lower	upper
2011	441	403	340	479
2012	231	370	321	428
2013	378	343	304	386
2014	262	316	285	350
2015	192	288	262	317
2016	270	265	239	295
2017	212	245	217	277
2018	148	225	194	261
2019	140	206	173	247
2020	NA	190	155	235
2021	NA	175	138	223
2022	NA	161	122	212
2023	NA	148	109	202
2024	NA	136	96	193
2025	NA	126	86	184
2026	NA	115	76	175
2027	NA	106	67	167
2028	NA	98	60	159
2029	NA	90	53	152
2030	NA	83	47	145
2031	NA	76	42	138
2032	NA	70	37	131
2033	NA	64	33	125
2034	NA	59	29	119
2035	NA	54	26	114
2036	NA	50	23	109
2037	NA	46	20	104
2038	NA	42	18	99
2039	NA	39	16	94
2040	NA	36	14	90
2041	NA	33	13	86
2042	NA	30	11	82
2043	NA	28	10	78
2044	NA	26	9	74
2045	NA	24	8	71
2046	NA	22	7	68
2047	NA	20	6	64
2048	NA	18	5	62
2049	NA	17	5	59
2050	NA	16	4	56

Annex 5 Examples of SUP and SEA models

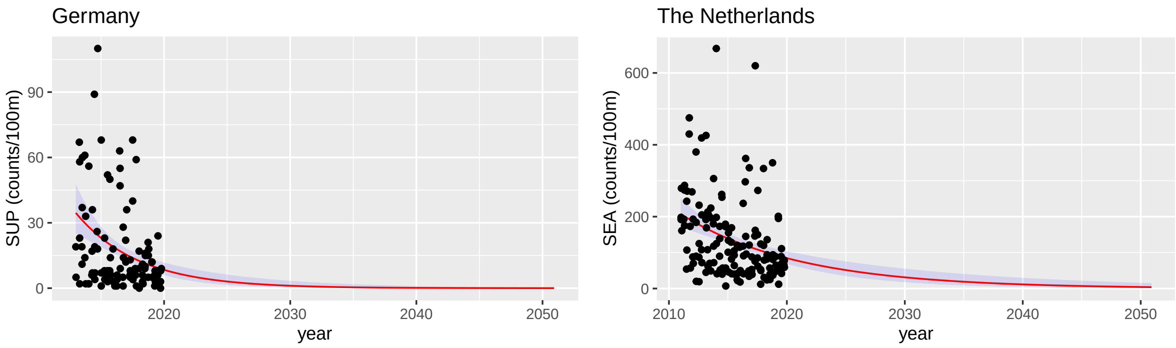

Figure Annex 5.1 *Fitted NB-GLM for Germany (single use plastics (SUP), left) and the Netherlands (maritime related litter (SEA), right). The dots are the survey data, the red line is the model fit, and the blue ribbon represents the 90%-confidence interval of the fit.*

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