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Analysing a Multi-Criteria Analysis to Prioritise Munition Piles in the German Baltic Sea for Remediation

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Abstract. In the aftermath of World War II, significant amounts of munitions were dumped into the German coastal waters. These unremedied munitions harbour various risks. The Multi-Criteria Analysis for Dumped Munition Prioritisation (MCA-DuMP) was developed as part of the efforts of the CONMAR project and enables the prioritisation of these munitions for remediation. To better understand the formation and structure of these prioritisation results, a Sensitivity Analysis (SA) was conducted. As part of this analysis, two approaches to SA, VARS and PAWN, were applied to three input/output series obtained using different sampling strategies. The results of this SA were used to identify influential factors and to rank the factors according to their influence on the prioritisation results. Both aspects are helpful to decision makers as they enable them to better assess and categorise the prioritisation results, thus allowing them to utilise the findings as best as possible in their decision-making process. They can also be utilised by the developers of MCA-DuMP to verify its behaviour.

Submission Type. Case study, Analysis

BoK Concepts. [AM5-7] Multi-criteria evaluation, [GS3-4] Use of geospatial information in environmental issues

Keywords. Submerged Munitions, Sensitivity Analysis, Multi-Criteria Analysis, CONMAR, VARS, PAWN

1 Introduction

In the aftermath of World War II, an estimated 1.6 million tons of munitions were dumped into German waters of the Baltic and the North Seas. These largely unremedied munitions pose numerous risks to the environment, economy and human health (Greinert et al., 2020) (see Fig. 1).

Until 2010, these problems were largely ignored and no significant actions for their management were taken. Since then, a number of scientific endeavours have taken up the challenge to advance the understanding of the role and future handling of these munitions. Among these is the CONMAR project, which aims at integrating existing and new data for the evaluation of marine munitions, pooling the expertise of research institutions, government agencies, and industry, thus increasing the scientific understanding of the effects of marine munitions, and developing and implementing solutions for monitoring and large-scale remediation in close collaboration with stakeholders (GEOMAR Helmholtz Centre for Ocean Research, 2023; Frey et al., 2024).

As part of these efforts, a Multi-Criteria Analysis (MCA), called Multi-Criteria Analysis for Dumped Munition Prioritisation (MCA-DuMP), was developed on the basis of stakeholder workshops using the Analytic Hierarchy Process (AHP) approach to evaluate identified munition piles with regard to the risks they pose for the environment, the economy, to the human health and for misuse. Possible socio-economic benefits which might result from the remediation of munition piles, as well as the expected cost-effectiveness, are also evaluated. MCA-DuMP enables the prioritisation of munition piles for remediation (Ensenbach et al., 2023, 2024). These efforts have gained further importance against the backdrop of an immediate action programme with funds totalling 100 million Euros, which is envisioned to help pave the way for the remediation efforts on an industrial scale (Federal Ministry for the Environment, Nature Conservation, Nuclear Safety and Consumer Protection, 2024). Comparable approaches have been presented and discussed by Landquist et al. (2016), van der Wulp (2021) and Frey (2024). While Landquist et al. (2016) developed a probabilistic method called VRAKA to assess the risks posed by potentially polluting shipwrecks, van der Wulp (2021) describes a decision support system named DAIMON DSS which integrates artificial intelligence as well as spatial and non-spatial data to perform risk assessment of detected munition objects. Frey (2024) explores various risk assessment methods concerning submerged munitions from an explosive ordnance disposal (EOD) perspective. While also arguing for structured approaches which integrate various spatial and non-spatial data, Frey (2024) also highlights the need to consider temporal effects as well as interdependencies.

To better understand the formation and structure of MCA-DuMP's prioritisation results, a Sensitivity Analysis (SA) was carried out employing the VARS and PAWN frameworks. The analysis aimed at identifying factors with negligible influence on the prioritisation results and ranking of the remaining factors according to that influence. The findings may be used to simplify or adapt MCA-DuMP or to further refine underlying data to allow for more efficient and precise prioritisations. They also allow to verify that MCA-DuMP is capable of generating robust prioritisation results which reflect not only the intentions of the developers of the model, but also the stakeholder expertise. Further, decision-makers are enabled to better assess and categorise the prioritisation results, thus allowing them to utilise the findings as best as possible in their decision-making process.

2 Methodology

Multi-Criteria Analysis

MCA-DuMP was developed applying the AHP approach, which guides complex decisions to be made through a set of alternatives. The complex decision problem at hand can be summed up by the following question: *How should munition piles in the German Baltic Sea be prioritised for remediation?* This is done by arranging the relevant decision criteria in a hierarchy tree. Each of the branches of that hierarchy tree comprises a number of criteria. A weight is assigned to each branch and criterion in order to control the relative influence to the model results. These weights were determined via workshops and reflect the expertise of stakeholders with regard to the overarching question. MCA-DuMP is divided into six branches (see Fig. 2). The individual criteria are computed on the basis of geophysical, biological, chemical, toxicological, economic, and other spatial data (Ensenbach et al., 2023, 2024). Some of the underlying data exhibit a temporal dimension as well. Following Greinert et al. (2020) the spatial resolution of the underlying data was, wherever possible, kept below or equal to 100 metres. The temporal resolution of the SA was set to months. MCA-DuMP was implemented using the programming language Python.

The datasets from which values of the factors are drawn can be assigned to one of six groups. When executing MCA-DuMP, values for the factors are extracted and normalised for each munition pile. The normalisation bounds are defined globally to ensure comparability and robustness of the prioritisation results. These values are then used in the computation of the individual criteria. MCA-DuMP incorporates a total of 23 factors and an additional dummy factor to facilitate factor fixing (see Tab. 1). It should be noted that there is no one-to-one relationship between factors and the criteria. Some factors are used in the computation of multiple criteria. The prioritisation result is the weighted mean of the results of the criteria and branches, with higher values indicating a higher remediation priority.

Sensitivity Analysis

There is a plethora of methods and approaches to SA. In general, SA investigates how variations in the output can be attributed to variations in the inputs of a model. A model is described as a numerical procedure which simulates the behaviour of a system. Values of factors for such a model may be varied, thus inducing changes to its output. Factors may take the form of parameters appearing in equations, of initial states or of the boundary conditions of the model, as well as of temporal or spatial resolutions. The relationship between the factors, the numerical procedure facilitated by the model and the output is referred to as the response surface. Since this relationship is rarely available in analytical form, it has to be sampled. There are three main purposes for conducting an SA namely identifying factors with negligible influence on the output (factor fixing), ranking the factors with respect to their influence on the output (factor ranking) and identifying regions of the factor space which result in certain regions of the output space (factor mapping) (Pianosi et al., 2016).

The two approaches chosen for the analysis of MCA-DuMP are VARS and PAWN. Both can be classified as Global Sensitivity Analysis (GSA) methods, meaning they consider the entire variability space of the factors, a favourable characteristic when dealing with complex or non-linear models. The sensitivity of a model towards variations in its inputs is often expressed by a sensitivity index (Reed et al., 2024; Saltelli et al., 2007).

VARS

The Variogram Analysis of Response Surfaces (VARS) approach to SA, proposed by Razavi and Gupta (2016a, b), represents a general SA framework capable of characterising sensitivity across the full spectrum of scales in the factor variability space. As a variogram-based approach to SA, variograms are regarded as a comprehensive manifestation of sensitivity information. Here, the Integrated Variogram Across a Range of Scales (*IVARS*) is used as the main sensitivity index. Additionally, approximations of two other commonly employed sensitivity indices, namely the variance-based Total-order sensitivity index (S_T) proposed by Sobol (2001) and Homma and Saltelli (1999) and the distribution-based Absolute Elementary-Effects sensitivity index (μ^*) proposed by Morris (1991) and Campolongo et al. (2007), can be derived. Razavi and Gupta (2016a, b) also provide a dedicated sampling strategy

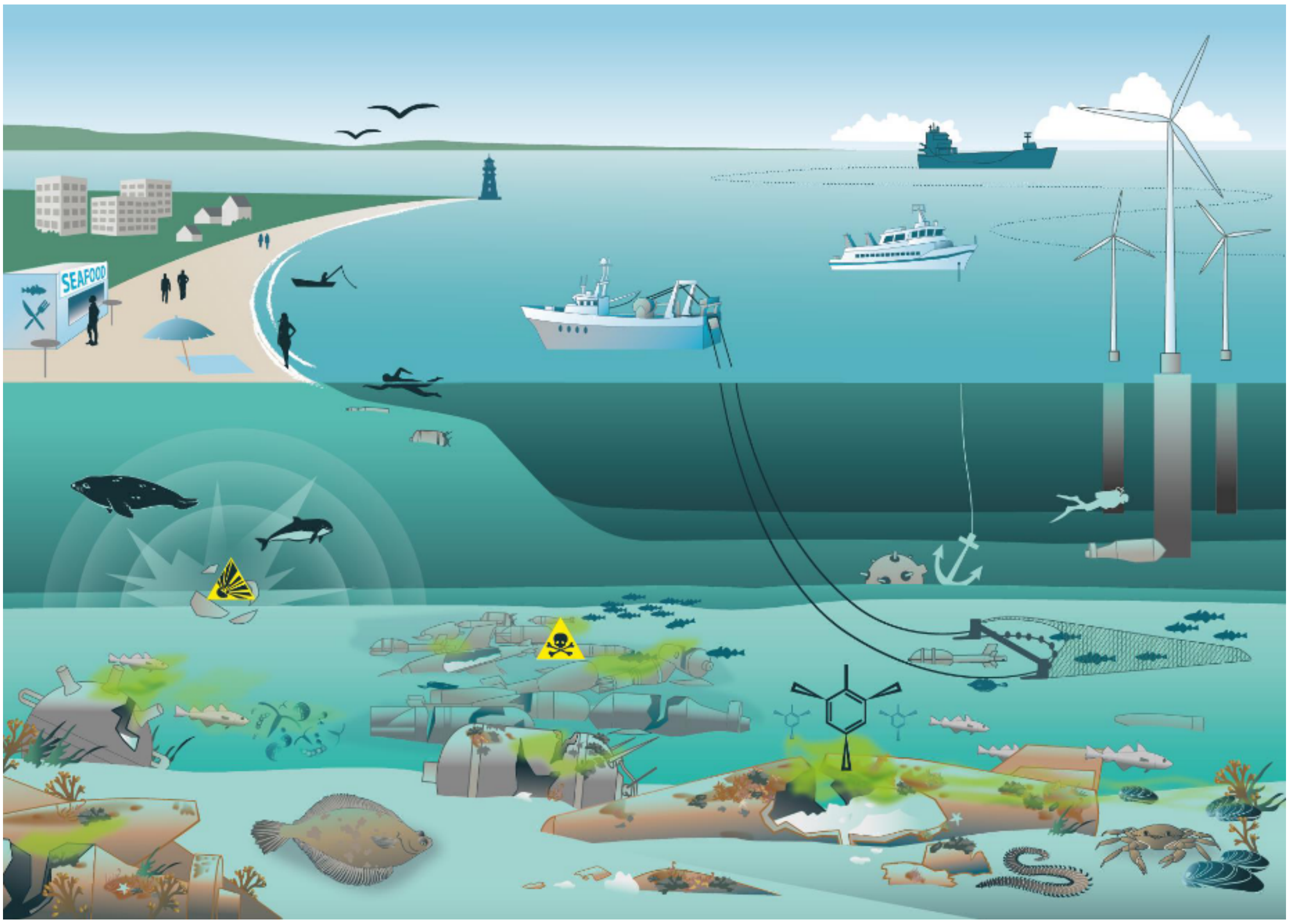

Figure 1. Risks posed by unremedied marine dumped munitions (GEOMAR Helmholtz Centre for Ocean Research, 2023)

Figure 2. Structure of MCA-DuMP (Ensenbach et al., 2023, 2024)

Table 1. Factors of the Multi-Criteria Analysis

Factor group	Factor	Spatial resolution	Temporal resolution	Source
Dummy	Dummy	-	-	-
Munition pile characteristics	Number of objects (*)	-	-	GEOMAR
	Size of objects (*)	-	-	GEOMAR
	Variability of objects (*)	-	-	GEOMAR
	Layering of objects (*)	-	-	GEOMAR
	State of the fuses (*)	-	-	GEOMAR
	Corrosion of objects (*)	-	-	GEOMAR
	Burial of objects (*)	-	-	GEOMAR
Distance to spatial features	Distance to coastlines (m)	10x10m	-	BSH
	Distance to harbours (m)	10x10m	-	BSH
	Distance to shipping lanes (m)	10x10m	-	BSH
	Distance to cables (m)	10x10m	-	EMODnet
	Distance to bathing sites (m)	10x10m	-	WM MV MJG SH
	Distance to protected areas (m)	10x10m	-	EMODnet
Munition related pollutants	Pollutants in molluscs (ng/g d.w.)	hex cells	-	UKSH
	Pollutants in mammals (ng/g d.w.)	hex cells	-	UKSH
	Pollutants in fishes (ng/ml)	hex cells	-	TI-OF
	Pollutants in seawater (ng/l)	hex cells	-	GEOMAR
Maritime operations	Shipping density (h)	1x1km	monthly medians	NGA
	Fishing effort (kWfh)	c-squares	quarterly medians	HELCOM
	Fishing effort MBCG (kWfh)	c-squares	quarterly medians	HELCOM
Evironmental features	Current velocity (m/s)	200x200m	monthly means	IOW
	Wave height (m)	200x200m	monthly means	IOW
	Seabed sediments	10x10m	-	BSH

Details on the availability of the underlying datasets can be found in the Data and Software Availability subsection. (*) denotes factors which represent characteristics of the munition piles themselves. The addendum MBCG refers to Mobile bottom-contacting fishing gear.

called STAR which is designed to facilitate computation of sensitivity-related information provided by VARS utilising techniques closely related to Latin Hypercube Sampling (LHS).

There are two extensions to VARS. A first extension proposed by Do and Razavi (2020), Generalised VARS (GVARS) alongside Generalised STAR (GSTAR), enables the VARS approach to accommodate correlated factors by describing the correlation structure through Pearson correlation coefficients. The second extension called Data-driven VARS (DVARS), proposed by Sheikholeslami and Razavi (2020), allow for the application of the VARS approach to a generic input/output series. Illustrative case studies using VARS and GVARS to analyse hydrological models can be found in Razavi and Gupta (2016b) and Do and Razavi (2020) respectively.

PAWN

PAWN, proposed by Pianosi and Wagener (2015), represents an efficient density-based approach to SA. As opposed to many comparable density-based approaches that use Probability Density Functions (PDF) in the computation of their sensitivity indices, PAWN uses Cumulative Distribution Functions (CDF), which are easier to derive than PDFs. Sensitivity is expressed by the PAWN sensitivity index T.

An extension to the PAWN approach, also proposed by Pianosi and Wagener (2018), allows for the approach to be applied to a generic input/output series. An exemplary case study which applies PAWN to a hydrological model can be found in Pianosi and Wagener (2018).

Experiment

Following Pianosi et al. (2016) the experiment was divided into sampling, evaluation, and post-processing phases. Three input/output series were generated and analysed. The first was generated employing LHS, utilising the SAFE Toolbox software package. The factor values were sampled from uniform distributions within the factor value ranges. After applying MCA-DuMP to the resulting input/output series, the sensitivity index T was derived using PAWN (see Fig. 3).

A second input/output series was generated employing GSTAR. The factor values were sampled from non-uniform distributions within the factor value ranges. An identity matrix was used to describe the correlation structure between the factors, as reliable Pearson correlations coefficients could not be derived. The sensitivity indices μ^*, S_T and $IVARS_{50}$ were derived from this input/output series using GVARS (see Fig. 3).

With the third input/output series factor values were not sampled in feature space but rather from the spatial data directly. Since not all factors exhibit a spatial dimension, like the characteristics of the munition piles, value ranges for these also had to be defined beforehand. To generate the locations for simulating munition piles and extracting values for factors with a spatial dimension, a homogeneous Poisson point process was used and applied to the German Baltic Sea. Such a process generates uniformly distributed independent random locations (Diggle, 2013). PAWN and DVARS were applied to the resulting input/output series to derive the sensitivity indices T and $IVARS_{50}$. A sample size of 46000 was chosen, which is double the size recommended by Pianosi et al. (2016), who suggest 1000 samples per factor. Confidence bands were reported for a confidence level of 95% and computed using common bootstrapping. To ensure acceptable computation times when applying DVARS an additional subsampling had to be conducted employing LHS (see Fig. 3).

The experiment was carried out for each month of the year. The identification of influential factors was conducted through means of comparison of the sensitivity indices of a factor under examination and those of the dummy factor. The remaining factors were subsequently ranked in accordance with their sensitivity indices (see Fig. 3).

Data and Software Availability

Many datasets utilized in MCA-DuMP are publicly available. Data regarding the generalised coastline, harbour and cable infrastructures, shipping lanes and seabed sediments can be retrieved from the Federal Maritime and Hydrographic Agency (BSH) via their GeoSeaPortal (https://www.geoseaportal.de/). Data describing the shipping density can be retrieved from the National Geospatial-Intelligence Agency (NGA) via their Global Maritime Traffic Density Service (GMTDS) (https://globalmaritimetraffic.org/gmtds.html). Data regarding the fishing effort in the Baltic Sea can be retrieved from the Baltic Marine Environment Protection Commission (HELCOM) via their HELCOM Map and Data Service (MADS) (https://maps.helcom.fi/website/mapservice/index.html). Data regarding the current velocity and wave height were provided by the Leibniz Institute for Baltic Sea Research Warnemünde (IOW) and are not openly accessible. They originate from current velocity models described, e.g., in Gräwe et al. (2015). Not all datasets on the concentrations of munition related pollutants are openly available. These were provided by the University Hospital Schleswig-Holstein (UKSH), Helmholtz Centre for Ocean Research (GEOMAR) and Thünen Institute of Baltic Sea Fisheries (TI-OF). The latter dataset is available via the earth system research information system PANGAEA (https://www.pangaea.de/) (Kammann et al., 2024). Data regarding the munition piles, their locations and characteristics, are available at GEOMAR but are not available to the public for security reasons.

Python implementations of VARS and PAWN and their extensions are available via the VARS-TOOL (https://github.com/vars-tool/vars-tool) and the SAFE Toolbox (https://github.com/SAFEtoolbox/SAFE-python) software packages respectively (Razavi et al., 2018; Pianosi et al., 2015).

High resolution versions of the figures shown in this article are available via figshare (https://doi.org/10.6084/m9.figshare.28343009).

3 Results

Factor fixing

Influential factors were identified by comparing the sensitivity indices obtained for the individual factors with the sensitivity indices obtained for the dummy factor. While the sensitivity indices μ^*, S_T and $IVARS_{50}$ obtained from the GSTAR input/output series and T obtained from the spatial input/output series identified all factors as being influential to the formation of the prioritisation results the remaining sensitivity indices could not assert the influential nature of all factors. It could, however, not be verified that they were not influential (see Tabs. A1 to A3). It must further be noted that the factor pollutants in mammals was omitted during the analysis, since the underlying data did not exhibit any variation.

Factor ranking

The sensitivity indices obtained were also used to rank the factors with regard to their influence. Although the rankings obtained from the three input/output series do exhibit differences, the majority of sensitivity indices agree that the factors pollutants in fish, fishing effort with Mobile bottom-contacting fishing gear (MBCG), fishing effort and pollutants in molluscs are by far the most influential factors. Only, the sensitivity index T obtained from the LHS input/output series exhibited substantially lower values for certain factors like the fishing effort and fishing effort MBCG (see Figs. B1 to B6).

The influence of factor groups were also assessed. One such factor group contained the munition pile characteristics. The sensitivity indices obtained agree that the factors size of objects and burial of objects are the most influential munition pile characteristics. When considering the entire factor group in terms of its influence, most sensitivity indices tend to agree that it exerts middling influence on the prioritisation results when compared to the other factor groups. A noteworthy deviation from this assessment is reached when considering the sensitivity index T ob-

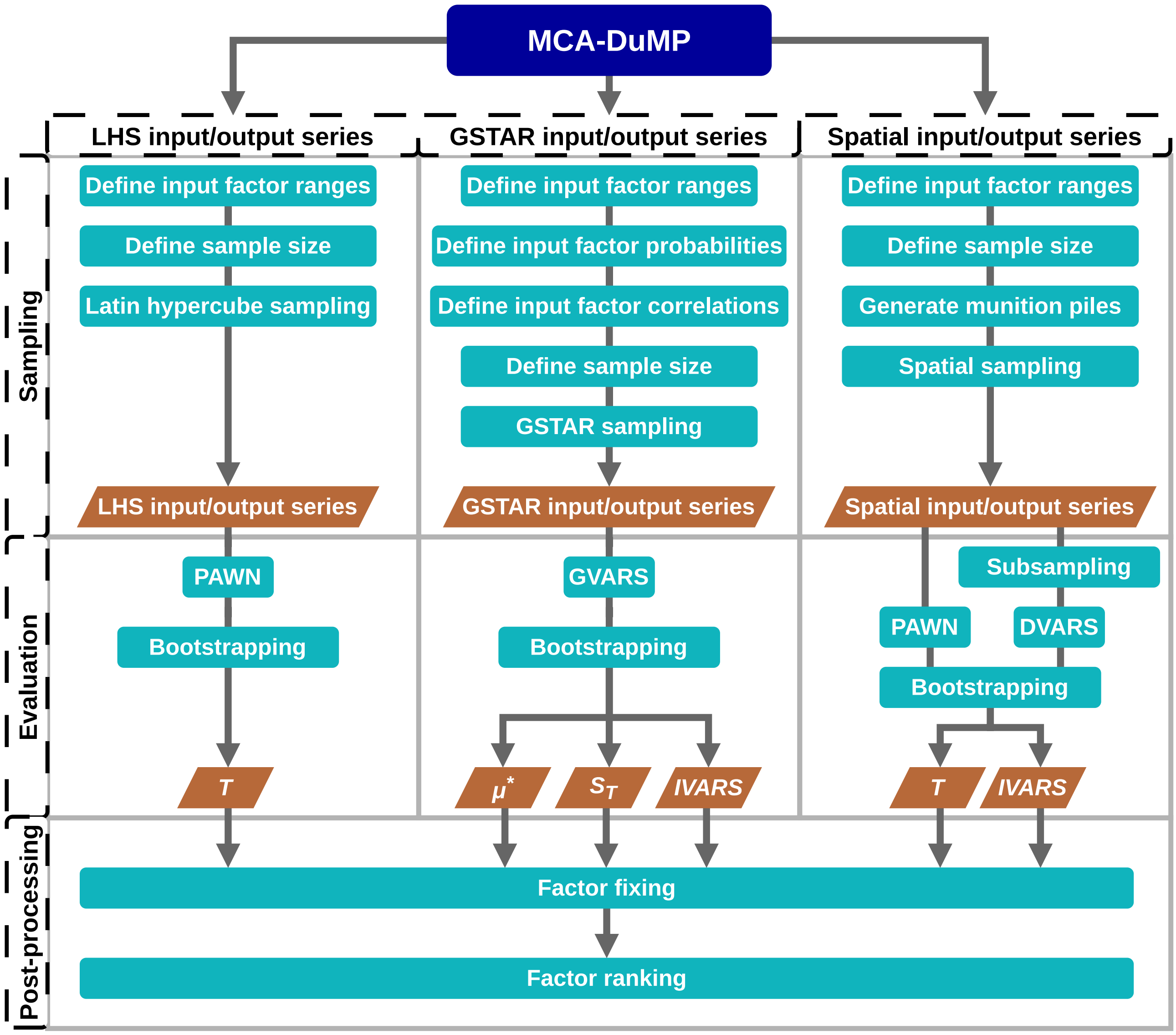

Figure 3. Experimental set-up

tained from the LHS input/output series. A second group contains the time variable factors. The influence of these factors on the prioritisation results and possible changes in this influence over time were of interest.

According to the majority of sensitivity indices obtained, the factor fishing effort and fishing effort MBCG are also the most influential factors from the time variable factors. The majority of sensitivity indices also agree that the time variable factors do exert major influence on the prioritisation results. Except for the sensitivity indices T obtained from the LHS input/output series and $IVARS_{50}$ obtained from the spatial input/output series, all sensitivity indices exhibit substantial changes on a quarterly basis (see Figs. C1 to C6).

4 Discussion

The factor fixing results did not uncover possibilities for simplifications of MCA-DuMP through the removal of criteria, since no factors could be identified as non-influential. It needs to be stressed that the comparison with the sensitivity indices obtained for the dummy factor only allows the identification of influential factors. Statements about a potential non-influential nature could not be derived. Thus, the introduction of and subsequent comparison with a dummy factor, although straightforward, is lacking in utility. For the sensitivity indices T, S_T and $IVARS_{50}$, a value equal to 0 would be sufficient to identify a non-influential factor. More elaborate considerations would be necessary with regard to the sensitivity index μ^*. It would also be possible to determine a threshold to separate influential and non-influential factors, though such an approach would require extensive domain knowledge about the model to be analysed and the sensitivity indices utilized.

The rankings obtained for the individual factors and factor groups, although exhibiting some variation, are plausible considering the structure of MCA-DuMP. The most influential factors all feature in highly weighted, in some cases multiple, criteria which are part of highly weighted branches of MCA-DuMP. Similar arguments apply to the assessments regarding the munition pile characteristics. The quarterly changes apparent in the majority of sensitivity indices are also congruent with the changes in the two most influential time variable factors. These changes are mainly driven by the two most influential factors.

When comparing the different sensitivity indices, two discrepancies become apparent. The sensitivity index T obtained from LHS input/output series drastically underestimated the influence of some factors and only exhibited minor changes over time. This differing and potentially false assessment of the sensitivity of MCA-DuMP is attributable to the sampling setup rather than lacking capabilities of PAWN. Similar arguments apply to the sensitivity index $IVARS_{50}$ obtained from the spatially sampled input/output series. It is likely that the necessary subsampling has impacted the computation of the sensitivity index negatively. In addition, the spatial sampling approach was hampered by the extreme spatial sparsity exhibited by some data underlying those factors describing the concentrations of munition related pollutants.

5 Conclusion and Outlook

The authors conducted an SA of MCA-DuMP developed in the context of the CONMAR project to enable the prioritisation of munition piles in the German Baltic Sea for remediation, by assessing the potential risks they pose. Two approaches to SA, namely VARS and PAWN, were applied to three input/output series that were sampled by means of different sampling techniques. A useful baseline for further investigations regarding the sensitivity of MCA-DuMP towards its various factors was established on the basis of the results obtained and discussed in this study. They also enable the developers of MCA-DuMP to assess whether the sensitivities exhibited by MCA-DuMP are congruent with their intentions and by extension reflect the expertise of the stakeholders involved in its development. Whether or not these assessments lead to adjustments of MCA-DuMP, this study contributes to risk-based, considerate, and efficient remediation efforts of the munition piles in the German Baltic Sea.

No possibilities for simplifying MCA-DuMP could be uncovered from the factor fixing results. The factor ranking results were congruent with the underlying model and allowed for an assessment of the influence of the individual factors and for identifying the most influential ones. The study also uncovered several opportunities to further optimise and develop the presented approaches. Since limitations of the chosen approach to factor fixing could be identified, statistically stronger approaches which allow for a clear identification of influential and non-influential factors should be implemented and evaluated. In order to enable an improved assessment and categorisation of the prioritisation results, a complementary Uncertainty Analysis (UA) should be carried out. Whether and how uncertainties in the factors would translate to their corresponding sensitivity indices would be of particular interest. When considering the underlying data, approaches to counteract the negative impacts of extreme spatial sparsity should be explored and tested.

Future studies might also consider adapting the approach presented in this study to allow for individual branches of MCA-DuMP to be analysed, and regard the individual branch and criterion weights as factors. Such an approach could show the influence of the expert opinions on the prioritisation results. The sample sizes for future works could be established more carefully, e.g., by using convergence analysis. The PAWN, DVARS approaches could further be coupled with a more sophisticated sampling setups to allow for a more meaningful comparison with the VARS approach. To fully utilise the capabilities of the VARS approach and in the hopes to derive more accurate sensitivity indices, correlations between the factors of MCA-DuMP should be considered in future studies.

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References

Campolongo, F., Cariboni, J., and Saltelli, A.: An effective screening design for sensitivity analysis of large models, Environmental Modelling & Software, 22, 1509–1518, https://doi.org/10.1016/j.envsoft.2006.10.004, 2007.

Diggle, P. J.: Statistical Analysis of Spatial and Spatio-Temporal Point Patterns, no. 128 in Monographs on Statistics and Applied Probability, Chapman & Hall/CRC, New York, 3rd edn., https://doi.org/10.1201/b15326, 2013.

Do, N. C. and Razavi, S.: Correlation Effects? A Major but Often Neglected Component in Sensitivity and Uncertainty Analysis, Water Resources Research, 56, https://doi.org/10.1029/2019WR025436, 2020.

Ensenbach, S., Pechmann, A., Frey, T., Hinkel, J., and Greinert, J.: Implementing geophysical and geochemical data in multicriteria analysis for prioritization of munition dump site clearance, https://doi.org/10.5194/egusphere-egu23-14271, 2023.

Ensenbach, S., Frey, T., Pechmann, A., Pilz, A., and Greinert, J.: Prioritization of munition piles in the German BalticSea using multi-criteria analysis, https://doi.org/10.13140/RG.2.2.34617.07521, 2024.

Federal Ministry for the Environment, Nature Conservation, Nuclear Safety and Consumer Protection: Pressemitteilung Nr. 105/24, https://www.bmuv.de/PM11114, 2024.

Frey, T.: What Is Missing in Offshore Explosive Ordnance Disposal Risk Assessment?, MDPI Toxics, 12, https://doi.org/10.3390/toxics12070468, 2024.

Frey, T., Greinert, J., Wilhelmsen, U., Maser, E., Scharsack, J., Brenner, M., Rankin, C., and Freiherr von Lukas, U.: Munition im Meer - Sachstand und Perspektiven, https://www.allianz-meeresforschung.de/app/uploads/2024/10/241021-dam-factsheet-munition.pdf, 2024.

GEOMAR Helmholtz Centre for Ocean Research: CONMAR Factsheet, https://www.sustainmare.de/imperia/md/assets/microsites/sustainmare/dokumente/factsheet_conmar23_en.pdf, 2023.

Greinert, J., Appel, D., Beck, A., Eggert, A., Gräwe, U., Kampmeier, M., Martin, H.-J., Maser, E., Schlosser, C., Song, Y., Strehse, J., Eefke van der Lee, Vortmeyer-Kley, R., Wichert, U., and Frey, T.: Practical Guide for Environmental Monitoring of Conventional Munitions in the Seas - Results from the BMBF funded project UDEMM "Umweltmonitoring für die Delaboration von Munition im Meer" Version 1.1, GEOMAR Report 54, GEOMAR Helmholtz Centre for Ocean Research, Kiel, Germany, https://doi.org/10.3289/GEOMAR_REP_NS_54_2019, 2020.

Gräwe, U., Naumann, M., Mohrholz, V., and Burchard, H.: Anatomizing one of the largest saltwater inflows into the Baltic Sea in December 2014, Journal of Geophysical Research: Oceans, 120, 7137–7698, https://doi.org/10.1002/2015JC011269, 2015.

Homma, T. and Saltelli, A.: Importance measures in global sensitivity analysis of nonlinear models, Reliability Engineering & System Safety, 52, 1–17, https://doi.org/10.1016/0951-8320(96)00002-6, 1999.

Kammann, U., Töpker, V., Schmidt, N., Rödiger, M., Aust, M.-O., Gabel, M., and Scharsack, J. P.: Health status of dab (Limanda limanda) exposed to dumped munition in German coastal waters, https://doi.org/10.1594/PANGAEA.967434, 2024.

Landquist, H., Rosen, L., Lindhe, A., and Hassellöv, I.-M.: VRAKA - A Probabilistic Risk Assessment Method for Potentially Polluting Shipwrecks, Frontiers in Environmental Science, 4, https://doi.org/10.3389/fenvs.2016.00049, 2016.

Morris, M. D.: Factorial Sampling Plans for Preliminary Computational Experiments, Technometrics, 33, 161–174, https://doi.org/10.1080/00401706.1991.10484804, 1991.

Pianosi, F. and Wagener, T.: A simple and efficient method for global sensitivity analysis based on cumulative distribution functions, Environmental Modelling & Software, 67, 1–11, https://doi.org/10.1016/j.envsoft.2015.01.004, 2015.

Pianosi, F. and Wagener, T.: Distribution-based sensitivity analysis from a generic input-output sample, Environmental Modelling & Software, 108, 197–207, https://doi.org/10.1016/j.envsoft.2018.07.019, 2018.

Pianosi, F., Sarrazin, F., and Wagener, T.: A Matlab toolbox for Global Sensitivity Analysis, Environmental Modelling & Software, 70, 80–85, https://doi.org/10.1016/j.envsoft.2015.04.009, 2015.

Pianosi, F., Beven, K., Freer, J., Hall, J. W., Rougier, J., Stephenson, D. B., and Wagener, T.: Sensitivity analysis of environmental models: A systematic review with practical workflow, Environmental Modelling & Software, 79, 214–232, https://doi.org/10.1016/j.envsoft.2016.02.008, 2016.

Razavi, S. and Gupta, H. V.: A new framework for comprehensive, robust, and efficient global sensitivity analysis: 1. Theory, Water Resources Research, 52, 423–439, https://doi.org/10.1002/2015WR017558, 2016a.

Razavi, S. and Gupta, H. V.: A new framework for comprehensive, robust, and efficient global sensitivity analysis: 2. Application, Water Resources Research, 52, 440–455, https://doi.org/10.1002/2015WR017559, 2016b.

Razavi, S., Sheikholeslami, R., Gupta, H. V., and Amin Haghnegahdar: VARS-TOOL: A toolbox for comprehensive, efficient, and robust sensitivity and uncertainty analysis, Environmental Modelling and Software, 112, 95–107, https://doi.org/10.1016/j.envsoft.2018.10.005, 2018.

Reed, P. M., Hadjimichael, A., Malek, K., Karimi, T., Vernon, C. R., Srikrishnan, V., Gupta, R. S., Gold, D. F., Lee, B., Keller, K., Thurber, T. B., and Rice, J. S.: Addressing Uncertainty in MultiSector Dynamics Research, Zenodo, https://doi.org/10.5281/zenodo.6110623, 2024.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., and Tarantola, S.: Global Sensitivity Analysis - The Primer, John Wiley & Sons, Chichester, https://doi.org/10.1002/9780470725184, 2007.

Sheikholeslami, R. and Razavi, S.: A Fresh Look at Variography: Measuring Dependence and Possible Sensitivities Across Geophysical Systems From Any Given Data, Geophysical Research Letters, 47, https://doi.org/10.1029/2020GL089829, 2020.

Sobol, I. M.: Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates, Mathematics and Computers in Simulation, 55, 271–280, https://doi.org/10.1016/S0378-4754(00)00270-6, 2001.

van der Wulp, S. A.: Decision Support System for Marine Munitions - User Manual 1.1, https://tinyurl.com/yzydpc8c, 2021.

Appendix A: Factor fixing results

Table A1. Factor fixing results obtained from LHS input output/series

Factor	T
Number of objects	✗
Size of objects	✓
Variability of objects	✗
Layering of objects	✗
State of the fuses	✗
Corrosion of objects	✗
Burial of objects	✓
Distance to coastlines	✗
Distance to harbours	✗
Distance to shipping lanes	✓
Distance to cables!	✗
Distance to bathing sites	✓
Distance to protected areas	✓
Seabed sediments	✗
Pollutants in molluscs	✓
Pollutants in mammals	–
Pollutants in fish	✓
Pollutants in seawater	✗
Shipping density	✓
Fishing effort	✗
Fishing effort MBCG	✗
Current velocity	✗
Wave height	✗

✓: identified as influential, ✗: not identified as influential, –: omitted in analysis

Table A2. Factor fixing results obtained from GSTAR input output/series

Factor	μ^*	S_T	*IVARS*$_{50}$
Number of objects	✓	✓	✓
Size of objects	✓	✓	✓
Variability of objects	✓	✓	✓
Layering of objects	✓	✓	✓
State of the fuses	✓	✓	✓
Corrosion of objects	✓	✓	✓
Burial of objects	✓	✓	✓
Distance to coastlines	✓	✓	✓
Distance to harbours	✓	✓	✓
Distance to shipping lanes	✓	✓	✓
Distance to cables!	✓	✓	✓
Distance to bathing sites	✓	✓	✓
Distance to protected areas	✓	✓	✓
Seabed sediments	✓	✓	✓
Pollutants in molluscs	✓	✓	✓
Pollutants in mammals	–	–	–
Pollutants in fish	✓	✓	✓
Pollutants in seawater	✓	✓	✓
Shipping density	✓	✓	✓
Fishing effort	✓	✓	✓
Fishing effort MBCG	✓	✓	✓
Current velocity	✓	✓	✓
Wave height	✓	✓	✓

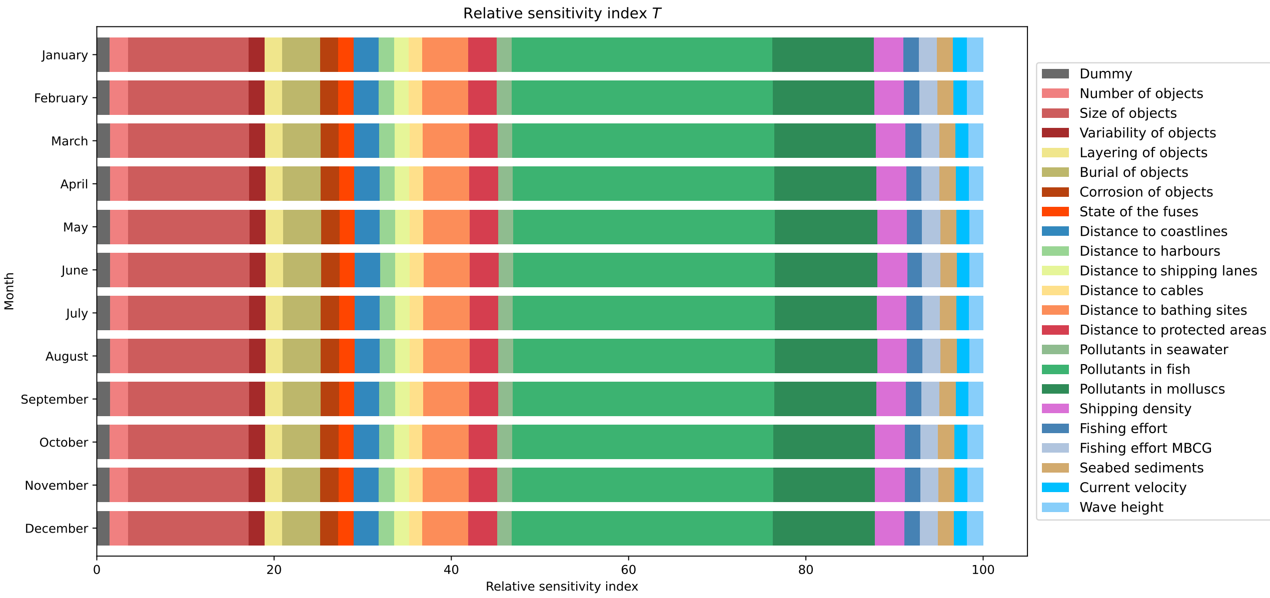
✓: identified as influential, ✗: not identified as influential, –: omitted in analysis

Table A3. Factor fixing results obtained from spatial input output/series

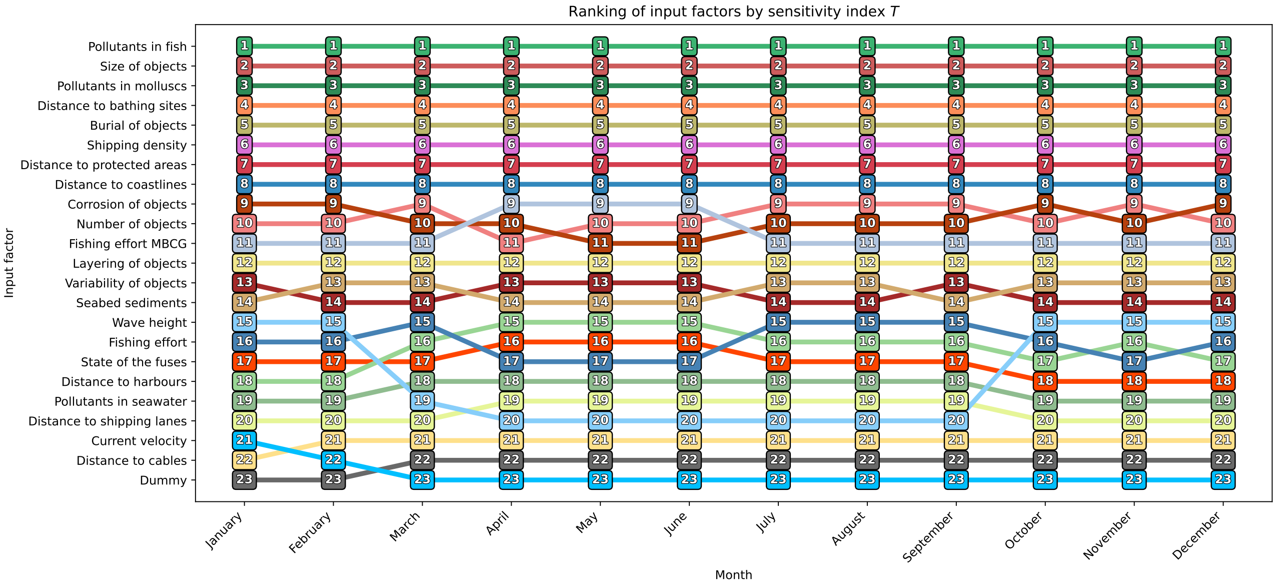
Factor	T	*IVARS*$_{50}$
Number of objects	✓	✗
Size of objects	✓	✓
Variability of objects	✓	✗
Layering of objects	✓	✗
State of the fuses	✓	✗
Corrosion of objects	✓	✗
Burial of objects	✓	✓
Distance to coastlines	✓	✗
Distance to harbours	✓	✗
Distance to shipping lanes	✓	✗
Distance to cables!	✓	✗
Distance to bathing sites	✓	✗
Distance to protected areas	✓	✓
Seabed sediments	✓	✗
Pollutants in molluscs	✓	✓
Pollutants in mammals	–	–
Pollutants in fish	✓	✓
Pollutants in seawater	✓	✓
Shipping density	✓	✗
Fishing effort	✓	✓
Fishing effort MBCG	✓	✓
Current velocity	✓	✗
Wave height	✓	✗

✓: identified as influential, ✗: not identified as influential, –: omitted in analysis

Appendix B: Factor ranking results

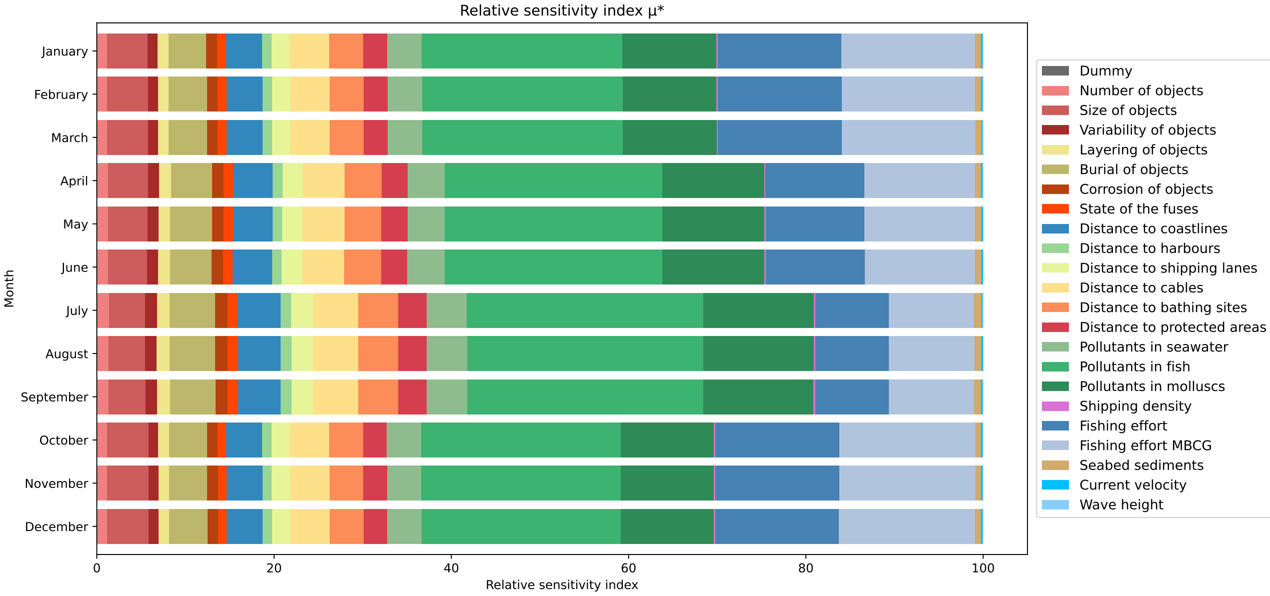


(a)

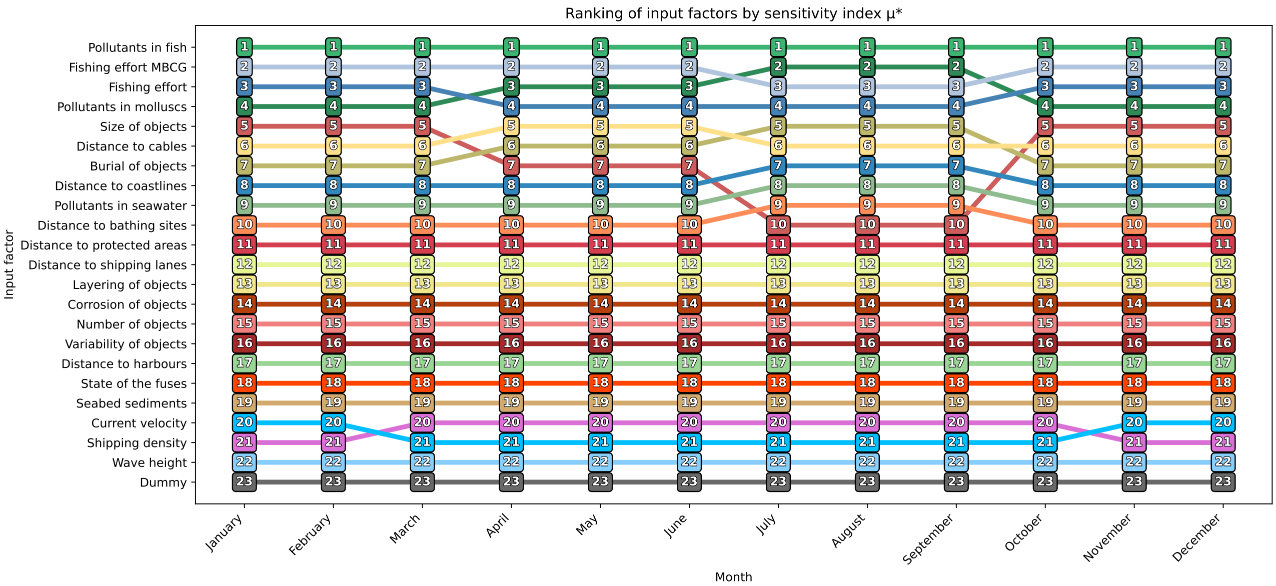


(b)

Figure B1. Sensitivity index T obtained from the LHS input/output series (a) and corresponding input factor ranking results (b)

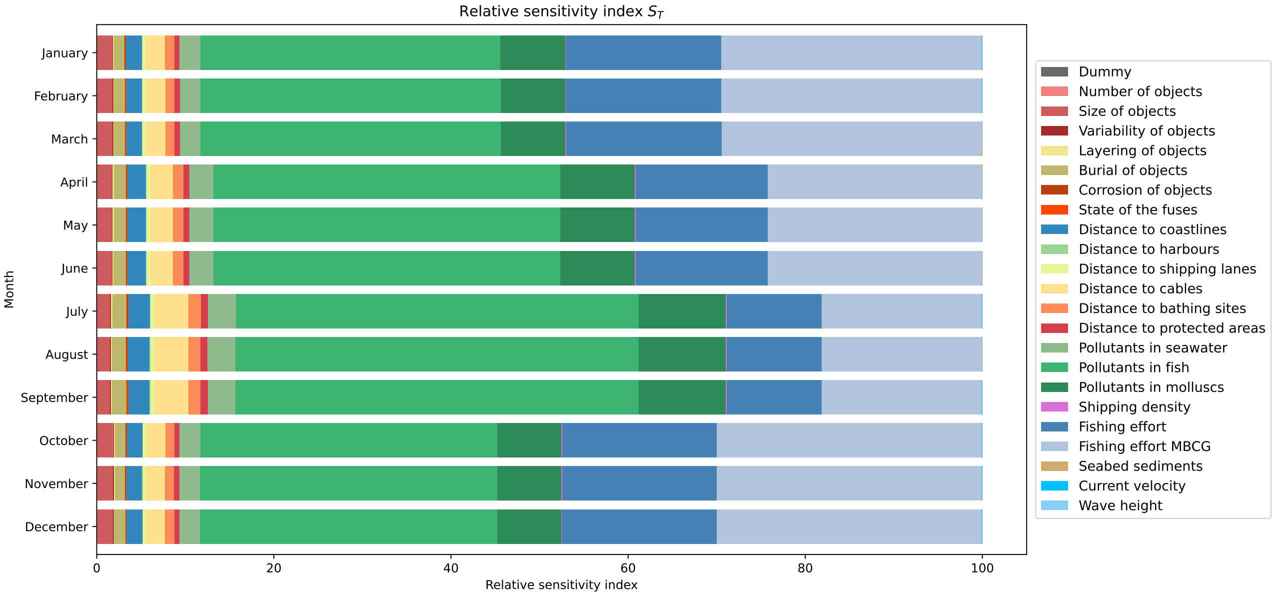


(a)

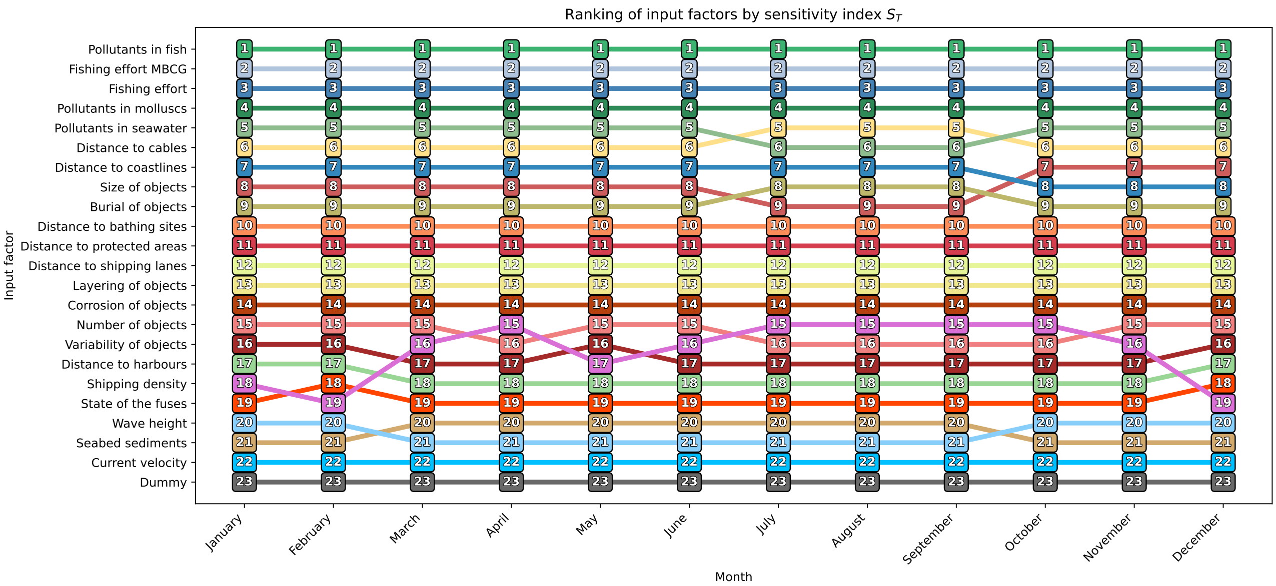


(b)

Figure B2. Sensitivity index μ^* obtained from the GSTAR input/output series (a) and corresponding input factor ranking results (b)

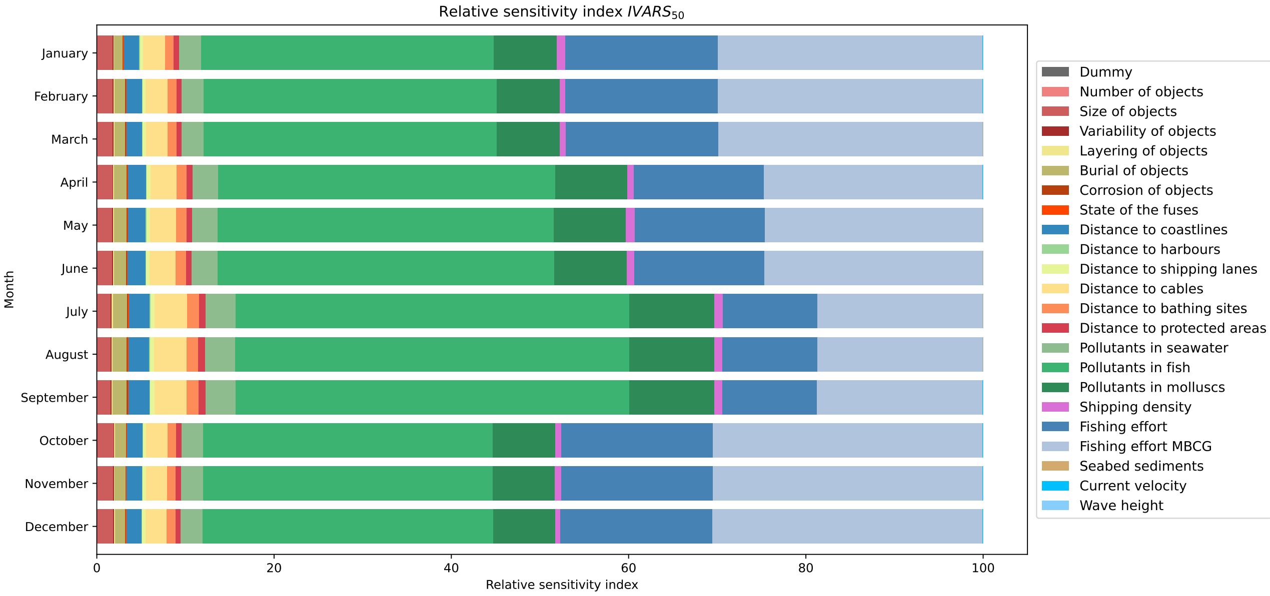


(a)

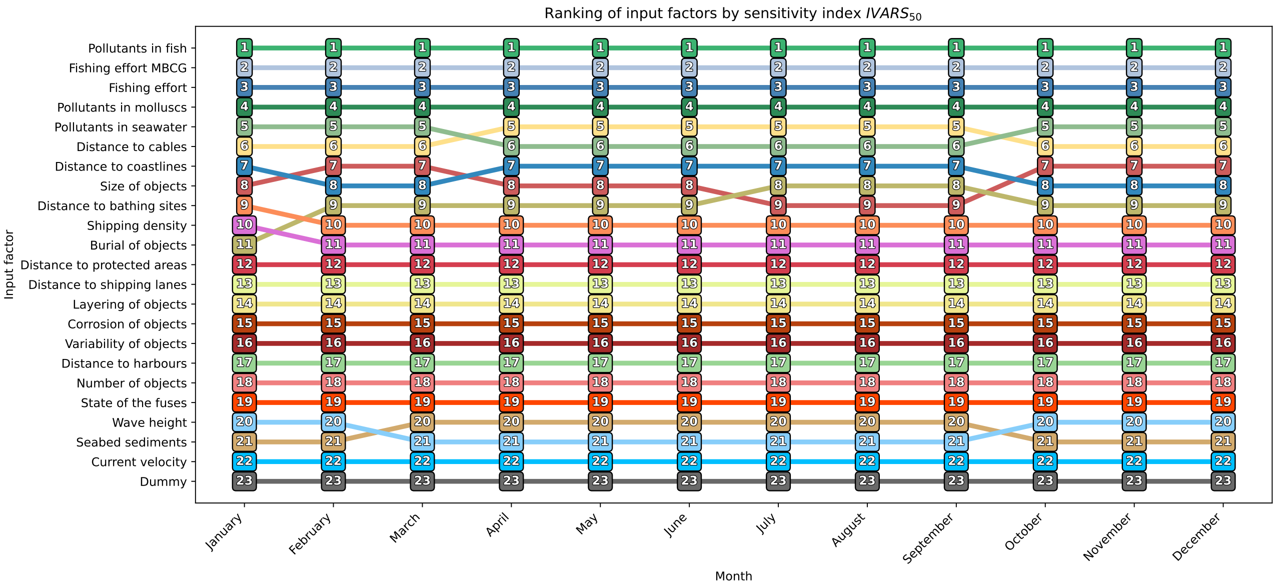


(b)

Figure B3. Sensitivity index S_T obtained from the GSTAR input/output series (a) and corresponding input factor ranking results (b)

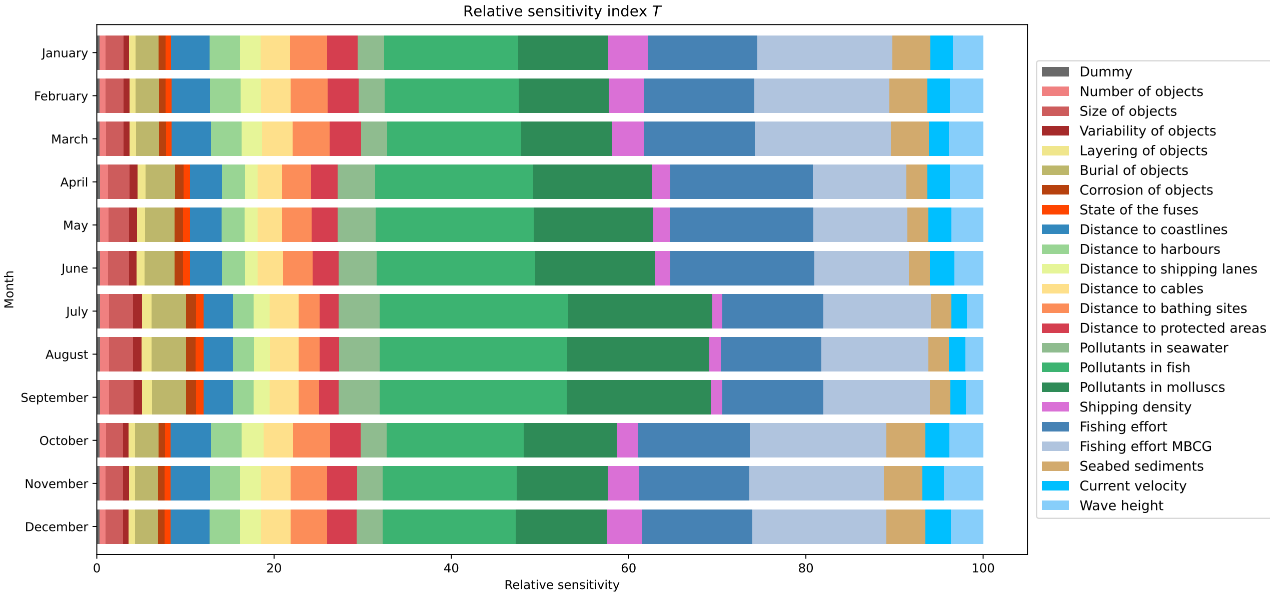


(a)

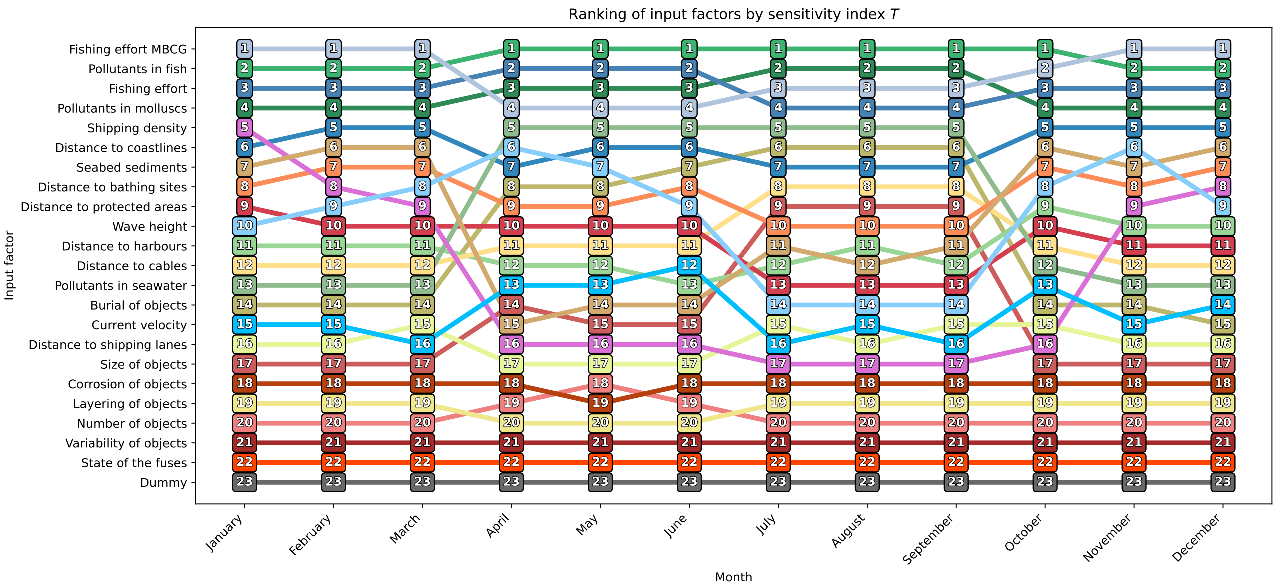


(b)

Figure B4. Sensitivity index $IVARS_{50}$ obtained from the GSTAR input/output series (a) and corresponding input factor ranking results (b)

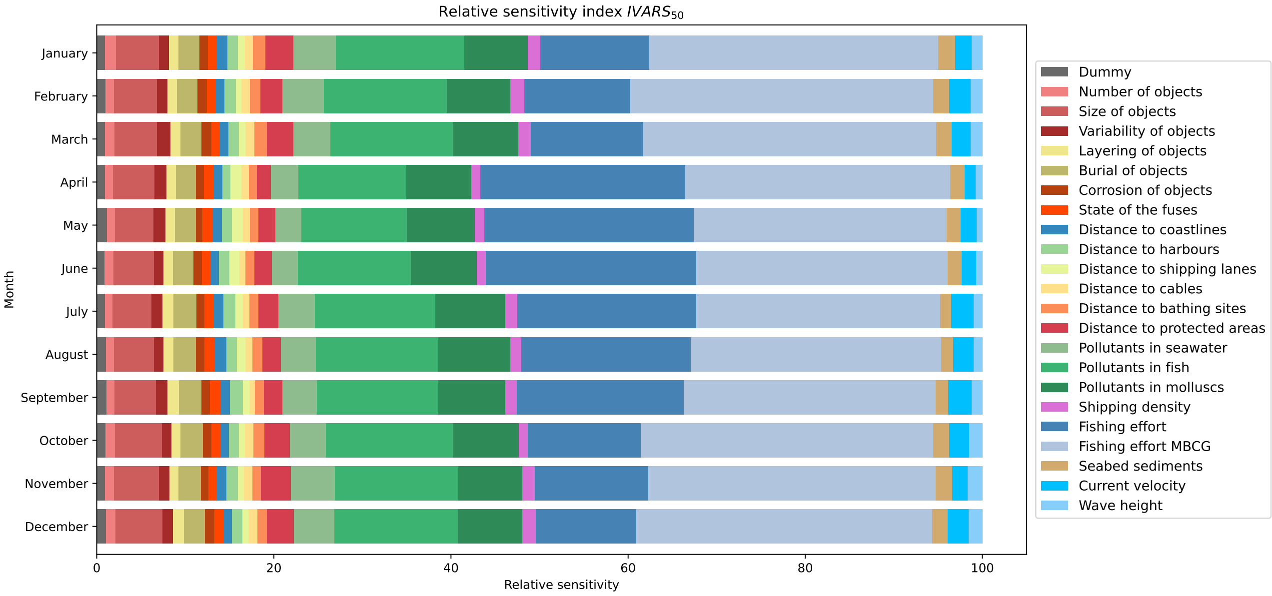


(a)

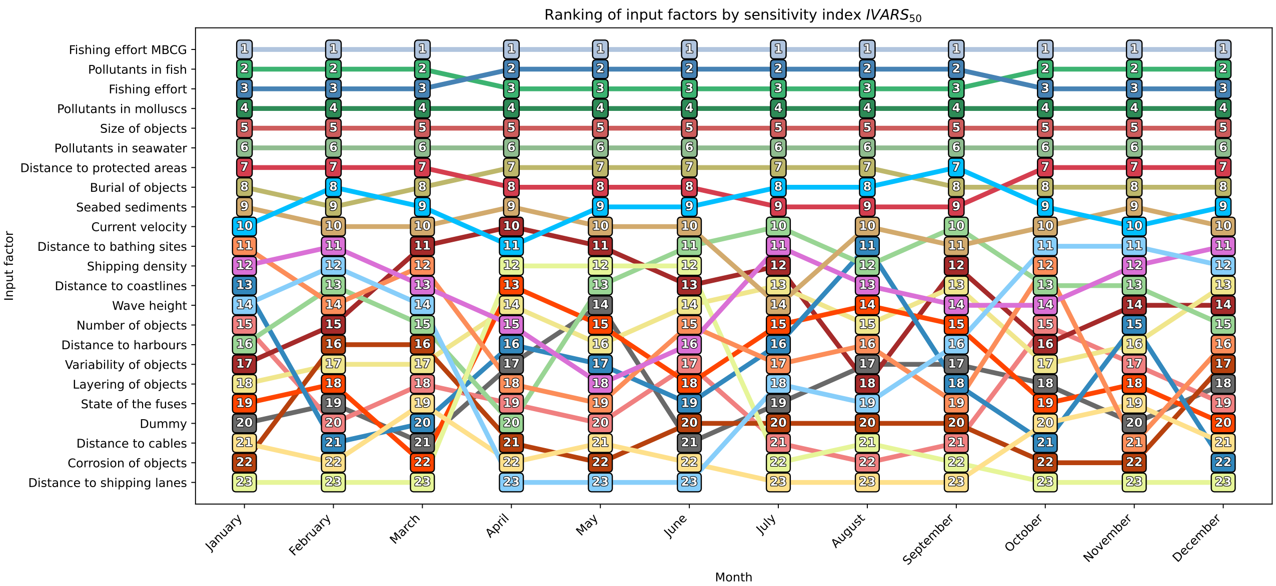


(b)

Figure B5. Sensitivity index T obtained from the spatial input/output series (a) and corresponding input factor ranking results (b)



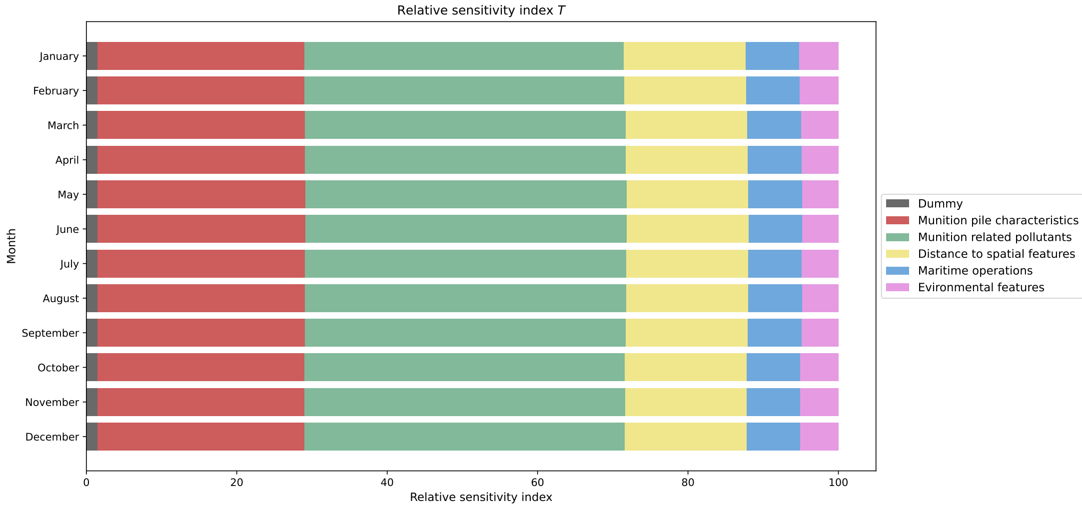
(a)



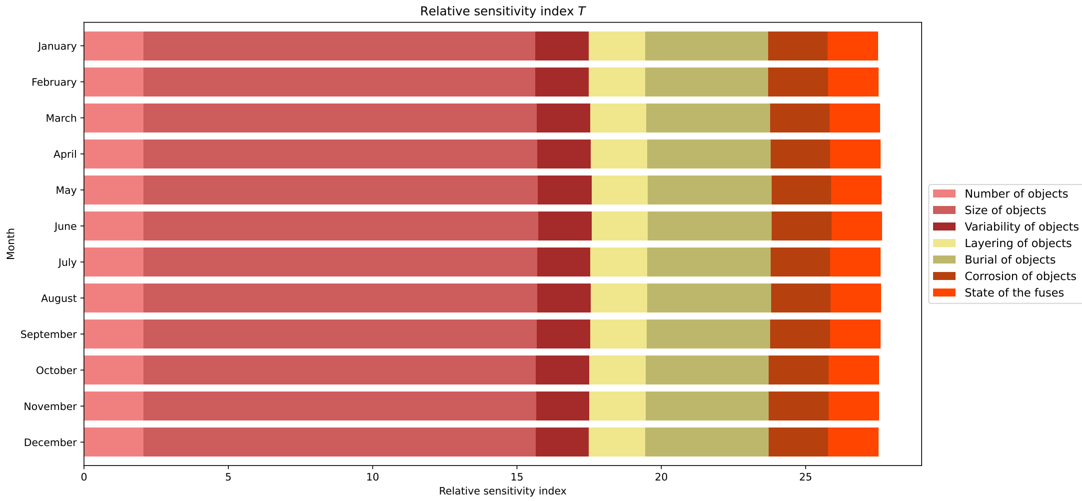
(b)

Figure B6. Sensitivity index $IVARS_{50}$ obtained from the spatial input/output series (a) and corresponding input factor ranking results (b)

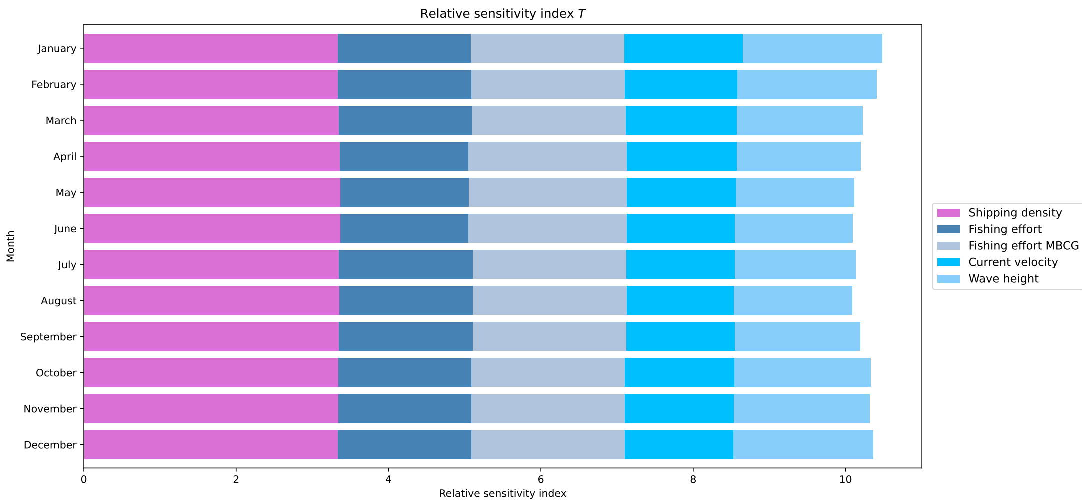
Appendix C: Factor group ranking results



(a)

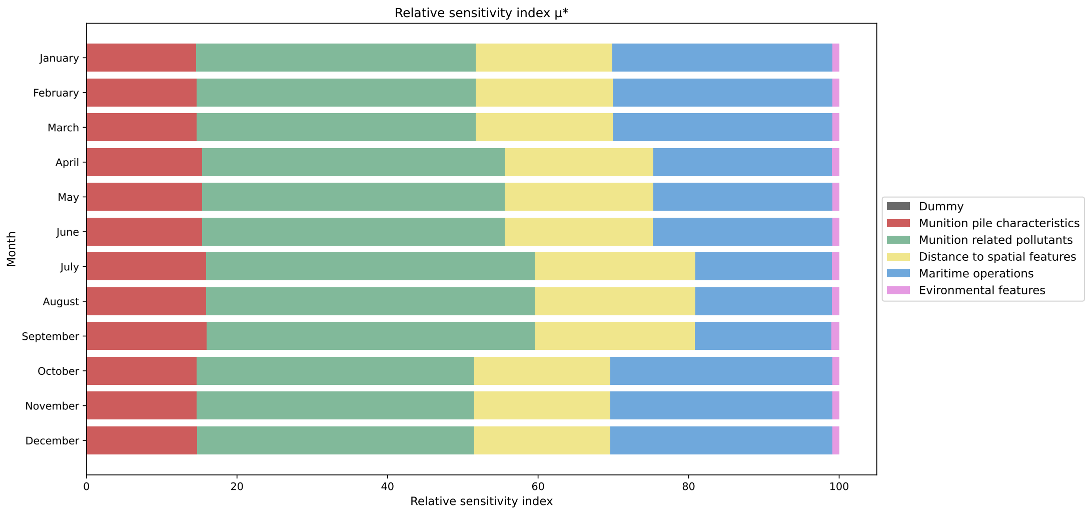


(b)

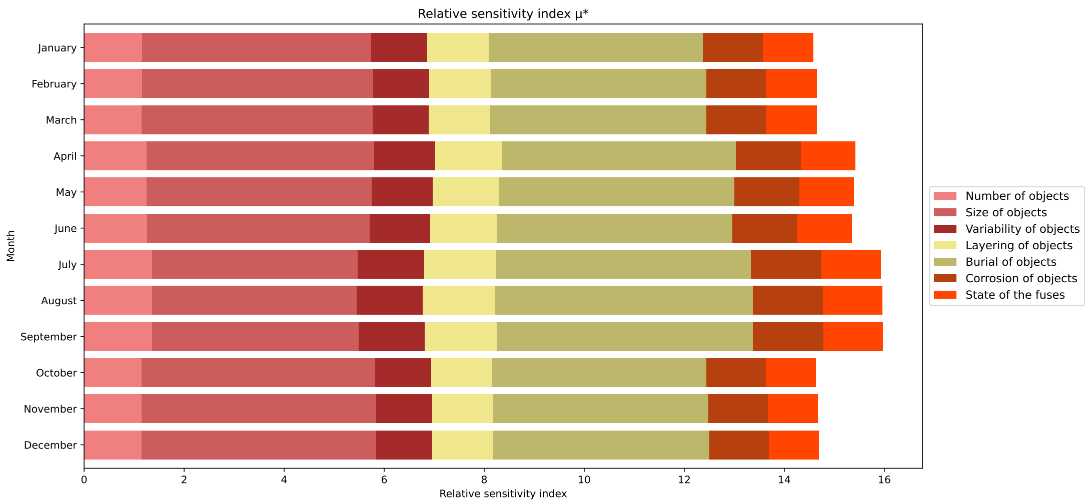


(c)

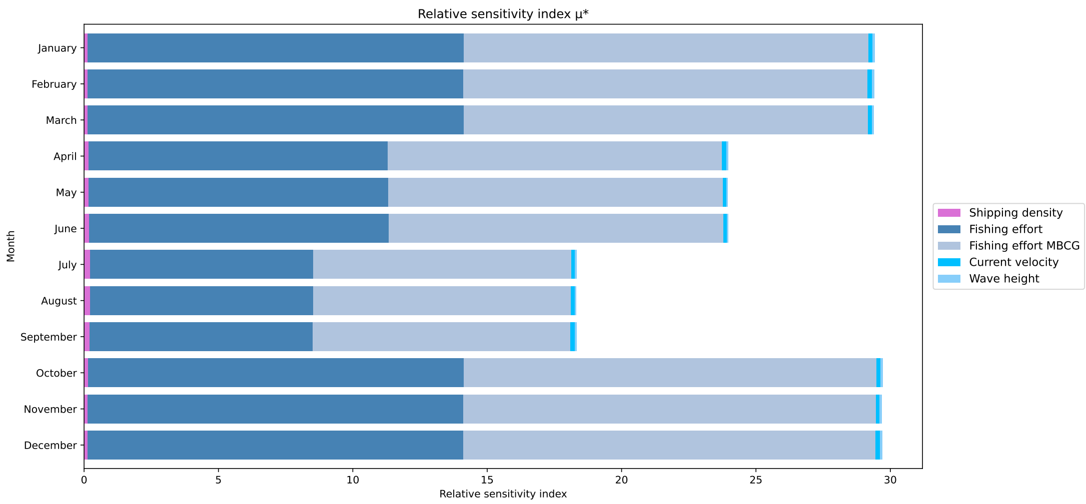
Figure C1. Factor group ranking results according to sensitivity index T obtained from the LHS input/output series (a) and composition of the factor groups containing the munition pile characteristics (b) and time variable factors (c)



(a)

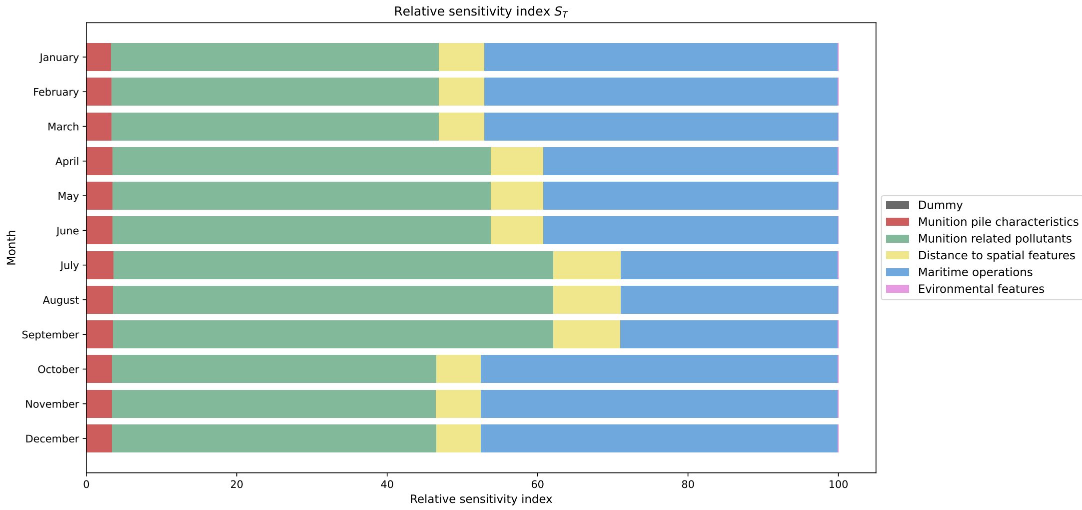


(b)

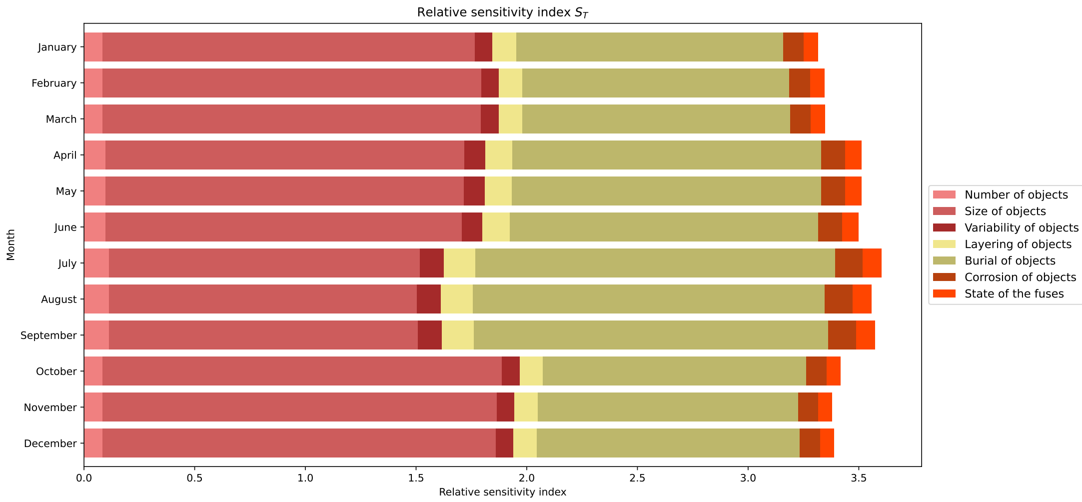


(c)

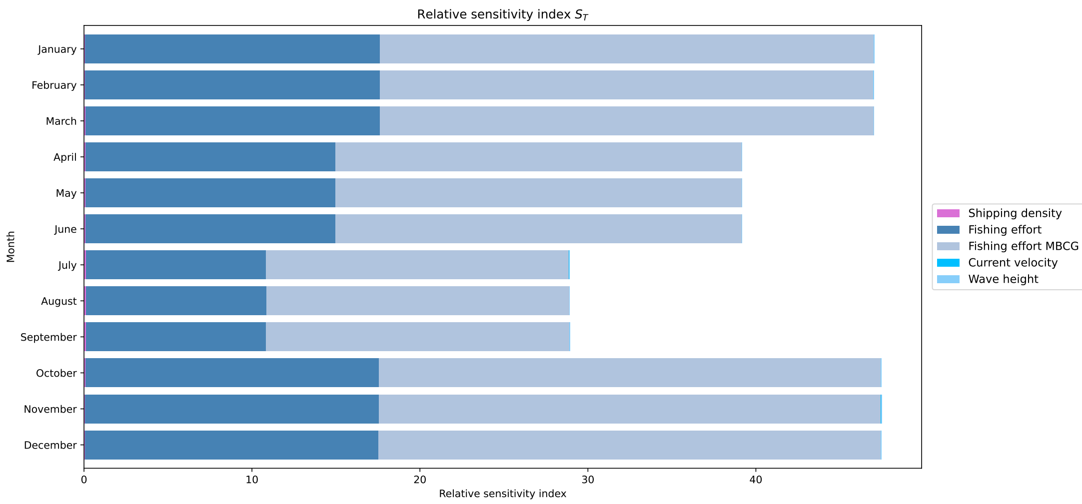
Figure C2. Factor group ranking results according to sensitivity index μ^* obtained from the GSTAR input/output series (a) and composition of the factor groups containing the munition pile characteristics (b) and time variable factors (c)



(a)



(b)



(c)

Figure C3. Factor group ranking results according to sensitivity index S_T obtained from the GSTAR input/output series (a) and composition of the factor groups containing the munition pile characteristics (b) and time variable factors (c)

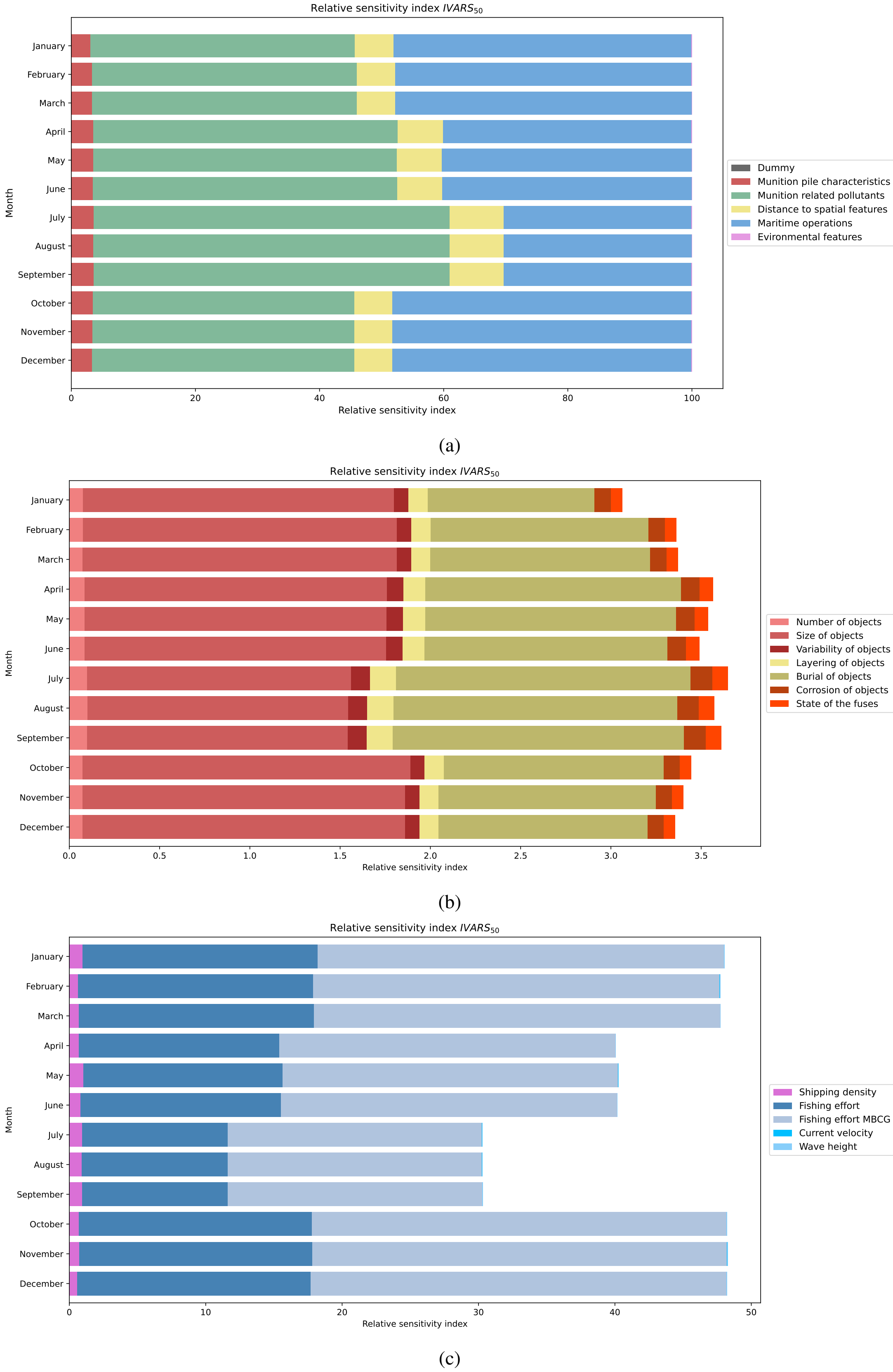
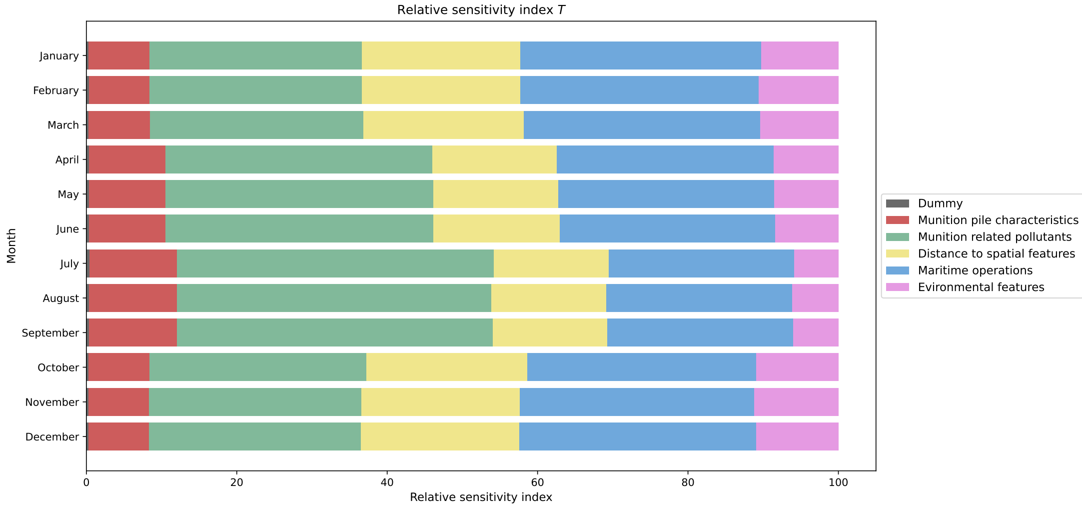
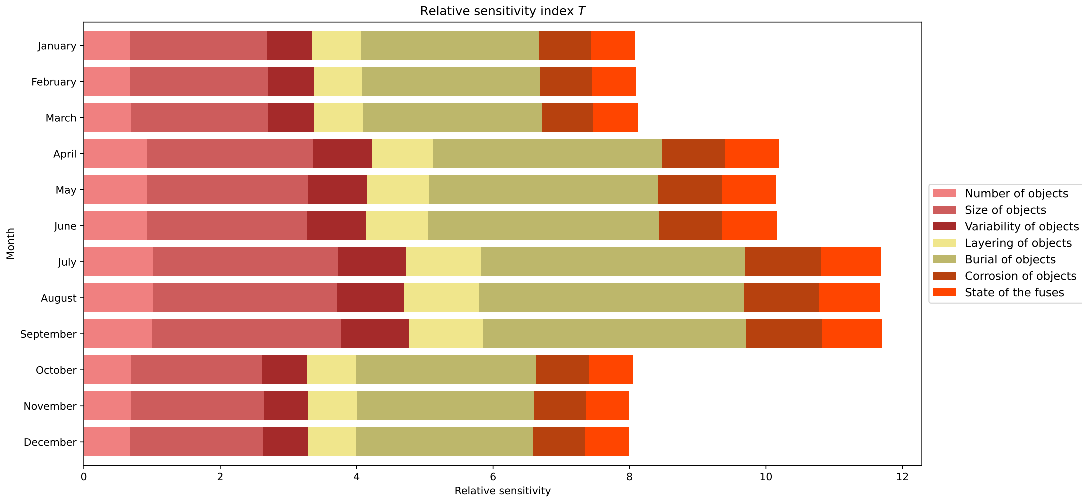


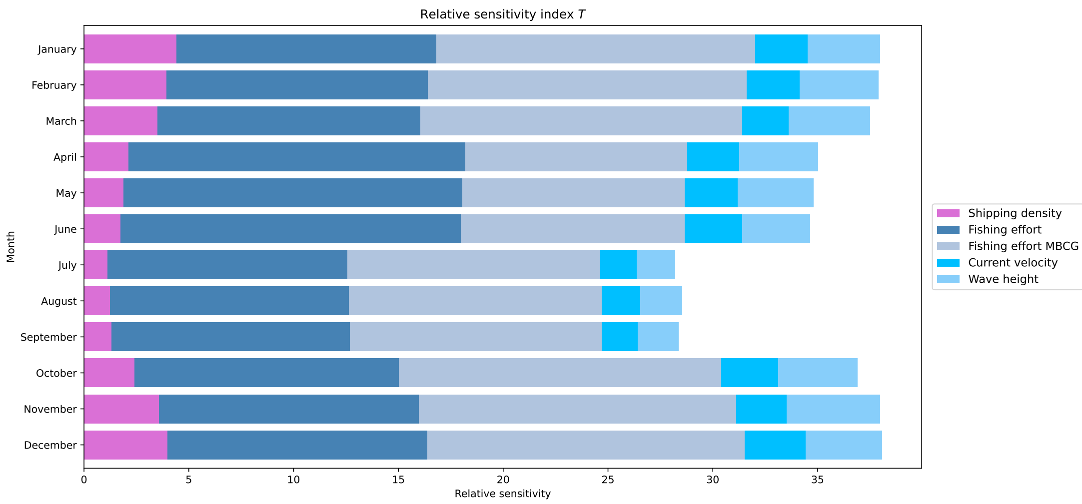
Figure C4. Factor group ranking results according to sensitivity index $IVARS_{50}$ obtained from the GSTAR input/output series (a) and composition of the factor groups containing the munition pile characteristics (b) and time variable factors (c)



(a)

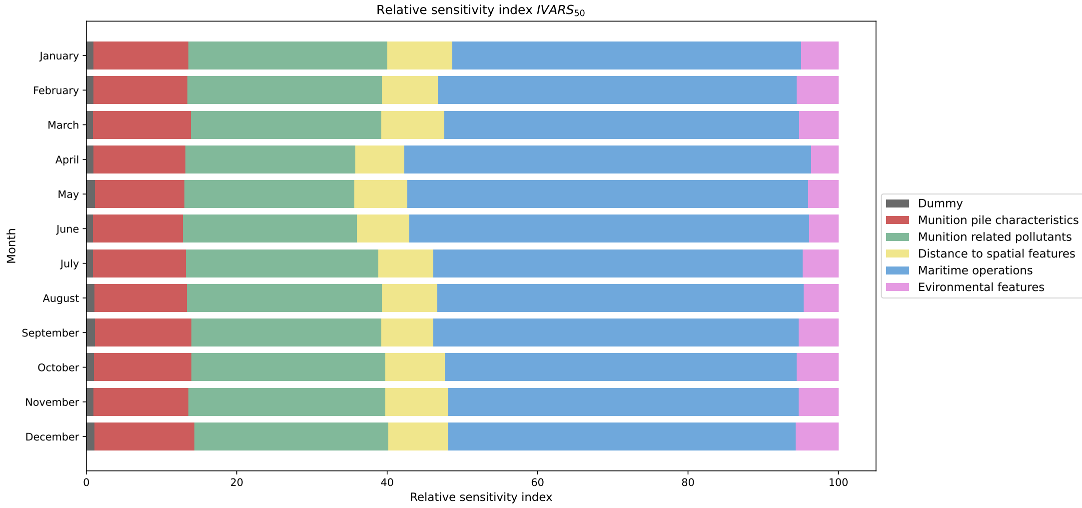


(b)

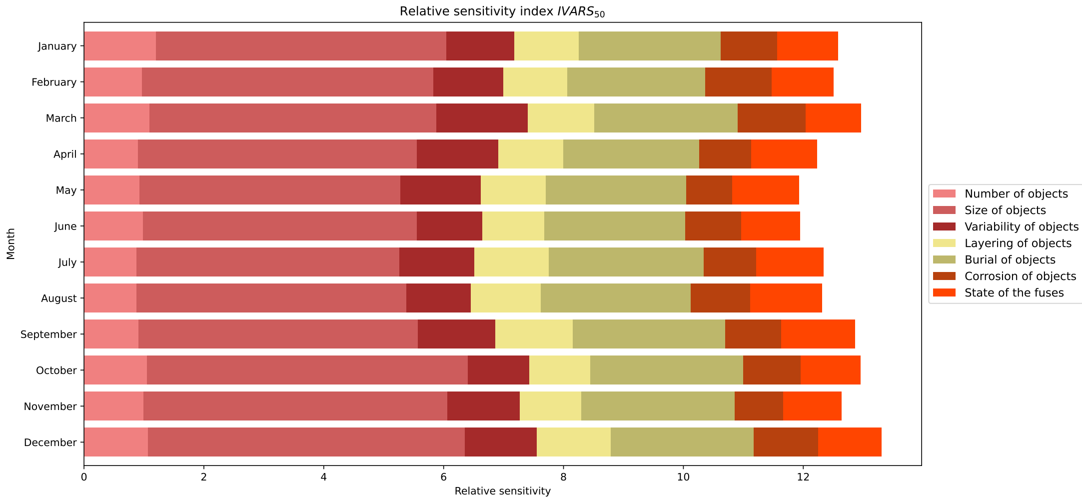


(c)

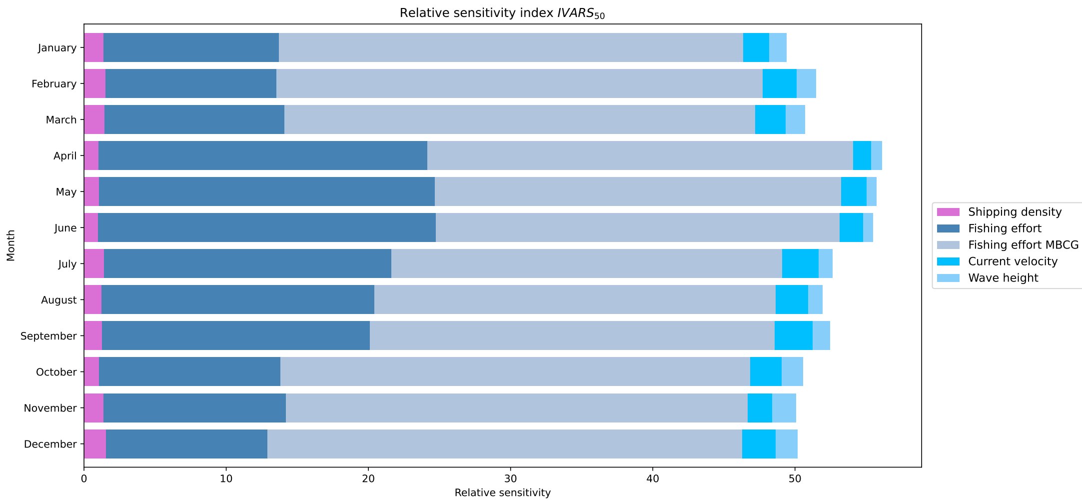
Figure C5. Factor group ranking results according to sensitivity indicex T obtained from the spatial input/output series (a) and composition of the factor groups containing the munition pile characteristics (b) and time variable factors (c)



(a)



(b)



(c)

Figure C6. Factor group ranking results according to sensitivity index $IVARS_{50}$ obtained from the spatial input/output series (a) and composition of the factor groups containing the munition pile characteristics (b) and time variable factors (c)