NPFC

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Standardized CPUE of Japanese Sardine (*Sardinops melanostictus*) caught by the Russia's fishery up to 2025

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1. Background of the Japanese sardine fishery

- Description of the Japanese sardine fishery.

The largest amount of Japanese sardine (JS) was caught by the mid-water trawls (MT): 87 % up to 2025 (table 1). Maximum catch of JS in the 21st century was taken by Russia in 2024 (592,564 tons), but then it suddenly dropped to 57,546 tons in 2025 (see NPFC summary footprint).

Table 1. Catch of the Japanese sardine by gear types

Catch, %	Gear			
Year	MT	NO	Others	PS
2014	0.00%	0.00%	100.00%	0.00%
2015	100.00%	0.00%	0.00%	0.00%
2016	99.00%	0.00%	0.03%	0.97%
2017	84.49%	0.00%	0.06%	15.45%
2018	95.04%	0.00%	0.00%	4.96%
2019	93.70%	0.00%	0.00%	6.30%
2020	89.38%	6.12%	1.09%	3.41%
2021	89.39%	6.57%	0.03%	4.01%
2022	84.95%	10.74%	0.52%	3.80%
2023	84.17%	9.49%	0.86%	5.48%
2024	84.88%	9.29%	0.00%	5.82%
2025	95.48%	2.62%	0.00%	1.90%
Total	**86.96%**	**7.71%**	**0.43%**	**4.91%**

MT – midwater trawl, NO – gear was not reported, PS – purse seine, Others – other gears

- Identify potential explanatory variables that may influence CPUE values by conducting a thorough literature review

In addition to obvious predictors such as years, months, gears, and regions the sea surface temperature (SST), sea surface salinity (SSS), chlorophyll *a* (Chla), sea surface height (SSH) were used in studies on JS more often than current velocity or flow rates (FR), dissolved oxygen (DO), and mixed layer depth (MLD), though occurrence of JS was more likely, when DO was high and FR were fast, while the MLD reflected food availability (Liu et al., 2025). Single species Generalized Additive Model (GAM) increased its explanation rate (ER) of JS log(CPUE+1) with addition to splines of years, month, longitude, and latitude of SST by 0.6 %, Chla by 1.2 %, SSS by

0.3 %, and SSH by 1.3 % resulting in 41.6 % ER or coefficient of determination r^2 = 0.408 (Tang et al., 2025). Unfortunately, there were very few sources of SST and other environmental variables (EV) available in TINRO. One of them was HYCOM. For the dates from 2020-01-01 to 2024-09-04 we used daily information at 12:00 UTC time step from Global Ocean Forecasting System (GOFS) 3.1, which updates had been finished on 2024-09-04, so after 2024-09-04 we used ESPC-D-V02 Analysis from HYbrid Coordinate Ocean Model (HYCOM, https://www.hycom.org/). The latter system produces forecasts 8 days ahead, starting from 3 days in the past. So, in fact we could get forecasts 5 days ahead for SST, SSS, eastward velocity (SSU), northward velocity (SSV) and other less important variables for JS. So, we calculated FR from SSU and SSV, but we didn't use SSH, Chla, DO, and MLD, because we didn't find them as forecast layers at HYCOM website.

2. METHOD

2.1 The data

- Description of the type of data and the "resolution" of the data

Response variable for "Period-1" (2014–2025) was catch of JS in tons per day per Russian vessel (Research Vessels – RV were excluded) with temporal resolution of 1 day for each vessel (vessel-day aggregation). For Period-2 (2020–2025) response variable was catch of JS in tons per 1 hour (t/h) of each operation of each vessel (set-by-set). Geographically Period-2 data consists of lines between start and finish coordinates of each operation (track), which then were used for aggregation of statistics of underlying values from HYCOM and calculated covariates with day-to-day relation. For the mesh construction used in spatiotemporal models we took centroids of those tracks. Resolution of downloaded HYCOM layers was daily (at 12:00 UTC) 1/25 (0.04) degrees latitude and 1/12 (≈0.08) degrees longitude.

- Catch and effort information, including the proportion of Japanese sardine within the observed catch, with the representativeness of the data by CPUE FLEET

Official coordinates of the catches were available only after 2020. Therefore, we described a catch per unit effort (CPUE), for 2 periods. The 1st one ("Period-1") is obtained from fishery dependent data without precise discrimination in geographical space, but it is the longest one (2014–2025). Japanese sardine (JS) was primarily a bycatch to the Pacific saury, Chub mackerel (CM) and other fish or in the catches made by research vessels (RV) before 2016, and after 2016 Japanese sardine was targeted, while it's share as the bycatch to Chub mackerel decreased a lot (Table 2). More than 90 % of Japanese sardine were caught in a very small region between Russia and Japan close to the shore – SKur (Fig. 1). Before 2025 there were around 95 % of annual catches (Table 3), but in 2025 more than 77 % of catches had been gotten in the Convention Area (CA). The Period-1 data were initially aggregated daily for each vessel, and we didn't change that level of aggregation, and we didn't filter the data in any way. So, the coverage of CPUE observations during Period-1 was 100 %.

Table 2. Catch of the Japanese sardine by targets

Target	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Average
JS	0.0%	63.1%	95.7%	76.7%	82.6%	92.6%	97.7%	94.8%	95.7%	99.7%	99.9%	97.8%	97.3%
CM	0.0%	36.8%	4.3%	23.3%	17.4%	7.1%	2.2%	5.1%	4.1%	0.3%	0.0%	2.2%	2.6%
etc	100.0%	0.1%	0.0%	0.1%	0.0%	0.2%	0.2%	0.0%	0.2%	0.0%	0.0%	0.0%	0.1%

JS – Japanese sardine, CM – Chub mackerel, etc – all other targets

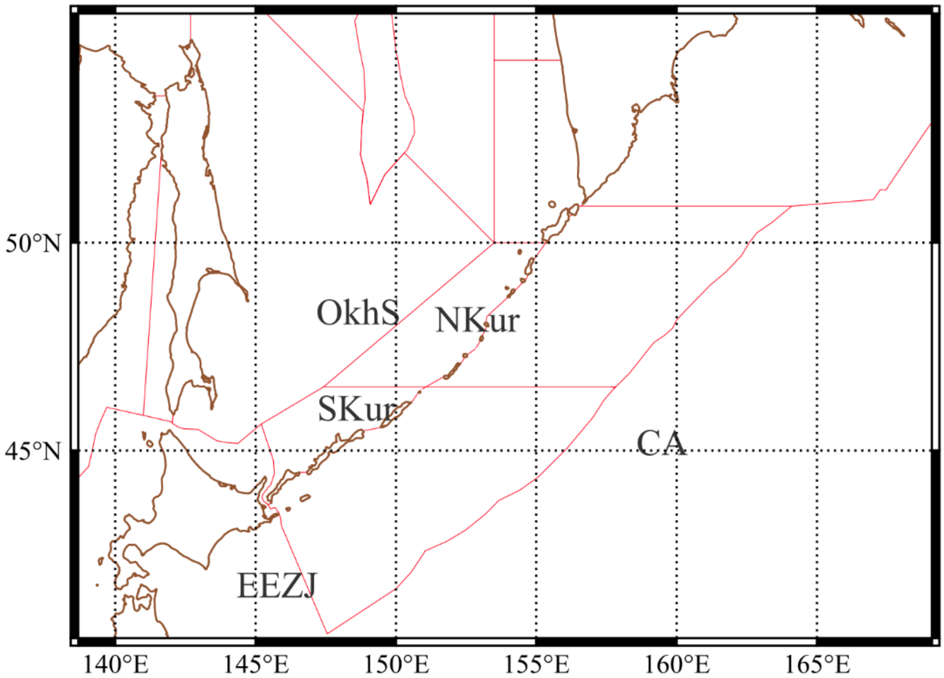


Fig. 1. The boundaries of Russian fishing zones and subzones: CA – Convention Area, EEZJ – Exclusive Economic Zone (EEZ) of Japan, NKur – Northern Kuril zone (upper 46°35' N and below 50°50'N) in Russian EEZ with exception of subzones from the Okhotsk Sea fishing zone, OkhS – Eastern Sakhalin subzone in the Okhotsk Sea zone, and SKur – Southern Kuril zone (below 46°35' N)

Huge vessels increased the amount of their efforts annually, except for 2025 (Fig. 2). More than half of the number of vessels which were targeting JS in 2024 (28 out of 46) went fishing in other regions, e. g. into the Bering or Okhotsk Seas for the Pacific herring and Walleye pollock in 2025. Those 28 vessels caught around 160 kilotons (kt) of JS in 2024 and 0 in 2025, though their total amount of pollock and herring increased everywhere and more than twice in the Bering Sea in 2025. The reasons for switching targets in 2025 were huge amount of JS juveniles in th CA (Baitaliuk et al., 2026), which Russian fishermen didn't want to catch, the absence of large JS in the Russian EEZ and the obligation to utilize total allowable catch (TAC) for pollock and herring. The latter was not so easy in recent years, while owners of TAC quotas should not allow low (< 70 %) TAC utilization for 2 consecutive years.

Table 3. Catch share (%) of the Japanese sardine by fishing regions

Year	CA	EEZJ	NKur	OkhS	SKur
2014	0.0%	0.0%	0.0%	0.0%	100.0%
2015	4.5%	0.0%	0.0%	0.0%	95.5%
2016	0.0%	0.0%	0.0%	0.0%	100.0%
2017	0.4%	11.1%	0.0%	0.0%	88.4%
2018	0.0%	4.9%	0.0%	0.0%	95.1%
2019	0.0%	1.2%	0.0%	0.0%	98.8%
2020	0.8%	1.3%	0.0%	0.0%	97.9%
2021	0.8%	7.4%	0.0%	0.0%	91.7%
2022	0.0%	6.1%	0.3%	0.0%	93.6%
2023	0.0%	1.1%	3.4%	0.0%	95.4%
2024	5.0%	1.5%	10.0%	0.0%	83.5%
2025	77.3%	9.1%	0.6%	0.5%	12.4%
Average	**3.5%**	**3.0%**	**3.5%**	**0.0%**	**90.1%**

CA – Convention Area, EEZJ – Exclusive Economic Zone of Japan, NKur – north Kuril Islands, OkhS – Okhotsk Sea, SKur – south Kuril Islands

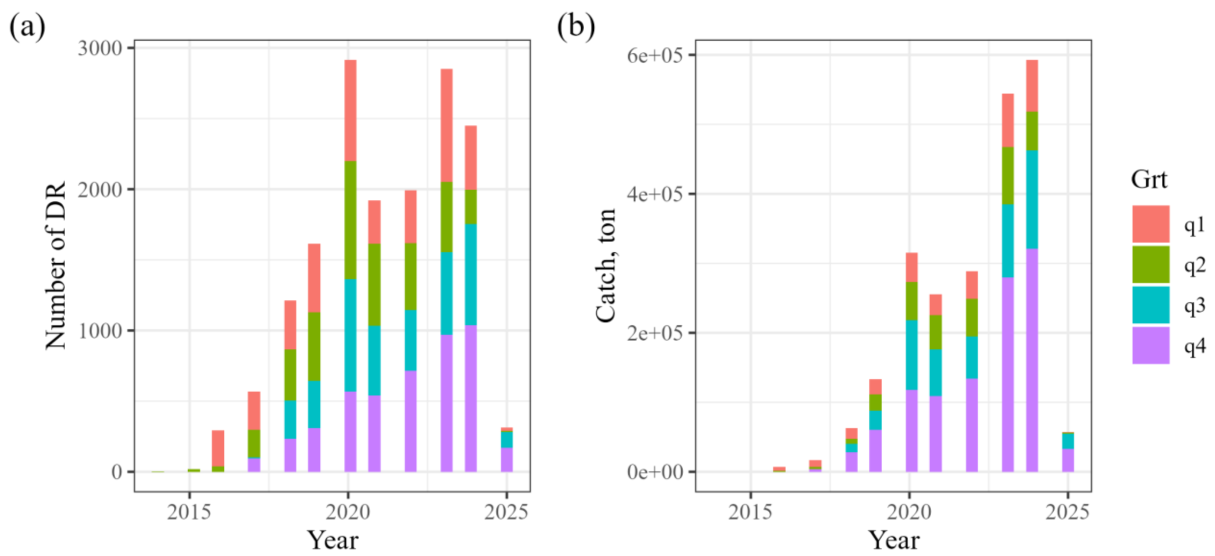


Fig. 2. Distributions of efforts — a (Number of DR) and catches of JS — b (ton) by quartiles of Gross tonnage (Grt): q1 < 1266, 1266 ≤ q2 < 4092, 4092 ≤ q3 < 7733, 7733 ≤ q4 < 9056

The 2nd period ("Period-2") was obtained from fishery dependent and independent (RV) data with precise discrimination in geographical space and real zero catches from RV and electronic fishing log (EFL). EFL was available in TINRO for the period of 2020–2025.

Most of the vessels reported the coordinates of catches, so the subset of data with operations conducted by mid-water trawls and purse-seines with reported coordinates contained up to 5 % less catch and up to 10 % less effort than the full set of EFL with JS catches (Table 4). We kept records, which speed of catch operation was less than 6 nautical miles (nm) and applied other filter Rules (Table 5).

Table 4. Catch and effort information by CPUE FLEET from EFL

Year	Number of observations	% Coverage of CPUE FLEET (catch)	% Coverage of CPUE FLEET (effort)	Total Catch CPUE FLEET (tons)	Total Effort for CPUE FLEET, (hours)	Percentage of overall catch by member (across all fleets/gears)
2020	5468	98%	92%	288,870	18,808	91.6%
2021	3873	98%	95%	234,729	12,511	91.8%
2022	3961	97%	96%	249,340	12,970	86.5%
2023	5790	95%	95%	467,710	19,232	86.0%
2024	5664	96%	94%	512,555	18,079	86.5%
2025	763	99%	90%	55,703	2,261	96.8%

Table 5. Filter "Rules" used on data for CPUE standardization and the effect on the overall sample size from EFL

Filter Applied	Number of Records Remaining	Number changed	Number of Records with JS Catch >0
Initial Data set (MT and PS gears, no RV, only positive catch)	25,519	-	25,519
Remove Records 6 minutes or less in duration	25,382	-137	25,382
Remove Records conducted at speed ≥ 6 knots, according to coordinates between start and finish of operation and spent time for operation (possible errors in the coordinates or time spent)	25,251	-131	25,251
Add records, following the same Rules above, but without JS catch within the depth of gear between 0 and 50, if a vessel reported the JS catch during other operations in the same month and year	26,356	+1,105	25,251
Remove Records with dates or locations not available in HYCOM	25,442	-914	24,618
Add RV MT gear catches in June-December 2021-2025	27,235	+1,793	25,034
Remove Records with dominant demersal fish in the catch	27,223	-12	25,033
Final Data Set (Including RV)	27,223 (1791)	-	25,033 (415)

Operations with 0 catch of JS were added not only from RV data, but also from EFL within the depth of MT or PS gears between 0 and 50, if a vessel reported the JS catch during other operations in the same month and year.

- Annual/monthly spatial distribution patterns of catch, effort and nominal CPUE

Original set-by-set JS catches are shown as annual (Fig. 3) and monthly (Fig. 4) patterns.

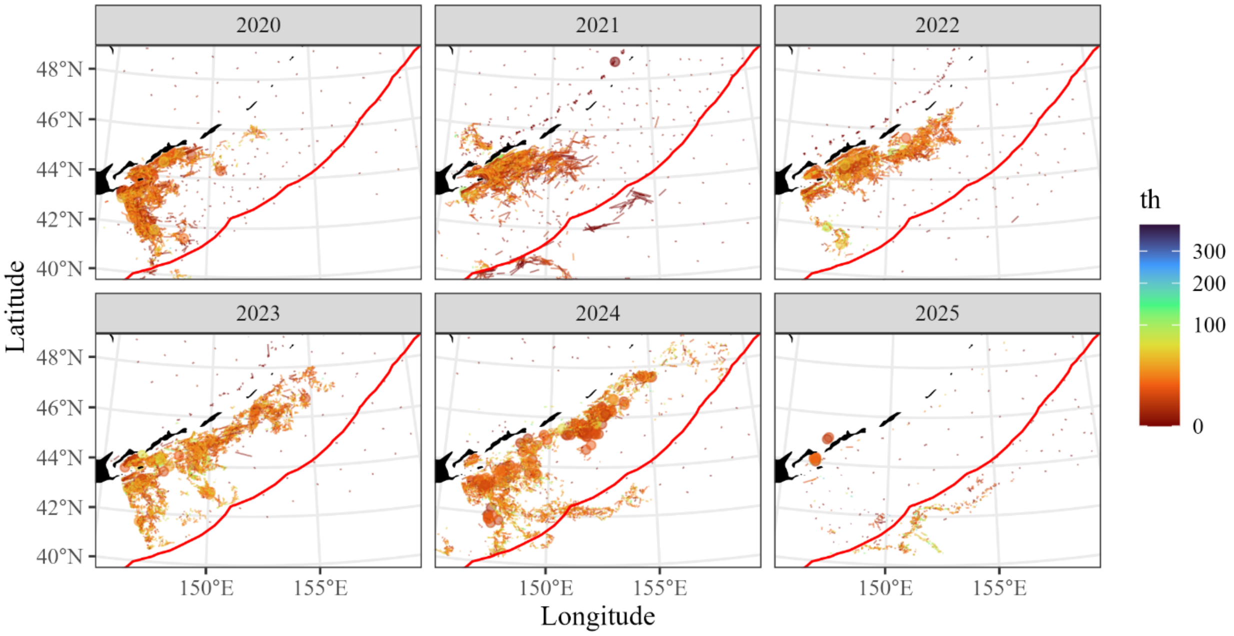


Fig. 3. Distribution of JS and 0 catches (th = tons/hour) by years

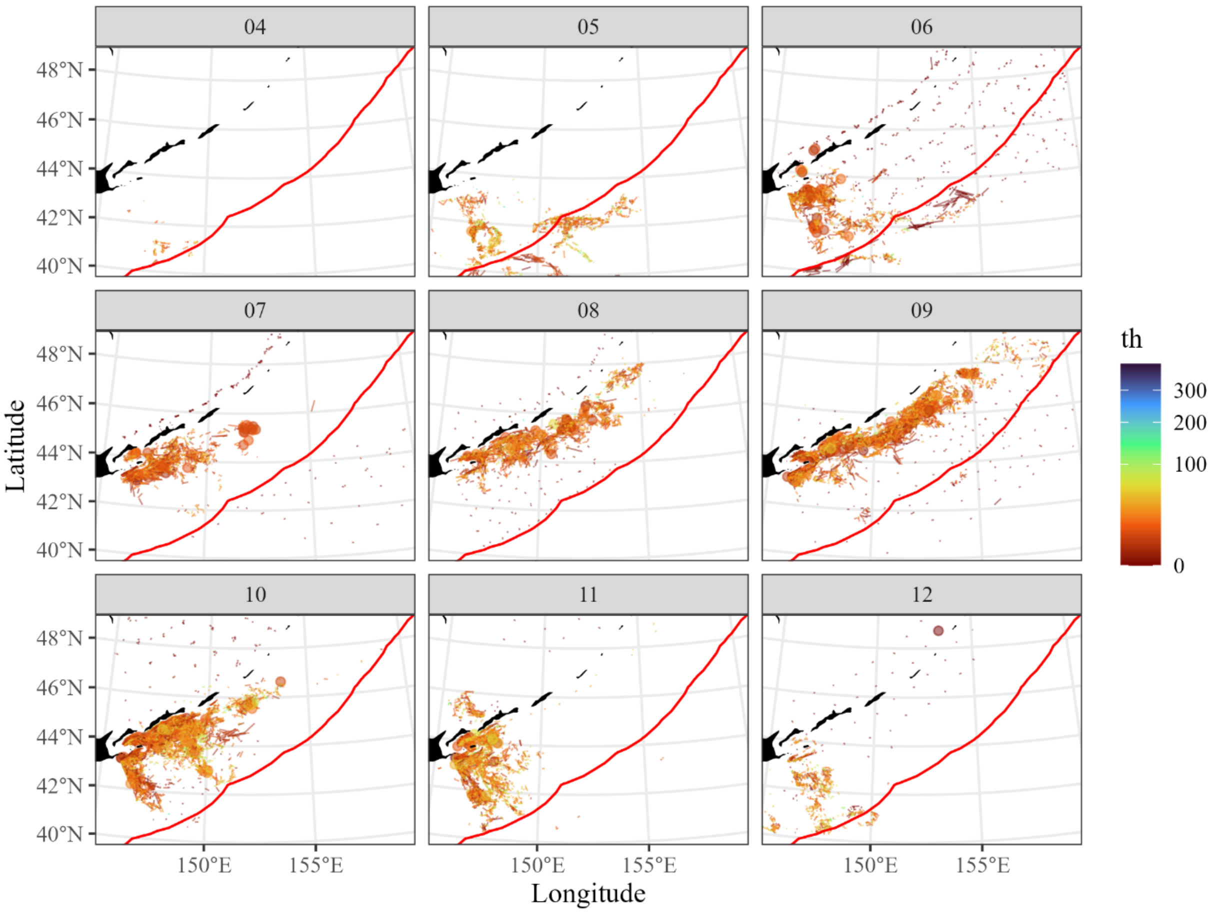


Fig. 4. Distribution of JS and 0 catches (th = tons/hour) by months

They were used for standardization without aggregation, but they cannot demonstrate patterns clearly, so we aggregated the JS catches by ISEA3H grid with resolution #9, average step 55 km (vertical 50.4 km and horizontal 63.0 km), cell area =2,591 km^2 in the R package dggridR (Barnes, Sahr, 2017) for visualization purpose only. The results are shown in the Appendix I (Fig. 1a–6a).

- Provide a summary of covariates considered in the CPUE standardization. Include details on the data source, resolution and coverage of the data over time and space. Provide justification supporting the relationship between the covariate and catchability that is assumed by including the covariate in the CPUE standardization.

A summary of covariates considered in the CPUE standardization for Period-1 in GLM is given below (Table 6). The data source was the Federal State Budgetary Institution "Center for Fisheries Monitoring and Communications System" (CFMC).

Table 6. Summary of explanatory variables for Period-1

Variables		Number of categories	Detail	Note
Year	*Year*	12	*2014–2025*	
Month	*Month*	12	*January–December*	
Fishing area	*Region*	5	*CA, EEZJ, NKur, OkhS, SKur*	*see* Fig. 1
Vessel size	*Grt*	4	*q1 < 1266, 1266 ≤ q2 < 4092, 4092 ≤ q3 < 7733, 7733 ≤ q4 < 9056*	by quartiles
	grt	numeric	*Min.: 97, Mean: 4334, Max.: 9055*	
Targets	*Target*	3	*JS (19382), CM (1978), etc (191)*	dominant fish
	drperc	numeric	*Min.: 0.39, 1st Qu.: 0.90, Median: 0.98, Mean: 0.92, 3rd Qu.:1, Max.: 1*	share in the catch

The summary of covariates considered in the CPUE standardization for Period-2 is given below (Table 7). Such numeric covariates as sstAVG, sstGmax, sssDavg, and msDavg were left after preliminary analysis of all available with forecasts sea surface layers from HYCOM and calculated FR, angles of current, gradients of SST, and SSS by equations 1–2 (Loarie et al., 2009; Burrows et al., 2011) using an AutoML tool in R (R Core Team, 2026) package "forester" (Ruczyński et al., 2023), which reports were saved in Appendices II-III. Maximums or mean values of EVs were taken because the tracks crossed several cells almost always during MT operations.

$$\text{sstGmax} = Maximum\left(\sqrt{dx^2 + dy^2}\right), \quad (1)$$

$$\text{sssDavg or msDavg} = Mean(\tan^{-1}(dx, dy) \cdot 180/\pi), \quad (2)$$

where dx and dy were calculated by published functions (Byrnes, 2017), but with corrected resolution for "raster" package for R (Hijmans, 2025).

Table 7. Summary of explanatory variables for Period-2

Variables		Number of categories	Detail	Note
Year	*Year*	numeric	*2020–2025*	
Research Vessel	*RV*	2	*yes (944) or no (23527)*	
Coordinates	*X, Y*	numeric	*Projected coordinates in the bounding box 145°E–160°E, 39.6°N–49.3°N*	*+proj=laea +lat_0=90 +lon_0=152 +x_0=0 +y_0=0 +datum=WGS84 +units=km +no_defs*
Last	*Term*	5	*Yes (10024) or No (14447)*	*Last operation in each date for each Vessel except RV (all No)*
Gear types	*geartype*	2	*MT (23309) or PS (1162)*	
Targets	*Target*	2	*Yes (22590) or No (1881)*	dominant fish
			Min., 1st Qu., Median, Mean, 3rd Qu., Max.	*Qu.* – quartile
SST	*sstAVG*	numeric	*1.82, 10.24, 11.93, 12.05, 13. 60, 25.31*	Average °C on a track
Maximum Gradient of SST	*sstGmax*	numeric	*0.00, 0.04, 0.08, 0.14, 0.18, 0.40*	Maximum °C/km on a track is set to 0.4 if it was > 0.4
Angle of SSS gradient	*sssDavg*	numeric	*0.18, 47.06, 167.07, 158.76, 247.21, 359.99*	°
Angle of current	*msDavg*	numeric	*0.00, 37.88, 136.70, 136.04, 213.09, 359.53*	°

- Scatter plots (for continuous variables) and/or box plots (for categorical variables) and, if possible, a correlation matrix to evaluate correlations between each pair of those variables

Environmental variables (EVs) were available for Period-2 only (Fig. 5). Other EVs were strongly correlated, thus they were dropped out. Strongly correlated, by Spearman rank, pairs of numerical values were: sssAVG - sstGmax: -0.94; sssAVG - sssGmax: -0.94; sssAVG - sstDavg: 0.73; sssAVG - msGmax: -0.94; sstGmax - sssGmax: 1; sstGmax - sstDavg: -0.71; sstGmax - msGmax: 1; sssGmax - sstDavg: -0.71; sssGmax - msGmax: 1; sstDavg - msGmax: -0.71. Strongly correlated, by Crammer's V rank, pairs of categorical values were: IdVes - RV: 1; IdVes - gear: 0.72; IdVes - geartype: 1; RV - fish: 0.89; RV - gear: 1; Target - fish: 0.99; gear - geartype: 1 (see Appendix II-III).

Predictors for Period-1 could contain more details about vessels, such as length, dedveit and power (kwt), but all of them were strongly correlated with grt (Fig. 6a). So, they were also excluded. Included EVs were correlated with each other significantly due to high number of observations, but Pearson's correlation coefficient was very close to 0 (Fig. 6b).

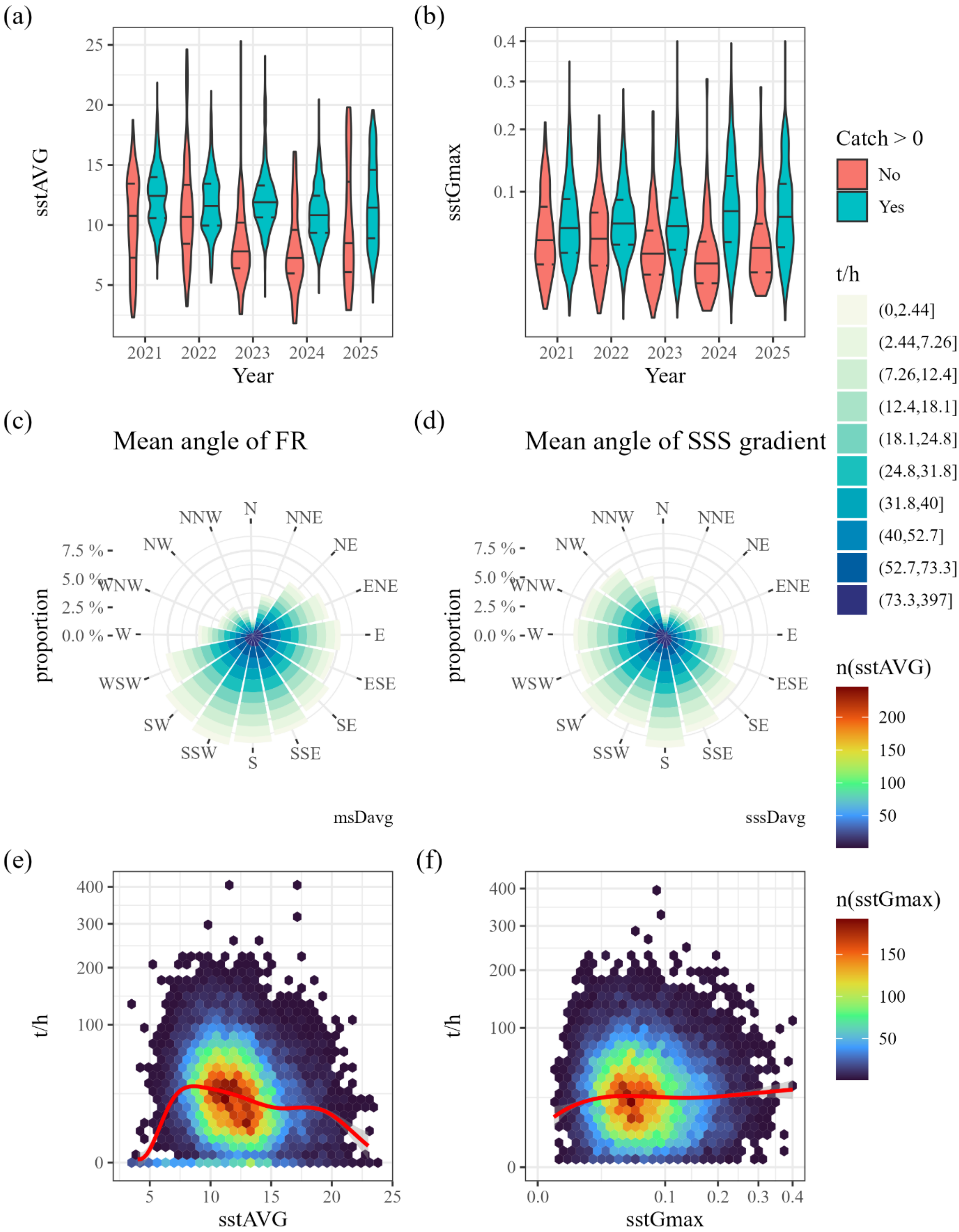
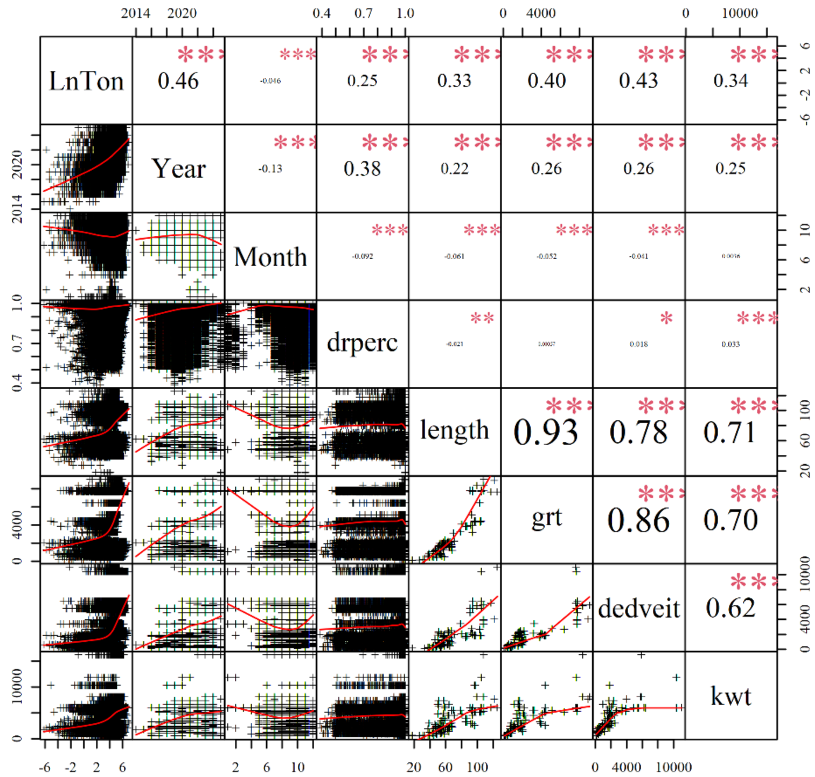


Fig. 5. Plots of environmental variables (EVs) and scatter plots between CPUE and EVs for the last 5 years (2021–2025)

(a)



(b)

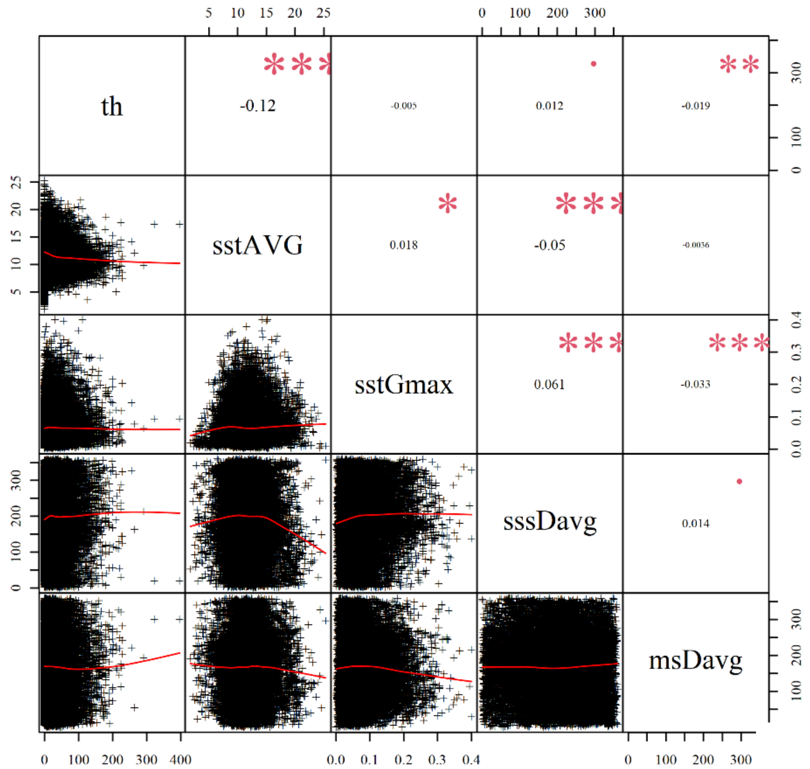


Fig. 6. Correlation matrix of EVs used in the analysis for Period-1 (a) and Period-2 (b). Numbers are Pearson's correlation coefficients, where "***" indicates $p < 0.001$, "**" – $p < 0.01$, "*" – $p < 0.05$ and "·" – $p < 0.1$

2.2 Full model description and model selection

- Model type and assumptions of the statistical model, assumed error distribution, model selection method, and software (packages) used

Period-1 JS catches per vessel for each date (C_i) were standardized (Eq. 3) and visualized following traditional approach in Generalized linear models, or GLMs in R package "influ" (Bentley et al., 2012), assuming multiplicative error distribution.

$$Ln(C_i) = \eta(t_i), \qquad (3)$$

where η – is a linear predictor, so GLMs distinguished only by linear predictors, and the best model was selected by the lowest values of BIC — Schwarz's Bayesian criterion and AIC — An Information Criterion AIC (Akaike 1974). The best GLM contained linear predictor No 18, because it had the lowest AIC and BIC (Table 8).

Table 8. Linear predictors and criteria of tuned GLMs for Period-1

η	df	formula	AIC	BIC
1	13	Year	57876.2	57976.2
2	24	Year + Month	57659.6	57844.2
3	88	Year + YM	56261.3	56938.0
4	226	Year + YM + Idves	46846.3	48584.2
5	91	Year + YM + Grt	53963.3	54663.1
6	89	Year + YM + grt	53809.0	54493.4
7	92	Year + YM + grt + gear	52872.9	53580.3
8	94	Year + YM + Grt + gear	53138.7	53861.5
9	96	Year + YM + grt + gear + Region	52618.0	53356.2
10	98	Year + YM + Grt + gear + Region	52898.8	53652.4
11	98	Year + YM + grt + gear + Region + Target	49521.6	50275.2
12	100	Year + YM + Grt + gear + Region + Target	49769.0	50538.0
13	34	Year + Month + grt + gear + Region + Target	50148.4	50409.8
14	36	Year + Month + Grt + gear + Region + Target	50373.2	50650.0
15	35	Year + Month + grt + gear + Region + Target + drperc	50125.4	50394.5
16	37	Year + Month + Grt + gear + Region + Target + drperc	50342.2	50626.7
17	235	Year + YM + Idves + gear + Region + Target	43410.3	45217.4
18	236	Year + YM + Idves + gear + Region + Target+ drperc	43183.7	44998.5

YM – was the interaction term between Year and Month

Period-2 JS catches in tons per hour were standardized in spatiotemporal model with Tweedie error distribution with natural log link and i.i.d. assumption on time autocorrelation in R package “sdmTMB” (Anderson et al., 2024). Spatial autocorrelation was in isotropic covariance in space. Boundary was found for the region, where Russian vessels operated during warm months, using convex function with ratio=0.5 in “sf” (Pebesma, 2018; Pebesma, Bivand, 2023) and mesh was constructed using R package “fmesher” (Lindgren, 2026) with 20 nautical miles cutoff (Fig. 7). We didn’t include the most part of Japanese EEZ, because availability of that area was not the same year to year and it was different by vessels. Moreover, the primary target there was CM. The NULL model didn’t include any predictors except for Years, spatial and spatiotemporal components. Its AIC and BIC were 209302.8 and 209351.5. It is much higher than in the FULL model (AIC = 204574.4 and BIC=204720.3), which included all significant predictors, so we kept all of them. Thus, the FULL model and best model are the same.

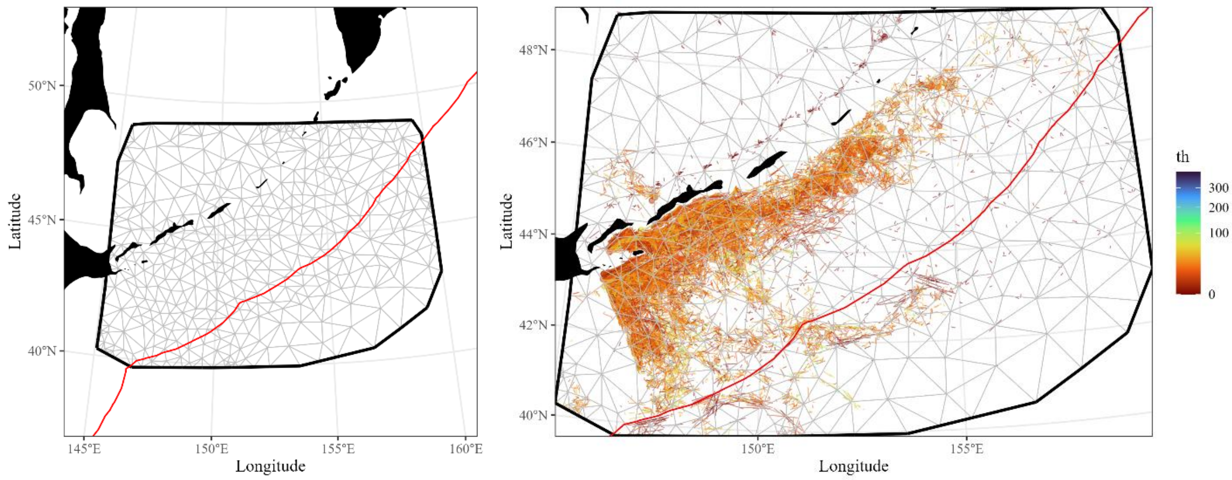


Fig. 7. Mesh for using Period-2 standardization in sdmTMB (th=t/h)

- Formulation of full model

  Period-1 full model in R script was formulated as glm18 = glm(formula = as.formula(LnTon ~ Year + YM + Idves + gear + Region + Target+ drperc), data = DataF)

  Period-2 full model in R script was formulated as fitFULL = sdmTMB(th ~ s(sstAVG) + s(sstGmax) + s(sssDavg) + s(msDavg) + RV + Target + Term + geartype, data = LinesAllssNcropProjDF, offset = 'perc', mesh = mesh, time = 'Year', family = tweedie(link = 'log'), spatial = 'on', spatiotemporal = 'iid'), where th =tons/hours.

2.3 Yearly trend extraction

- The method for extracting yearly standardized CPUE and its uncertainty such as standard error.

The method for extracting yearly standardized CPUE for Period-1 was based on prediction from the best GLM No 18 on expanded grid for Year and Month due to their interaction term, and the most frequent Idves = '10721', gear='MT', Region='SKur', Target='JS', drperc=1. Then statistics were gathered from the grid grouping by Year and average Year estimate inverting (exp) was done with bias correction.

The method for extracting yearly standardized CPUE for Period-2 was based on prediction from the FULL model with bias correction on the EVs for the most frequent dates (October, 10), bounded by the convex of real observations for all years during October, 10, and the most frequent predictors: RV='no', Target='Yes', Term='No', geartype='MT', and offset(perc) = 1.

3. RESULT and 4. DISCUSSION

- Result of the model selection, with interpretation of the selected model

For Period-1 the best GLM with linear predictor No 18 (see Table 8) was mostly influenced by the Vessel code (Idves), target fish (Target) and Year-Month (YM) interaction term (Fig. 8, Table 9).

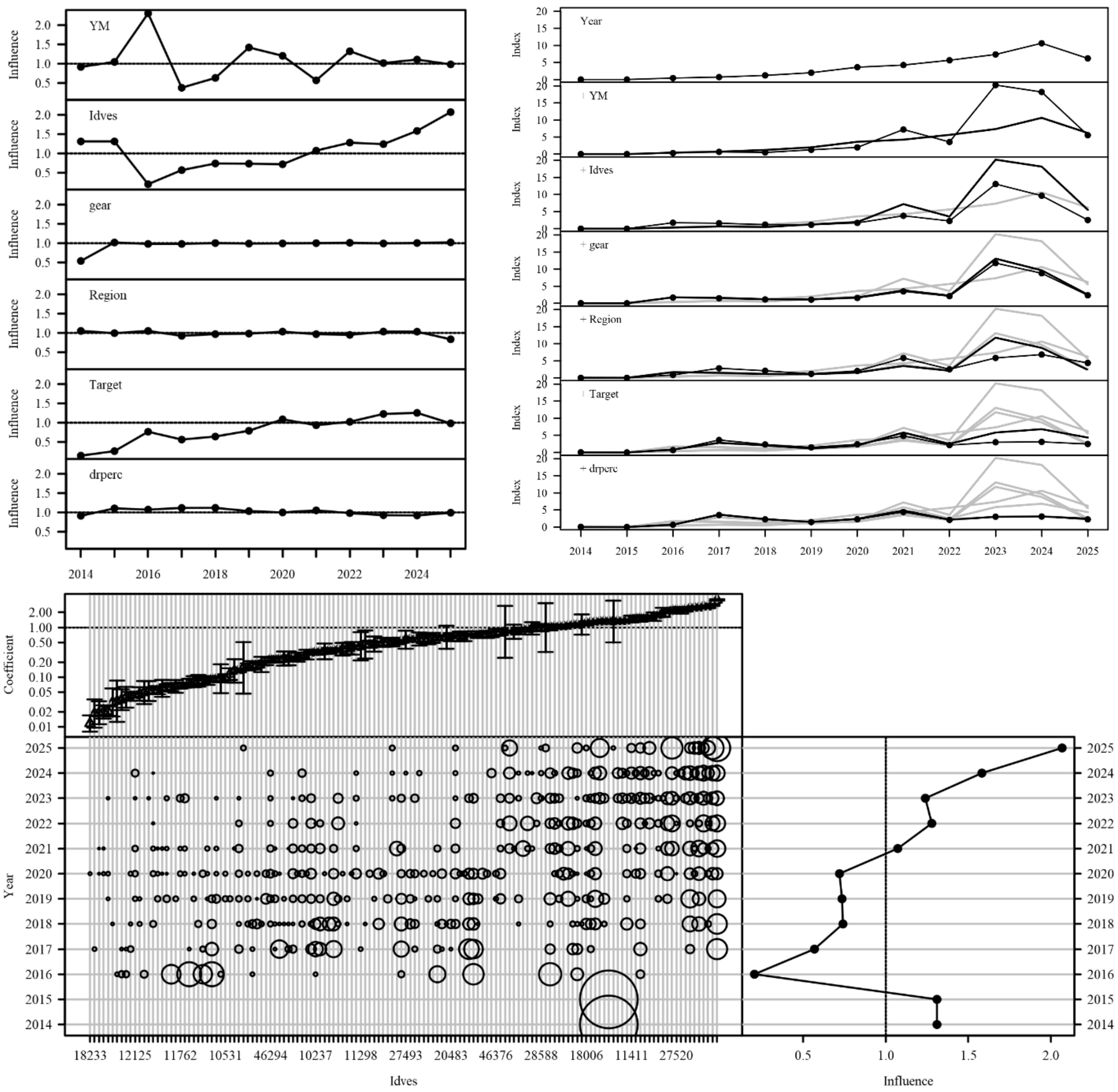


Fig. 8. Influence and step plots for Period-1 of the best GLM No 18

Table 9. Statistical properties of the best GLM No 18

term	k	logLike	AIC	r^2 (%)	Overall influence (%)
intercept	1	-31043.9	62091.8		
Year	11	-28925.1	57876.2	23.1%	
YM	86	-28042.6	56261.3	8.0%	0.384
Idves	139	-23197.1	46846.3	31.1%	0.559
gear	3	-23114.3	46686.6	0.4%	0.063
Region	4	-22887.6	46241.2	1.0%	0.050
Target	2	-21470.2	43410.3	5.9%	0.557
drperc	1	-21355.9	43183.7	0.4%	0.065

For Period-2 in the prediction area on October 10 spatial (Fig. 9) and spatiotemporal (Fig. 10) components played significant role and their parameters were found with narrow confidence intervals (C.I.): sigma_o = 0.438±0.0699 (C.I. 0.32-0.60), sigma_e = 0.586±0.048 (0.50-0.69), phi = 2.15±0.0243 (2.1-2.2), range = 219±25.6 (174-275) km.

(a) (b)

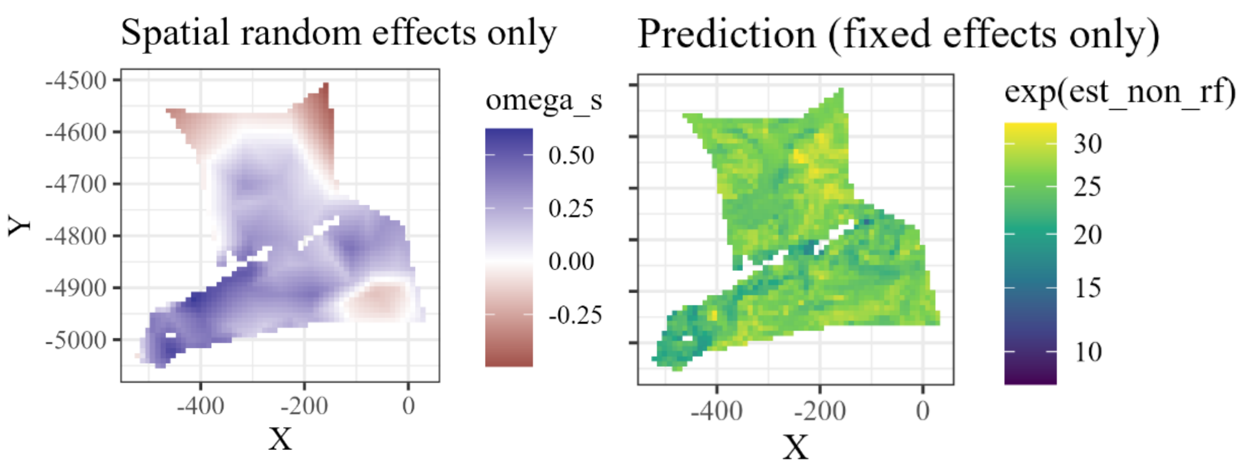


Fig. 9. Spatial component (a) in the full model for Period-2 and prediction with EVs and other fixed predictors on October 10 (b)

- Model diagnosis

For Period-1 analysis of deviance table, when terms were added sequentially (first to last) showed that all predictors were significant (Table 10). The total deviance explained was 69.9 % from the NULL deviance. There were no tendencies of the residuals (Fig. 11) Durbin-Watson test showed that Autocorrelations of median predictions by years with lags up to 5 years were not significant (p value 0.46-0.55), and the mean errors were almost equal to 0 (Figs. 12, 13).

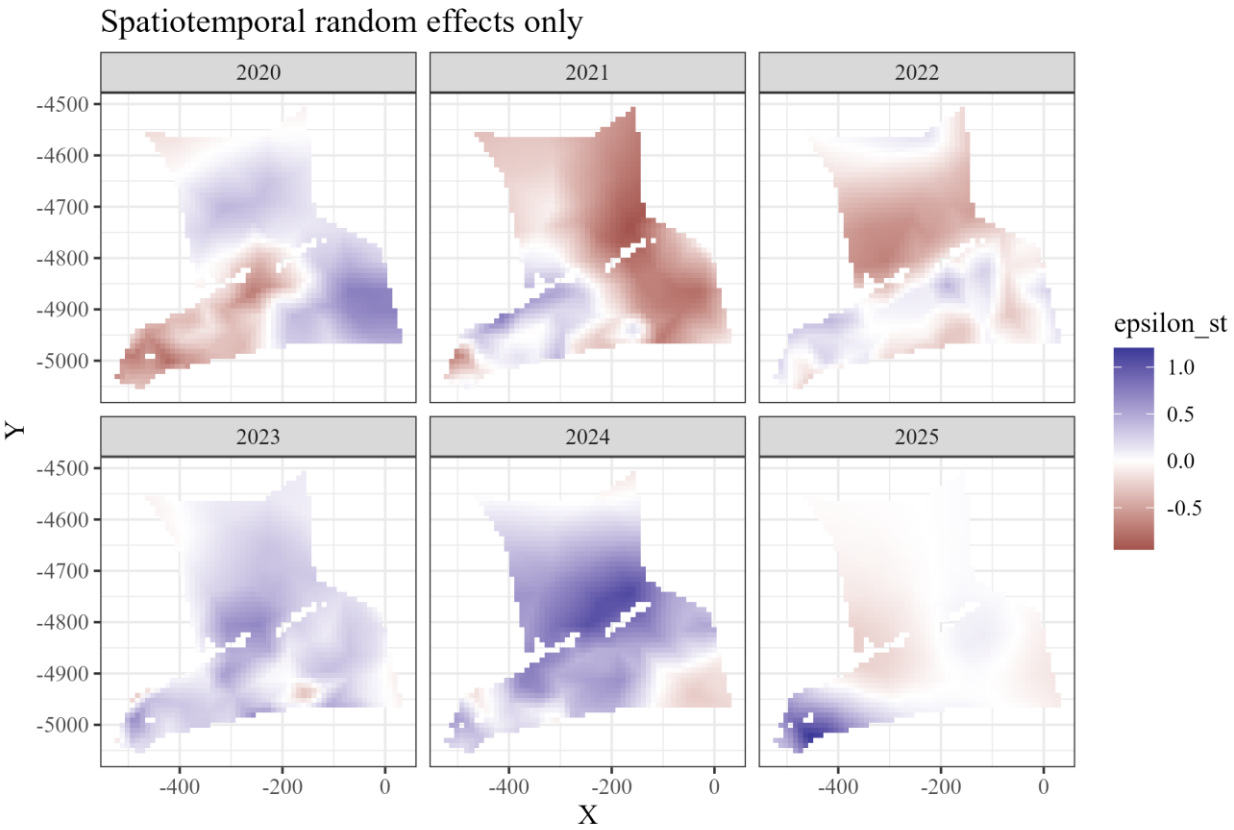


Fig. 10. Spatiotemporal component in the full model for Period-2

Table 10. Analysis of deviance table for the best GLM No 18 used for Period-1

Term	Df	Deviance	Resid.Df	Resid. Dev	F	Pr(>F), Signif. codes	
NULL	16150	44182					
Year	11	10196.1	16139	33986	1108.281	< 2.20E-16	***
YM	75	3518.1	16064	30468	56.086	< 2.20E-16	***
Idves	138	13747	15926	16721	119.107	< 2.20E-16	***
gear	3	170.6	15923	16550	68.008	< 2.20E-16	***
Region	4	458.1	15919	16092	136.941	< 2.20E-16	***
Target	2	2590.5	15917	13501	1548.688	< 2.20E-16	***
drperc	1	189.8	15916	13312	226.893	< 2.20E-16	***

Signif. codes: '***' < 0.001

For Period-2 there were no severe spatial patterns in the residuals (Fig. 14). Coefficient of determination r^2 = 41 % was lower than in GLM (71 %), but qqplot looked much better in the spatiotemporal model for Period-2 than in GLM for Period-1 (Fig. 15).

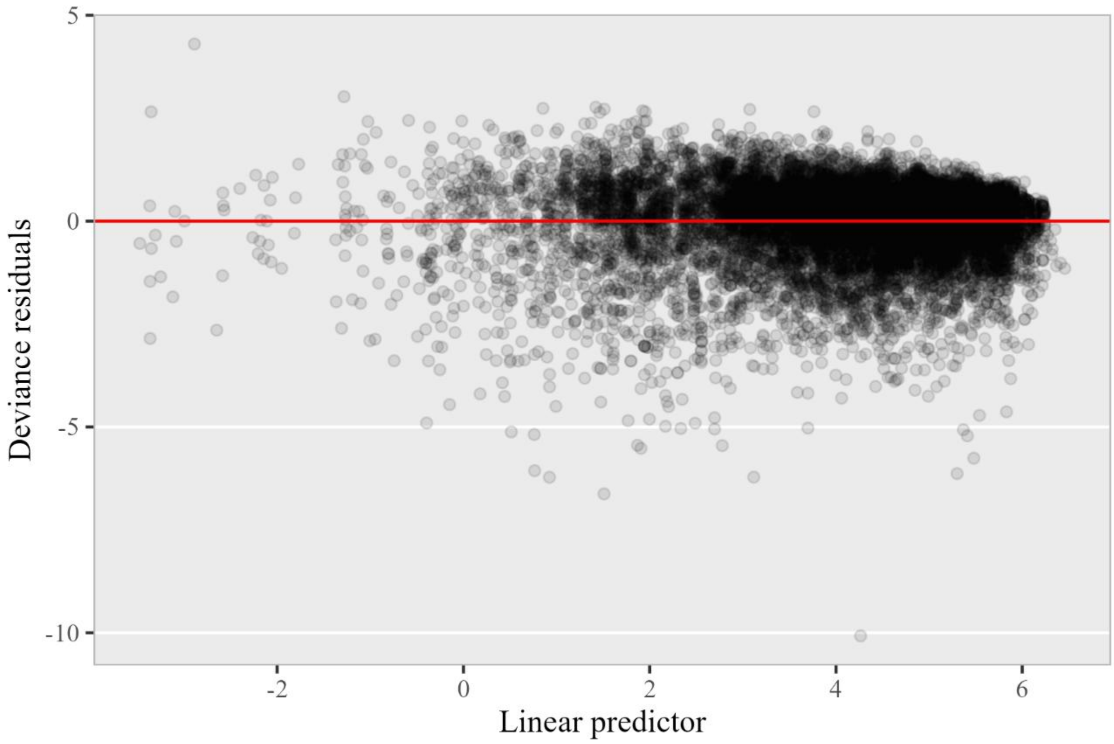


Fig. 11. Deviance residuals by linear predictor

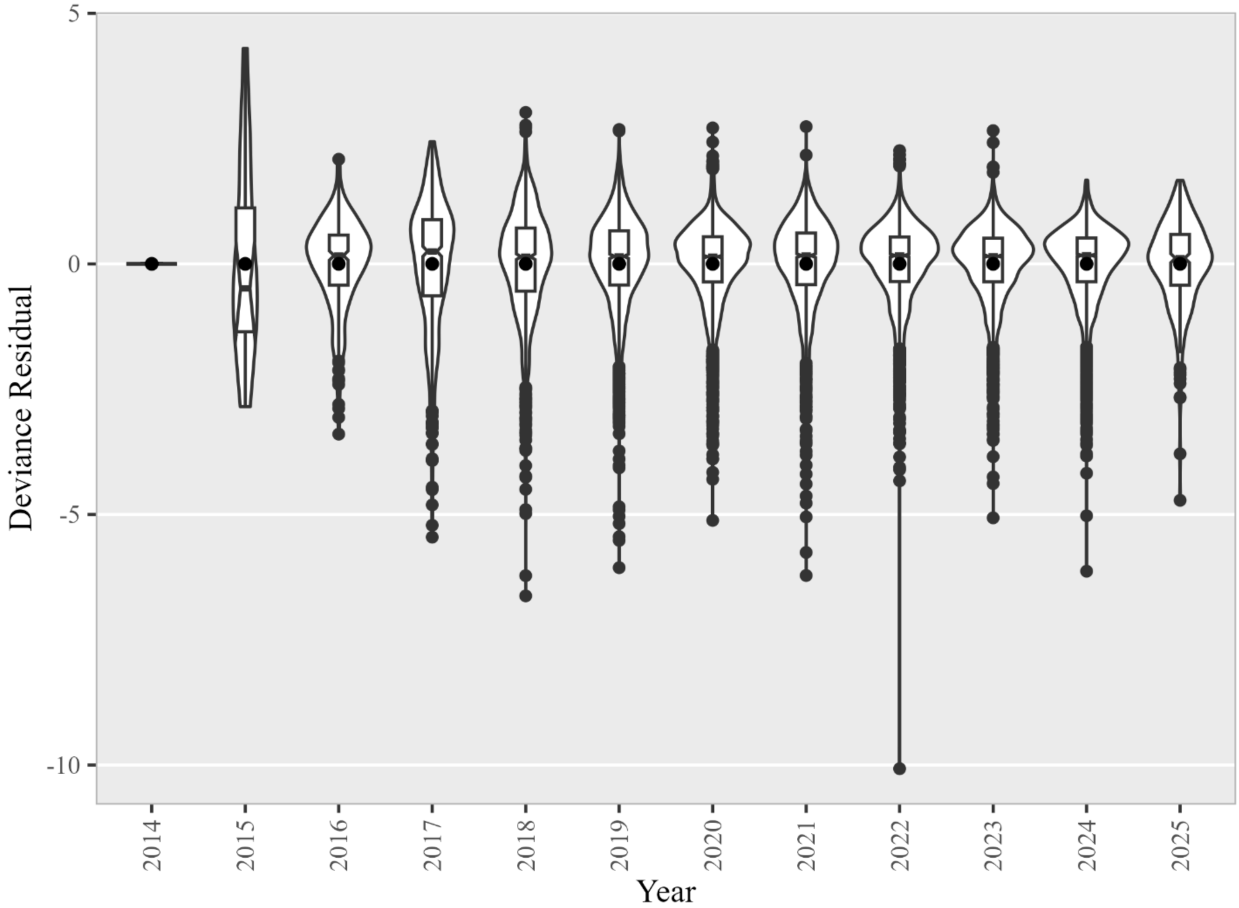


Fig. 12. Deviance residuals by Year

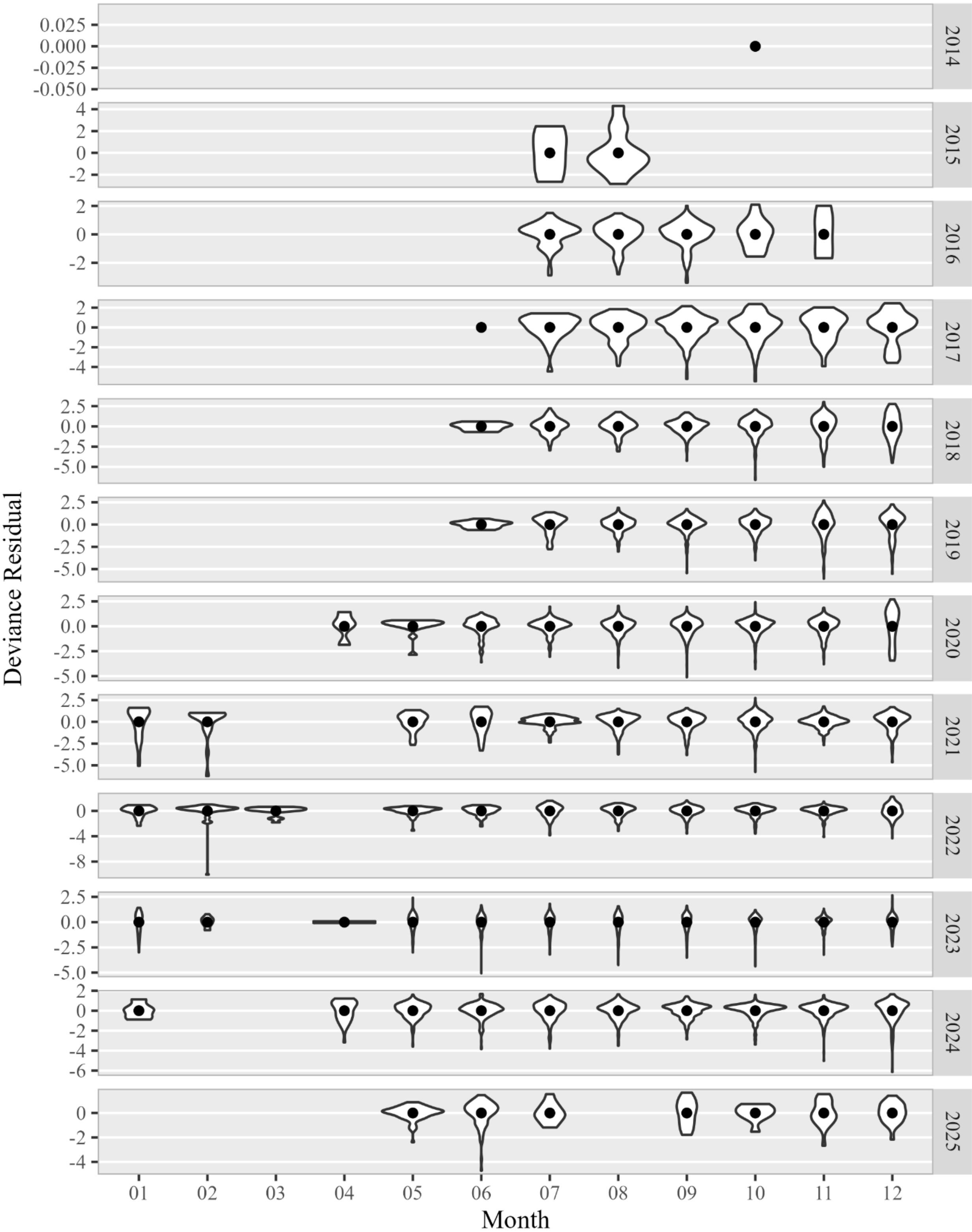


Fig. 13. Deviance residuals by Year and Month

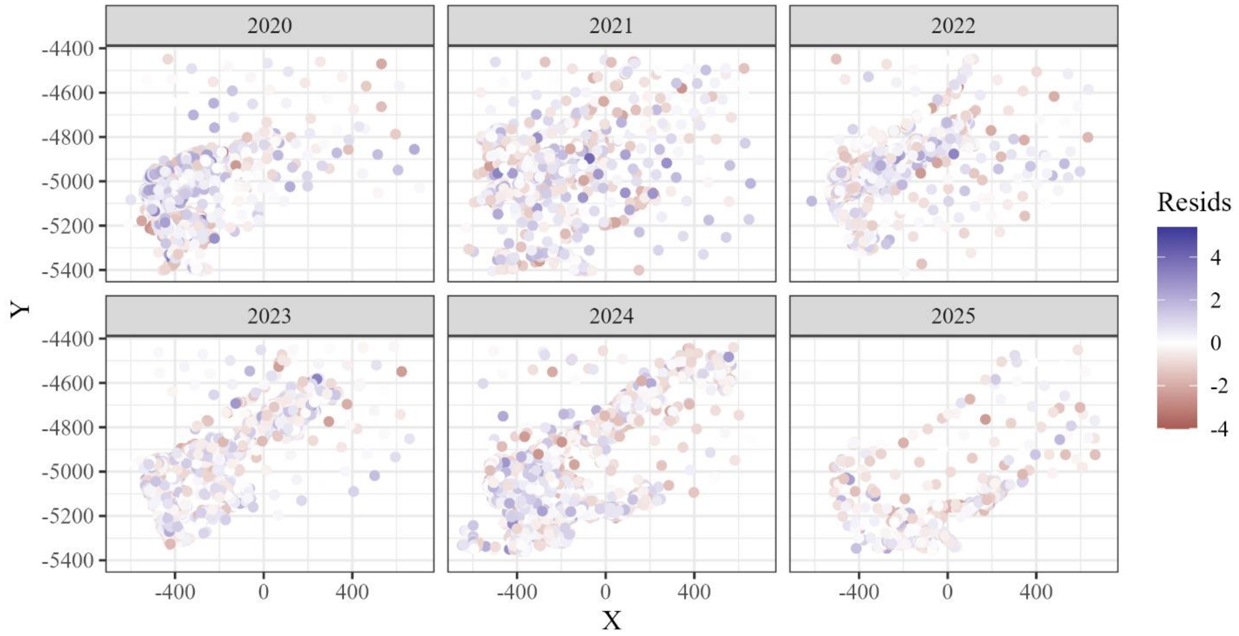


Fig. 14. Residuals by Year and coordinates

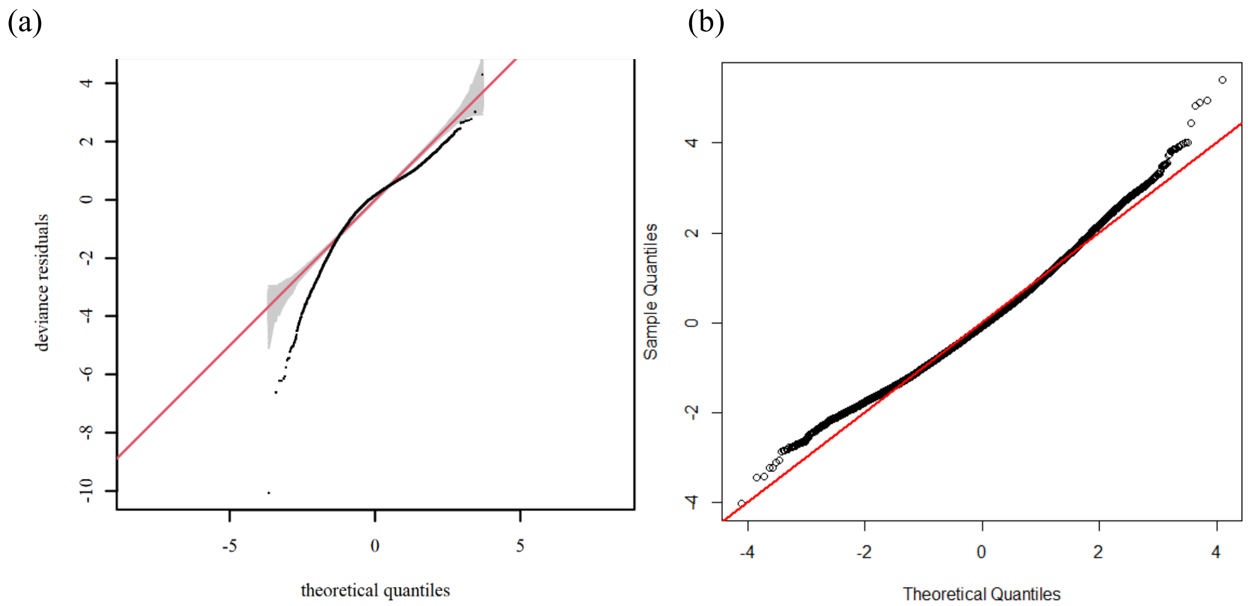


Fig. 15. Residuals qq-plots for Period-1 GLM No 18 (a) and Period-2 spatiotemporal model (b)

Sanity check for Period-2 model reported that non-linear minimizer suggested successful convergence, Hessian matrix was positive definite, there were no extreme or very small eigenvalues detected, no gradients with respect to fixed effects were >= 0.001, no fixed-effect standard errors were NA, no standard errors looked unreasonably large, no sigma parameters were < 0.01, no sigma parameters were > 100, and Range parameter didn't look unreasonably large. So, we considered spatiotemporal model for Period-2 corresponding to its assumptions.

- Estimated relationship between response and explanatory variables

Spatiotemporal EVs were approximated with splines similarly in the model as they were in the data (see Fig. 5) for SST and msDavg (mean angle of current), but not for other EVs (Fig. 16).

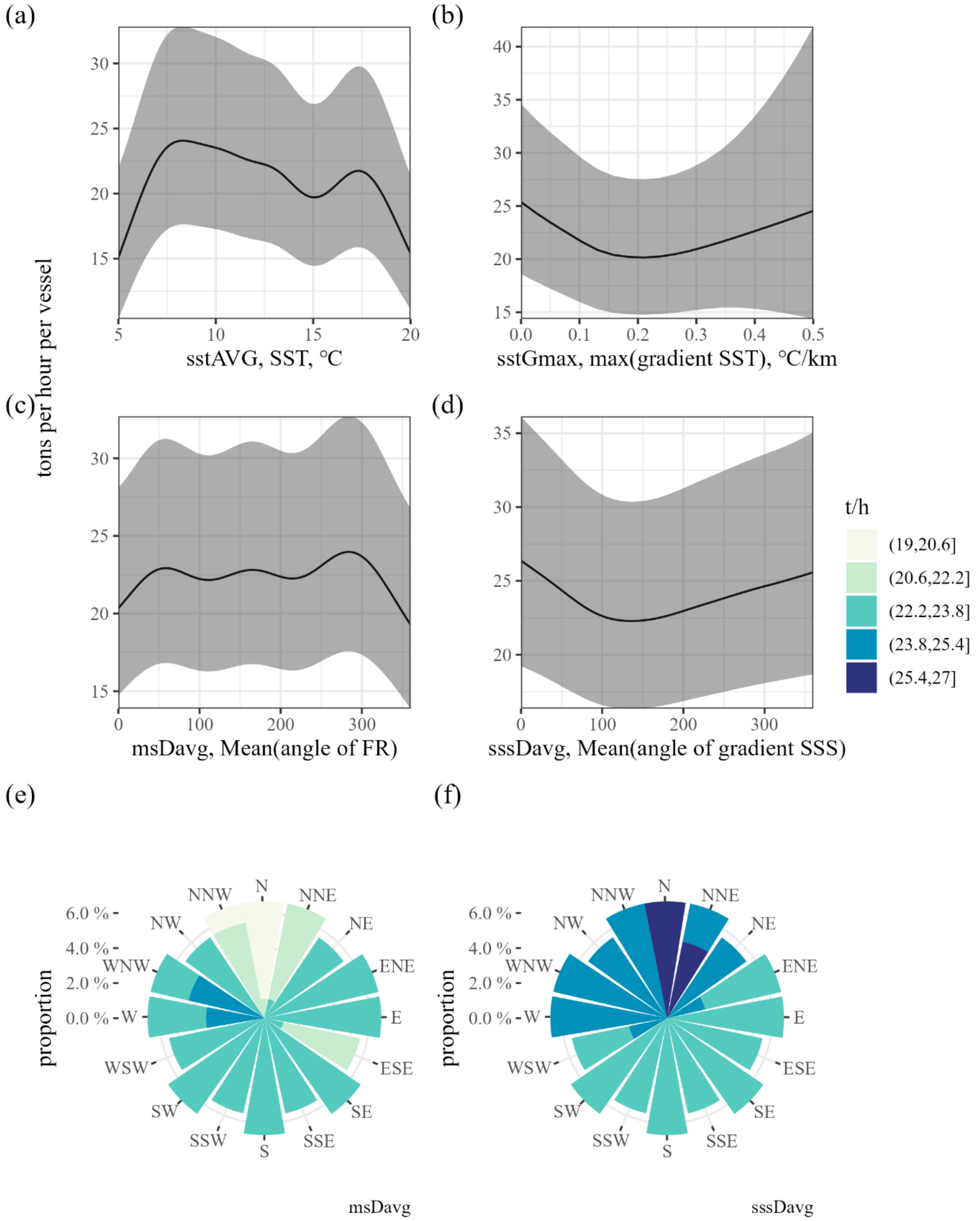


Fig. 16. Predictions without random effects for each fixed effect in 2025 keeping all others at median values or the most frequent values for factors (RV='no', Target='Yes', Term='No', geartype='MT') in Period-2 model

- Estimated values of parameters and uncertainty in the parameters

There were more than a hundred parameters for Idves and Year-Month interaction term in GLM No 18, so we omitted them from Table 11, but included in the Appendix IV.

Table 11. The estimated coefficients (mu) their Std. Error (se), t value, and significance (Pr(>|t|)) in the best model for Period-1

Term	mu	se	t value	Pr(>|t|)
(Intercept)	-0.08	0.93	-0.09	0.932
Year2015	-2.16	0.96	-2.25	0.024
Year2016	2.56	1.02	2.51	0.012
Year2017	4.23	0.94	4.50	0.000
Year2018	3.78	0.94	4.04	0.000
Year2019	3.35	0.93	3.59	0.000
Year2020	3.79	0.93	4.05	0.000
Year2021	4.45	0.93	4.77	0.000
Year2022	3.72	0.93	3.99	0.000
Year2023	4.08	0.93	4.38	0.000
Year2024	4.10	0.93	4.40	0.000
Year2025	3.77	0.94	4.02	0.000
gearNO	0.43	0.05	8.51	0.000
gearOthers	-0.63	0.11	-5.63	0.000
gearPS	-0.42	0.15	-2.73	0.006
RegionEEZJ	-0.66	0.09	-7.23	0.000
RegionNKur	0.18	0.10	1.85	0.064
RegionOkhS	0.53	0.99	0.54	0.591
RegionSKur	0.12	0.08	1.60	0.110
Targetetc	-0.39	0.08	-4.85	0.000
TargetJS	1.73	0.03	53.13	0.000
drperc	-1.14	0.08	-15.06	0.000

For Period-2 parameters were calculated in sdmTMB (Table 12).

Table 12. The estimated coefficients in the best model for Period-2

Term	mu	se	C.I. low	C.I. high
(Intercept)	0.542	0.159	0.231	0.853
RV|yes	-3.789	0.099	-3.983	-3.594
Target|Yes	1.618	0.035	1.549	1.688
Term|Yes	-0.351	0.011	-0.373	-0.329

Term	mu	se	C.I. low	C.I. high
geartype|PS	-0.247	0.028	-0.302	-0.193
s(sstAVG)	0.180	0.190	-0.192	0.552
s(sstGmax)	0.060	0.080	-0.097	0.217
s(sssDavg)	-0.040	0.050	-0.138	0.058
s(msDavg)	-0.060	0.100	-0.256	0.136
range	218.832	25.627	173.951	275.293
phi	2.151	0.024	2.104	2.199
sigma_O	0.438	0.070	0.320	0.599
sigma_E	0.586	0.048	0.500	0.688
tweedie_p	1.641	0.004	1.634	1.648
sd__s(sstAVG)	1.826		0.962	3.467
sd__s(sstGmax)	0.151		0.054	0.426
sd__s(sssDavg)	0.225		0.095	0.535
sd__s(msDavg)	0.686		0.317	1.487

- The extracted yearly trend with its uncertainty

The extracted yearly trend with its uncertainty is compared with the nominal CPUE for Period-1 (Fig. 17, Table 13) and for Period-2 (Fig. 18, Table 14). The scale of standardized CPUE differs a lot from the nominal CPUE, because it was predicted for the most frequent vessel (Idves = '10721', “Petr I”), which appeared to be the most efficient, because its coefficient was maximum among all other vessels (k=1.001 on a log scale). On a real scale it is found 2.7 times higher than the mean. Moreover, we had to omit 2014 year from the standardization due to low number of observations. Probably we should also skip the year 2015, because there were many JS catches as a bycatch to CM.

For Period-2 the scale of standardized CPUE is the same to nominal CPUE, because we didn’t succeed to include vessel codes in spatiotemporal model so far, but it was predicted for commercial fleet (RV=”no”).

Coefficient of variation (CV) was calculated as sqrt(exp(se^2) - 1)).

Means as exp(log_est+(se^2)/2).

confidence intervals (C.I.) as exp((log_est+(se^2)/2)-1.96*se) for the low limit and for the high limit as exp((log_est+(se^2)/2)+1.96*se).

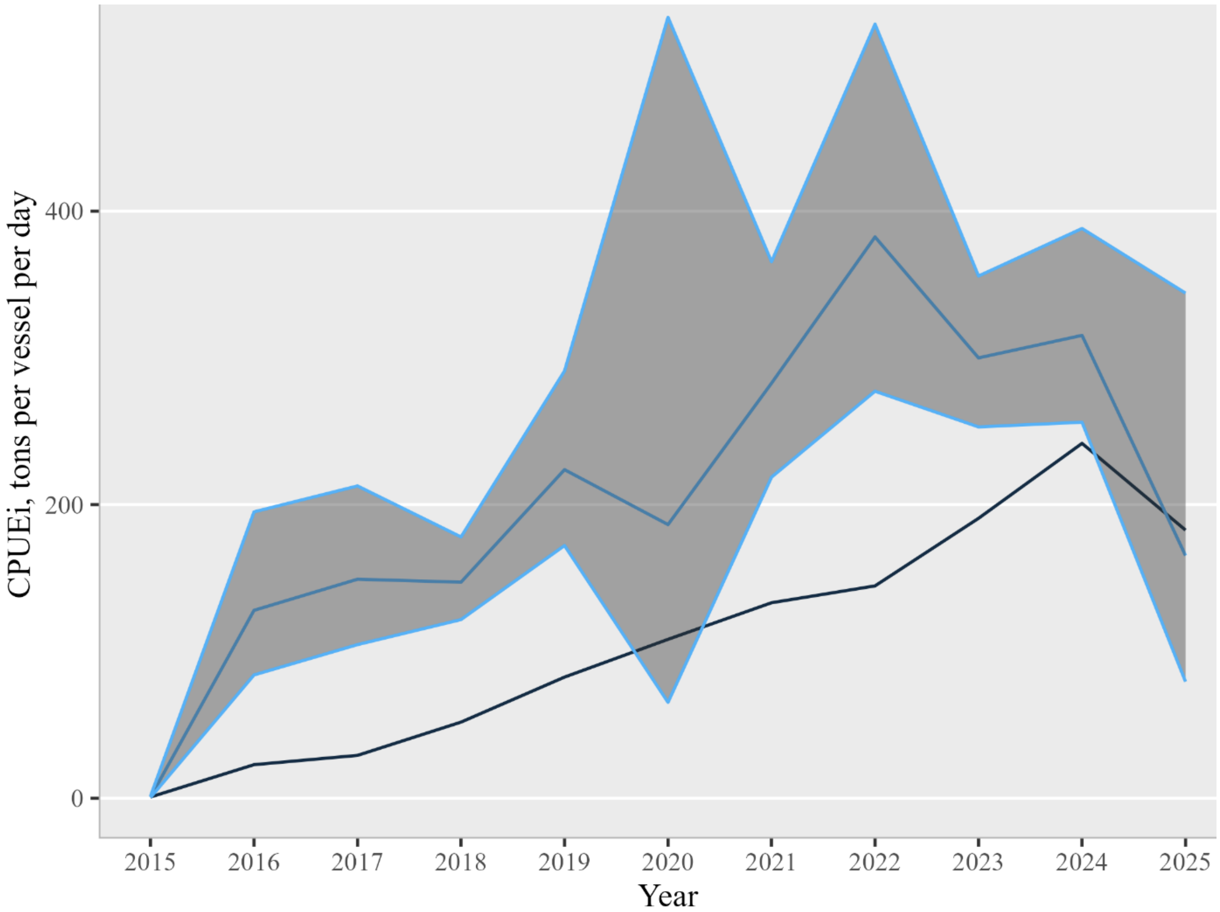


Fig. 17. Standardized CPUE (blue line) with its uncertainty (grey shading between blue lines) and nominal CPUE (black line) for Period-1

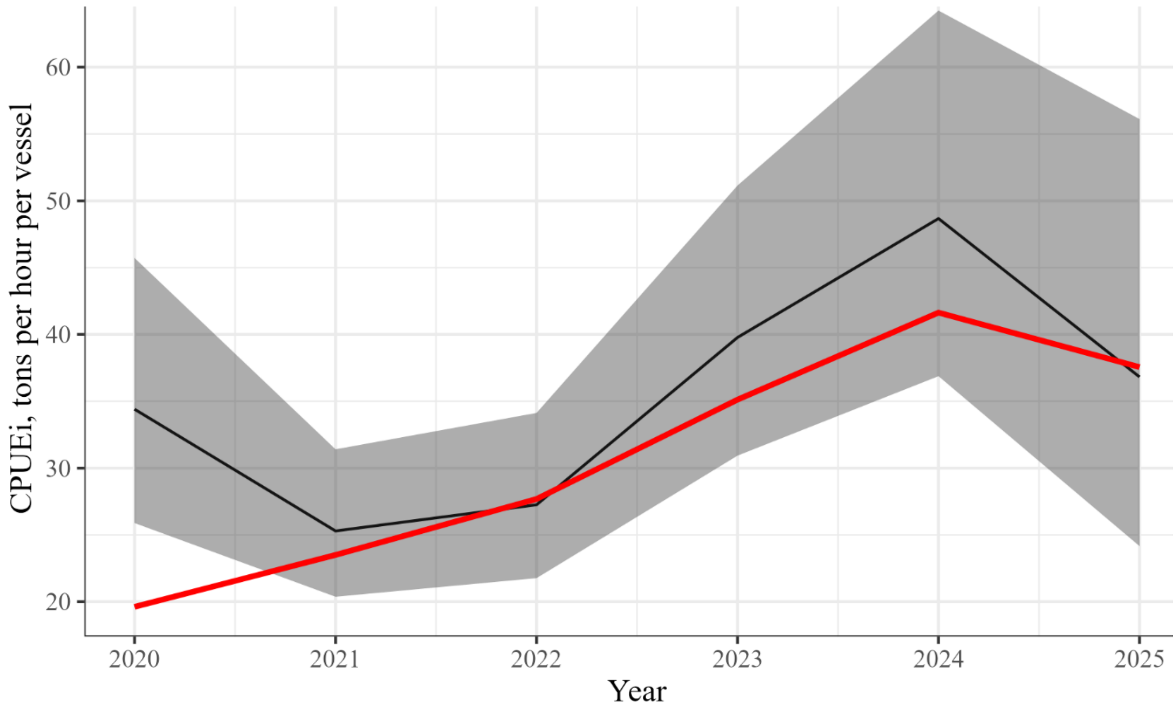


Fig. 18. Standardized CPUE (black line) with its uncertainty (grey shading) and nominal CPUE (red line) for Period-2

Table 13. Nominal from 2014 to 2025 and standardized CPUEs from 2015 to 2025 (tons per day per vessel) for Period-1

Year	Nominal CPUE	Standardized CPUE	CV (%)	95% CI Lower	95% CI Upper
2014	0.1				
2015	0.8	0.8	28.7%	0.5	1.4
2016	22.9	128.0	21.8%	84.0	195.1
2017	29.2	149.2	18.2%	104.6	212.8
2018	51.9	147.2	9.7%	121.7	178.0
2019	82.5	223.9	13.5%	172.1	291.1
2020	108.3	186.4	57.6%	65.3	532.0
2021	133.2	282.8	13.2%	218.7	365.5
2022	144.7	382.4	16.5%	277.3	527.4
2023	190.7	300.0	8.7%	253.0	355.8
2024	241.8	315.3	10.6%	256.2	388.1
2025	182.7	165.3	38.7%	79.4	344.1

Table 14. Nominal and standardized CPUEs (tons per hour) for Period-2 from 2020 to 2025

Year	Nominal CPUE	Standardized CPUE	CV (%)	95% CI Lower	95% CI Upper
2020	19.7	34.4	14.6%	25.9	45.7
2021	23.8	25.3	11.1%	20.4	31.4
2022	27.7	27.3	11.5%	21.8	34.1
2023	34.2	39.8	12.9%	30.9	51.1
2024	40.2	48.7	14.2%	36.9	64.2
2025	37.1	36.8	21.7%	24.2	56.1

- Further discussion

According to SDM, in the best AutoML method – ranger_model (see Appendix III) October 10 in 2025 should be the most productive (Fig. 19), but according to sdmTMB it was not in the selected region (Fig. 20). The latter is much closer to the expert's opinion in TINRO that was the main reason for our preference to sdmTMB instead of ranger_model, though ranger_model had higher explained deviance in validation ($r^2 = 0.44$) than sdmTMB ($r^2 = 0.41$) on a full set of data. Also, we suppose that spatiotemporal random effects in sdmTMB could capture important environmental information, that was not reflected by selected EVs. So, we recommend including both CPUE indices: from GLM (see Table 13) and sdmTMB (see Table 14), but not from ranger_model.

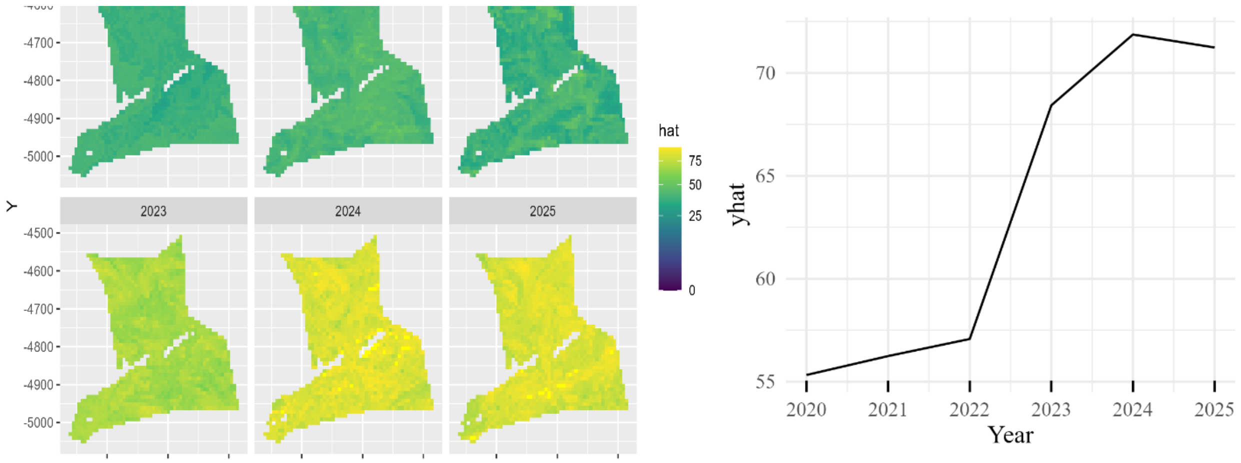


Fig. 19. Standardized CPUE in ranger_model for Period-2

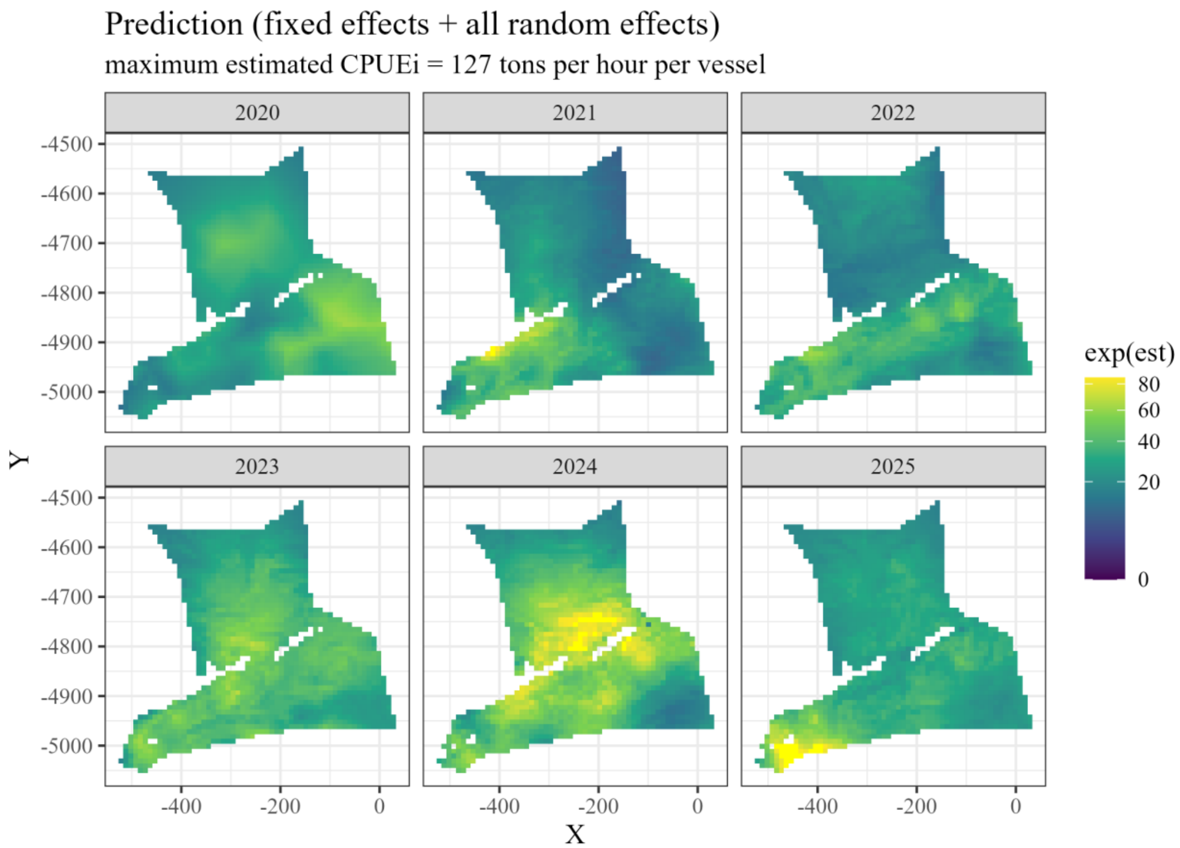


Fig. 20. Standardized CPUE in sdmTMB for Period-2

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APPENDICES

- **Appendix I:** Aggregated JS catch (t), number of operations (n) and CPUE (t/n)
- **Appendix II:** Report from AutoML regression of CPUE on all available environmental covariates from HYCOM and calculated for Period-2
- **Appendix III:** Report from AutoML regression of CPUE on selected environmental covariates from HYCOM and calculated for Period-2
- **Appendix IV:** parameter estimates and errors from GLM No 18
- **Appendix V:** Checklist for the CPUE standardization protocol

APPENDICES

Appendix I. Aggregated JS catch (t), number of operations (n) and CPUE (t/n)

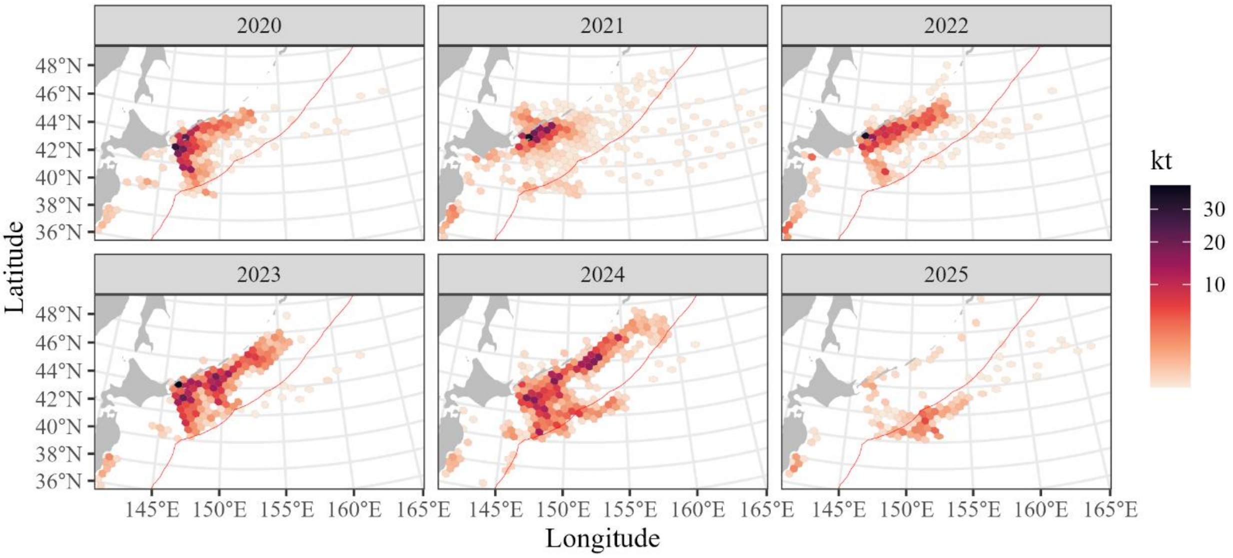

Fig. 1a. Distribution of JS catches (kt = t×10^3) by years

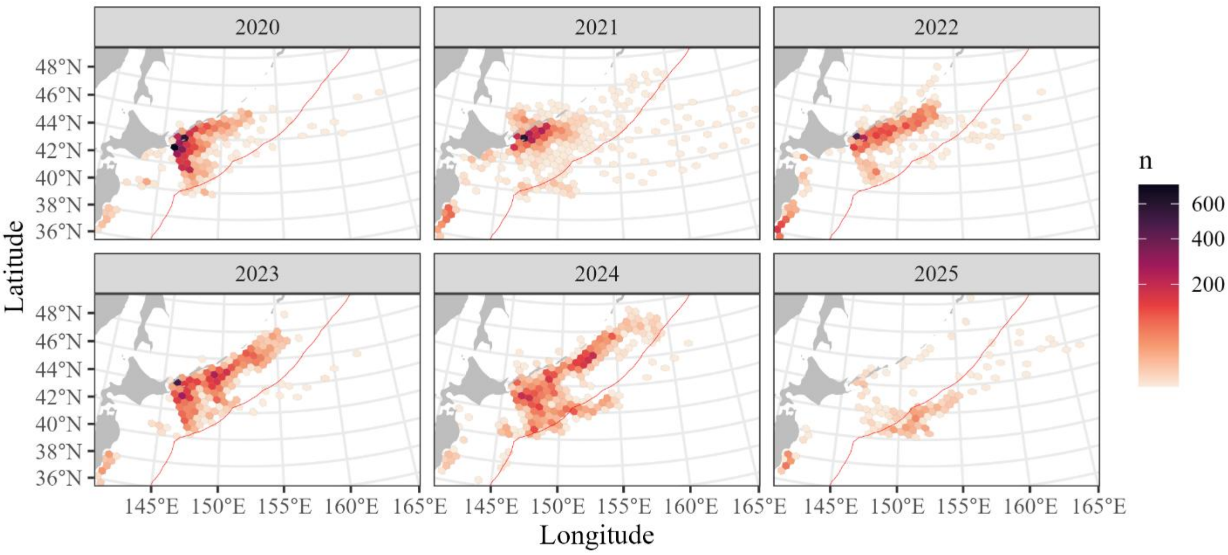

Fig. 2a. Distribution of operations (n) by years

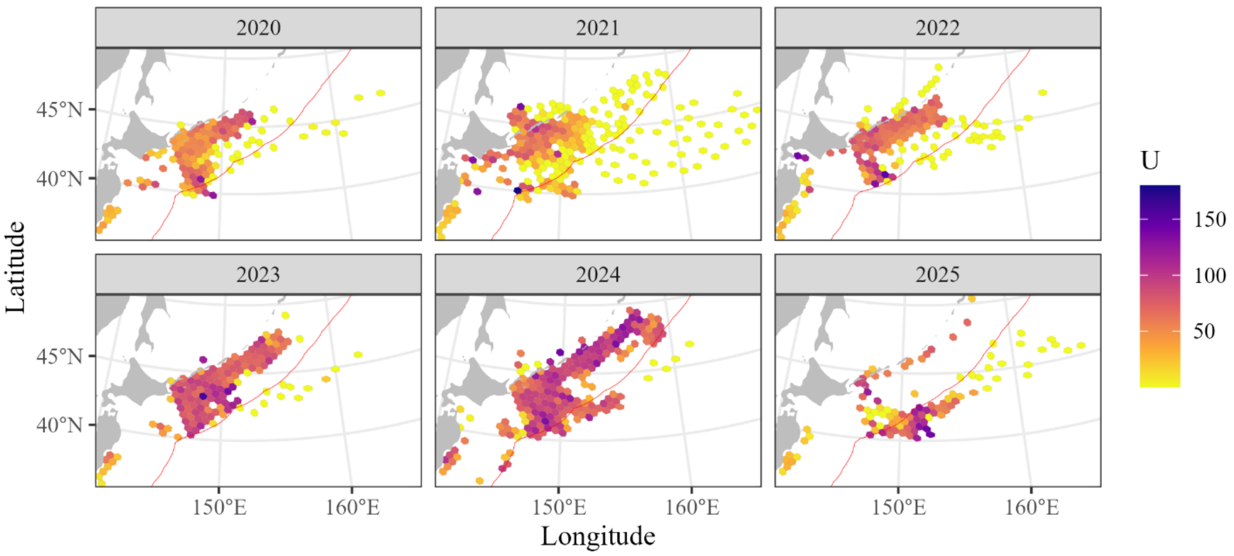

Fig. 3a. Distribution of JS CPUE (t/n) by years

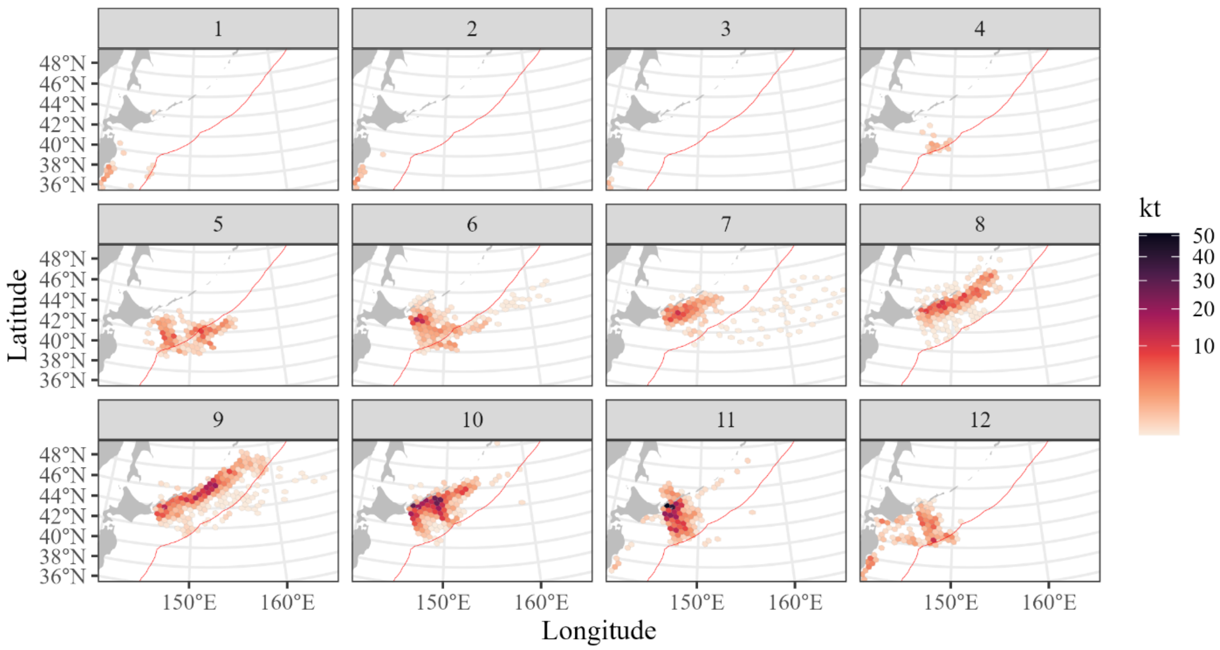

Fig. 4a. Distribution of JS catches (kt = t×10^3) by month

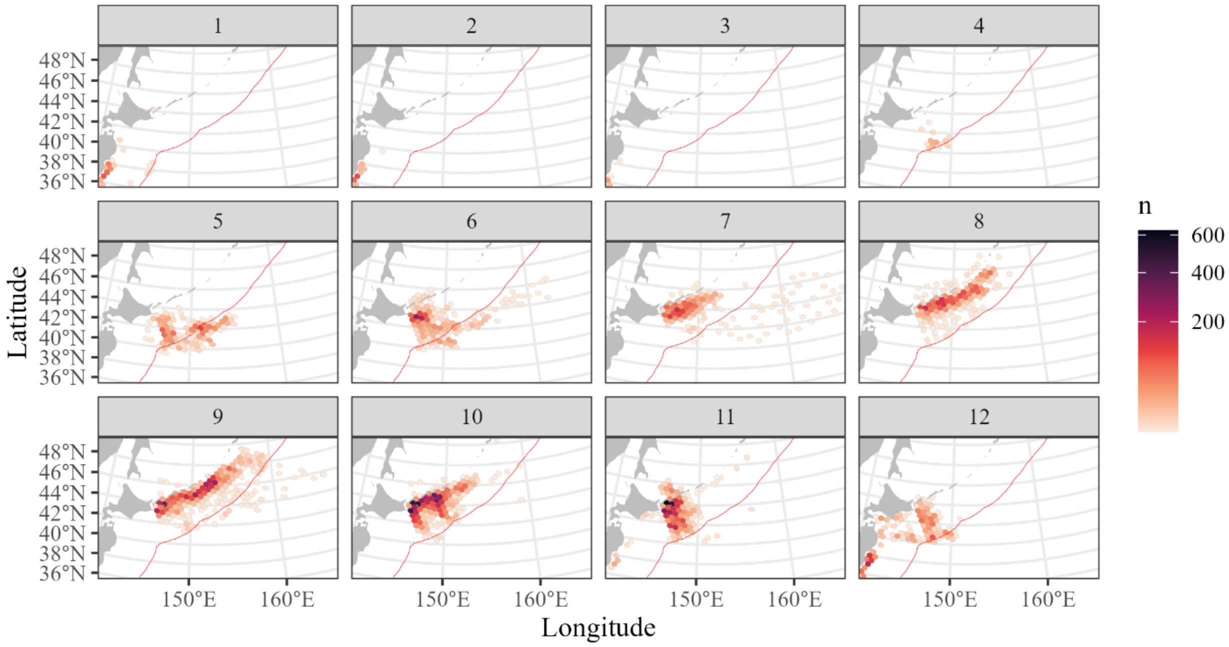

Fig. 5a. Distribution of operations (n) by month

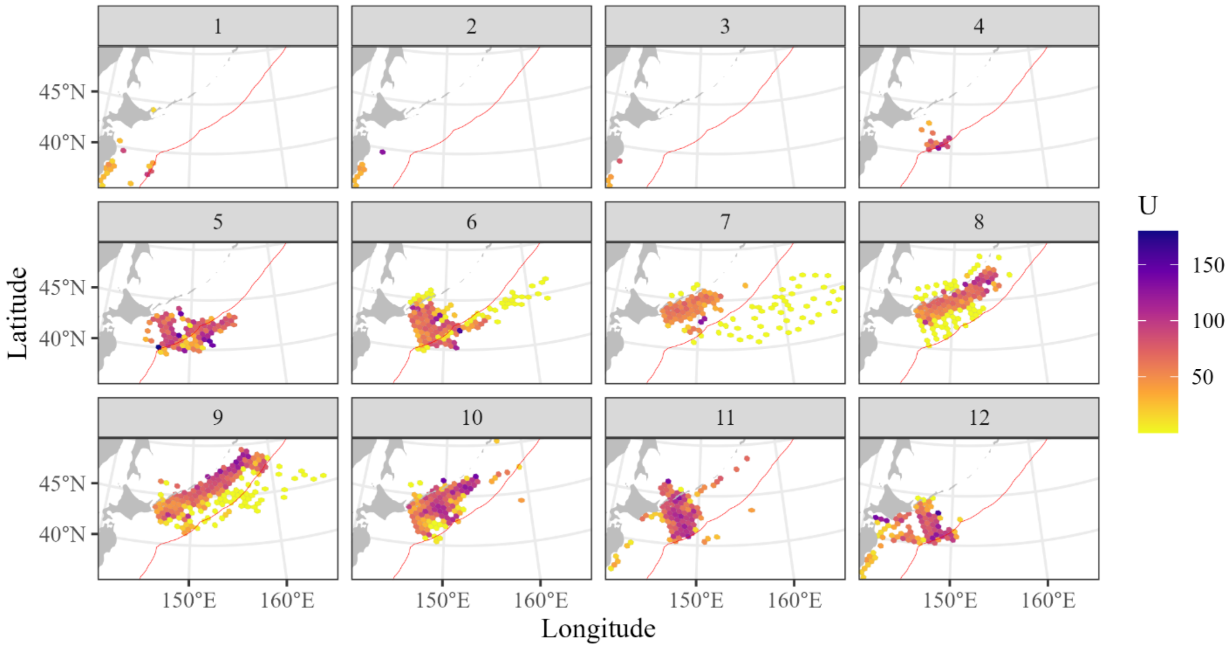

Fig. 6a. Distribution of JS CPUE (t/n) by month

forester report

version 1.6.1

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The best models

This is the **regression** task.

The best model evaluated on testing set is: **ranger_model**, whereas for the validation set it is: **ranger_model**.

The models inside the forester package are trained on the training set, the Bayesian Optimization is tuned according to the testing set, and the validation set is never seen during the training. The training set should not be used for evaluation as the models always perform the best for the data they have seen (overfitting). The least biased dataset is the validation set, however we can also use the testing set, ex. to check if the models overfit.

The names of the models were created by a pattern *Engine_TuningMethod_Id*, where:

- `Engine` - describes the engine used for the training (random_forest, xgboost, decision_tree, lightgbm, catboost),
- `TuningMethod` - describes how the model was tuned (`basic` for basic parameters, `RS` for random search, `bayes` for Bayesian optimization),
- `Id` - is used for separating the random search parameters sets.

More details about the dataset are present at the end of the report.

Best models for validation dataset

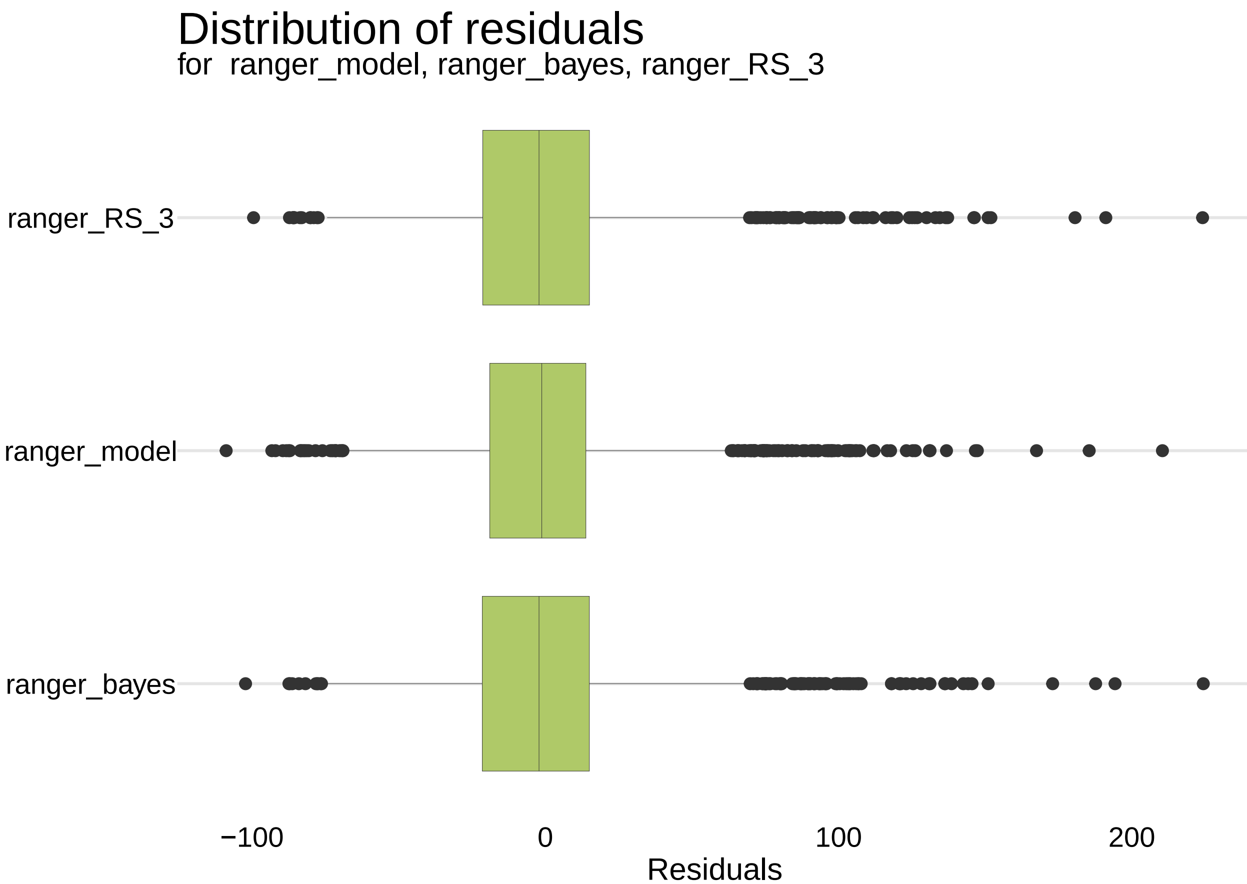
no.	name	rmse	mse	r2	mae
1	ranger_model	31.7985	1011.142	0.6203	22.1674
12	ranger_bayes	31.9564	1021.211	0.6165	22.3789
4	ranger_RS_3	32.3974	1049.592	0.6058	22.7942
3	ranger_RS_2	33.2038	1102.491	0.5860	23.6723
2	ranger_RS_1	33.6884	1134.905	0.5738	24.0893
6	ranger_RS_5	35.8822	1287.529	0.5165	26.1202
7	ranger_RS_6	35.8906	1288.135	0.5163	26.1292
5	ranger_RS_4	36.1174	1304.469	0.5101	26.2897
10	ranger_RS_9	36.1871	1309.509	0.5082	24.9413
9	ranger_RS_8	36.4785	1330.677	0.5003	26.6047

Model comparison

Residuals

The residual boxplot indicates whether the model generally fits well to the data or not. Ideally, the residuals are all close to 0, relative to the scale of the response variable (the larger true values, the larger residuals are considered small). It means, that when the box representing the interquantile range (IQR) is around 0, the model is well-fit. The dots on the plot represent the outliers of the model, which are incomparably large to other observations. Large amounts of the outliers might indicate, that the model doesn't fit well to the data.

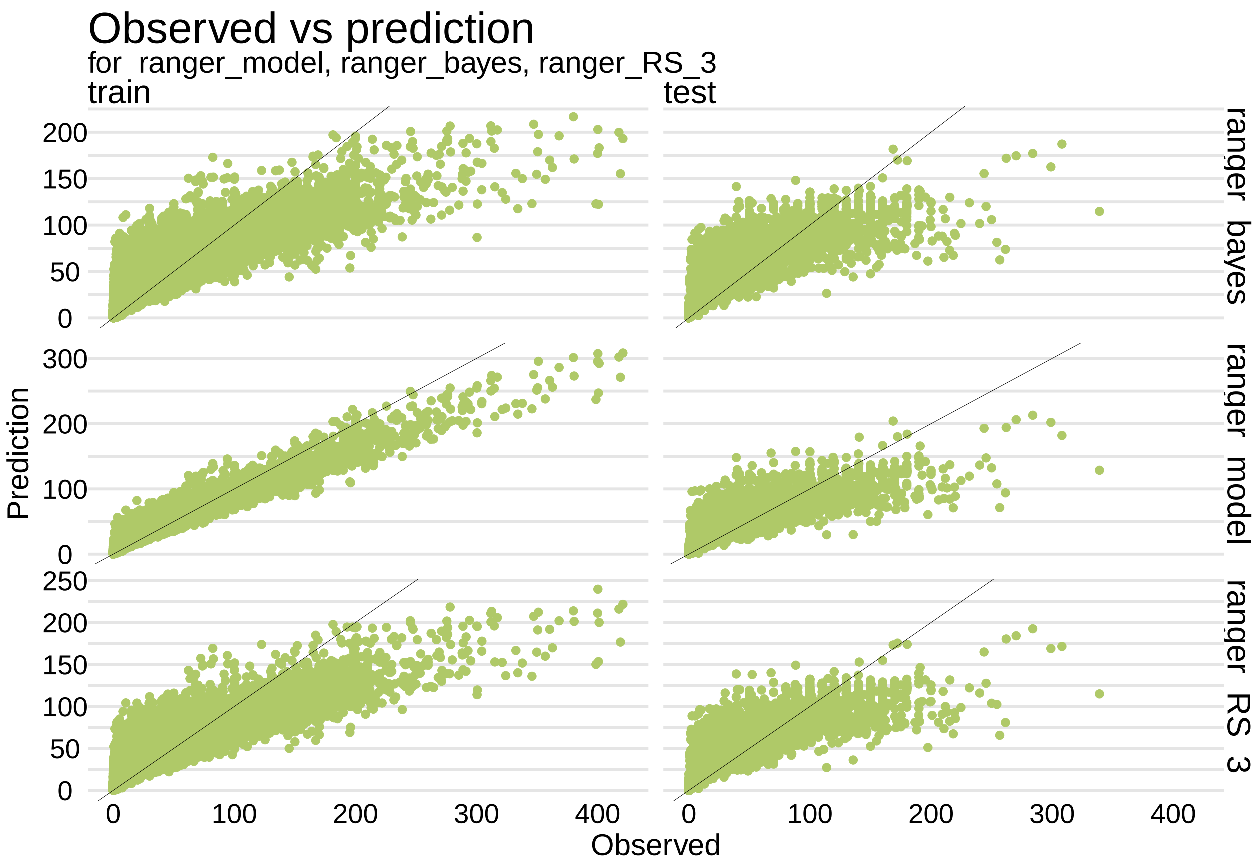
With the usage of this plot we can evaluate if best models fit well to the presented task (residuals close to 0, only a few outliers), and compare them between each other in order to choose the best one. We can suspect that the model with residuals closer to 0 (or a narrower IQR (box)) performs better.



Observed vs prediction

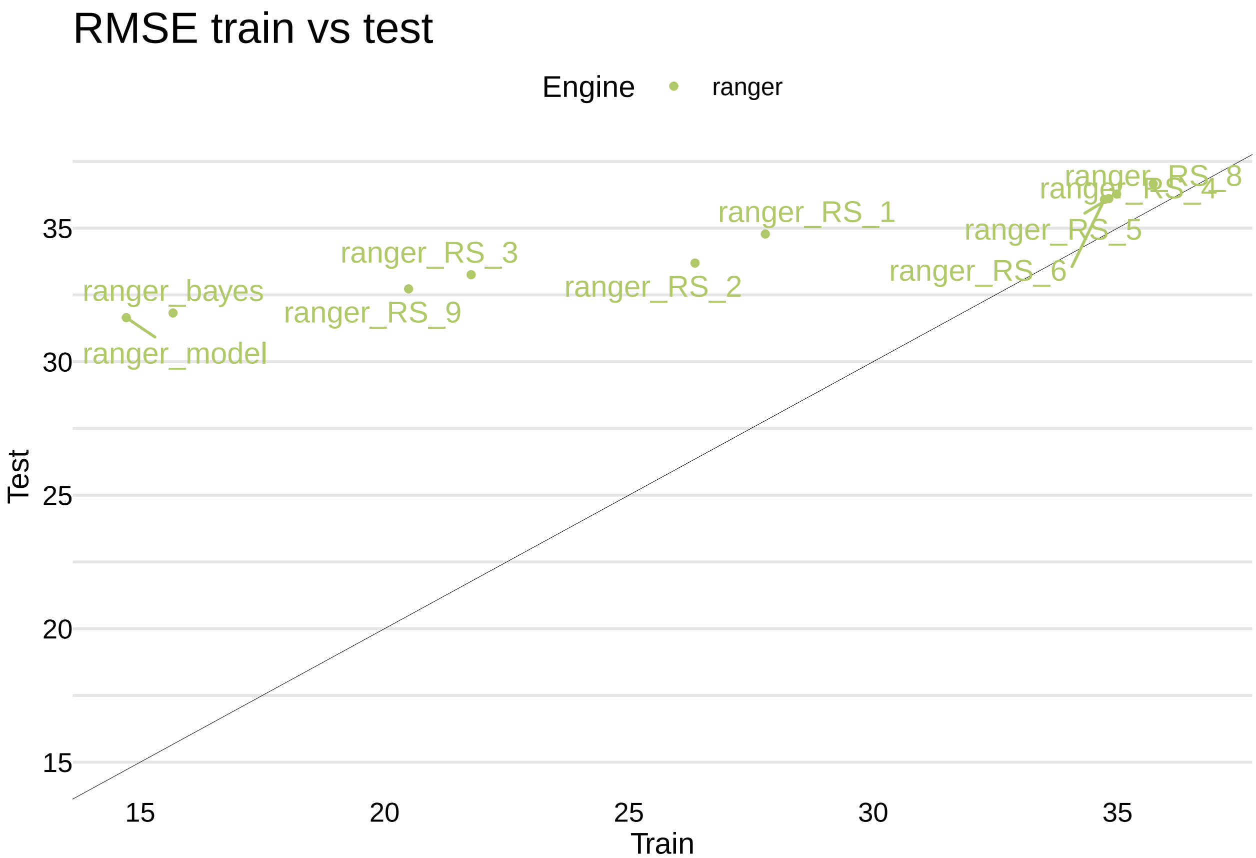
This scatter plot on the x axis presents us the observed values of the dataset, whereas the y axis corresponds to models predictions. The line drawn on the plot represents the estimated 'fit-line' where x = y. In this case we want particular observations (dots) to be close to each other (to estimated line). The further from the line an observation is, the worse the quality of this prediction is.

In this case we say that the model where observations are closer to each other is better. This visualization lets us also check if the model overfits or not. If predicted values for the train subplot are close to the line, whereas, for the train subplot are far from it, it suggests that the model might be overfitted, so it generalizes poorly for the unseen data.



Train vs test plot

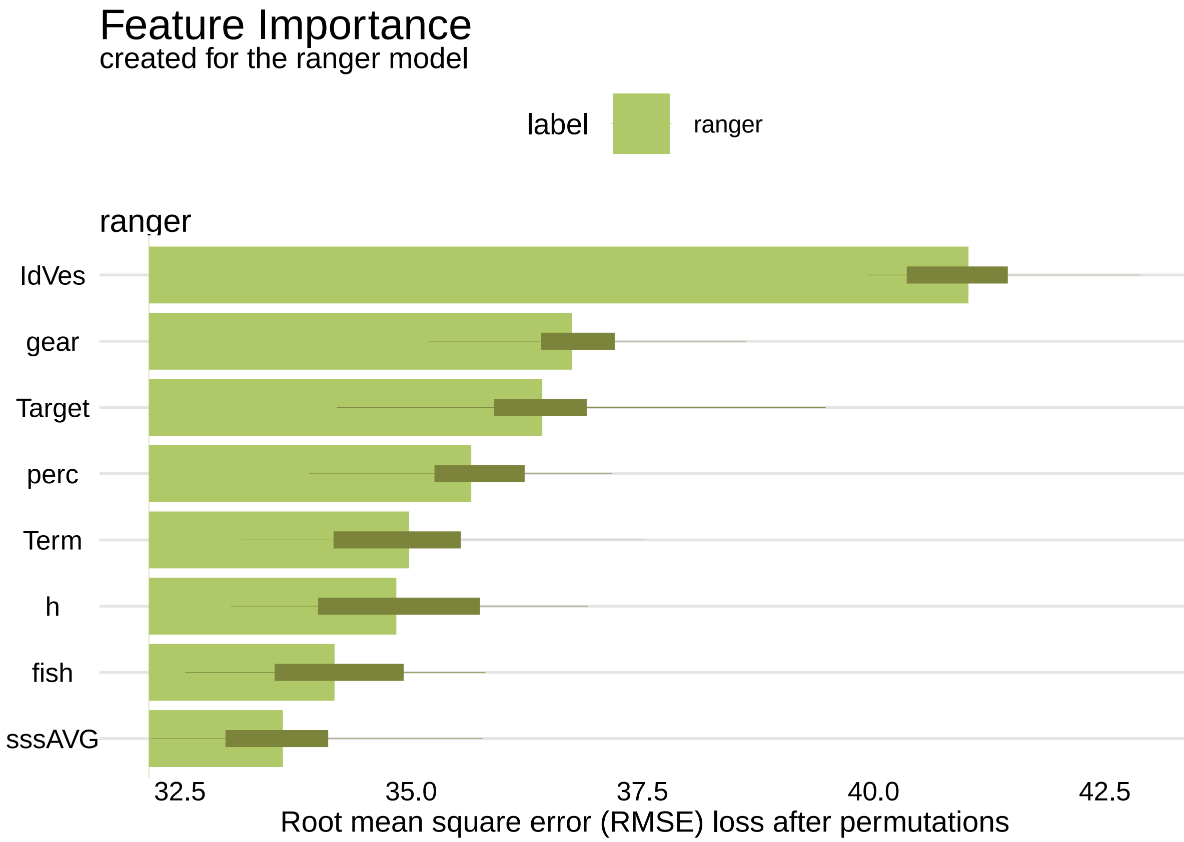
This scatter plot tackles the issue of the overfitting, and compares large amounts of models at once. On the x axis we provide the metrics value evaluated on the training dataset, whereas on the y axis we have the same for the testing dataset. Models performance is assessed in two ways. Firstly, we want the model to have as small value as possible on the testing dataset (so we want it to be lower than other models). Secondly, we want to choose the model which is close to the x = y line, because it means that the model is not overfitted, so it generalizes better. In most cases we want to chose the model that is less overfitted, even though it has worse performance.



Plots for the best model

Feature Importance

The final visualization presents us with the feature importance plot which lets us understand what's happening inside the best model evaluated on validation set. Feature Importance (FI) shows us the most important variables for the model, and the bigger the absolute value, the more important a variable is. Large FI values for a feature indicate that if we permute the values for the column randomly, it changes the final outcomes drastically.



Details about data

——————— CHECK DATA REPORT ———————

The dataset has 26195 observations and 19 columns which names are:

y; h; IdVes; RV; Target; fish; perc; Term; hours; gear; geartype; sstAVG; sssAVG; sstGmax; sssGmax; sstDavg; sssDavg; msGmax; msDavg;

With the target described by a column y.

No static columns.

No duplicate columns.

No target values are missing.

No predictor values are missing.

No issues with dimensionality.

Strongly correlated, by Spearman rank, pairs of numerical values are:

sssAVG - sstGmax: -0.94; sssAVG - sssGmax: -0.94; sssAVG - sstDavg: 0.73; sssAVG - msGmax: -0.94; sstGmax - sssGmax: 1; sstGmax - sstDavg: -0.71; sstGmax - msGmax: 1; sssGmax - sstDavg: -0.71; sssGmax - msGmax: 1; sstDavg - msGmax: -0.71;

Strongly correlated, by Crammer's V rank, pairs of categorical values are:

IdVes - RV: 1; IdVes - gear: 0.72; IdVes - geartype: 1; RV - fish: 0.89; RV - gear: 1; Target - fish: 0.99; gear - geartype: 1;

There are more than 50 possible outliers in the data set, so we are not printing them. They are returned in the output as a vector.

Target data is not evenly distributed with quantile bins: 0.25 0.31 0.18 0.27

Columns names suggest that none of them are IDs.

Columns data suggest that none of them are IDs.

——————— CHECK DATA REPORT END ———————

forester report

version 1.6.1

2026-06-11 20:18:18.592594

The best models

This is the **regression** task.

The best model evaluated on testing set is: **xgboost_RS_4**, whereas for the validation set it is: **ranger_model**.

The models inside the forester package are trained on the training set, the Bayesian Optimization is tuned according to the testing set, and the validation set is never seen during the training. The training set should not be used for evaluation as the models always perform the best for the data they have seen (overfitting). The least biased dataset is the validation set, however we can also use the testing set, ex. to check if the models overfit.

The names of the models were created by a pattern *Engine_TuningMethod_Id*, where:

- `Engine` - describes the engine used for the training (random_forest, xgboost, decision_tree, lightgbm, catboost),
- `TuningMethod` - describes how the model was tuned (`basic` for basic parameters, `RS` for random search, `bayes` for Bayesian optimization),
- `Id` - is used for separating the random search parameters sets.

More details about the dataset are present at the end of the report.

Best models for validation dataset

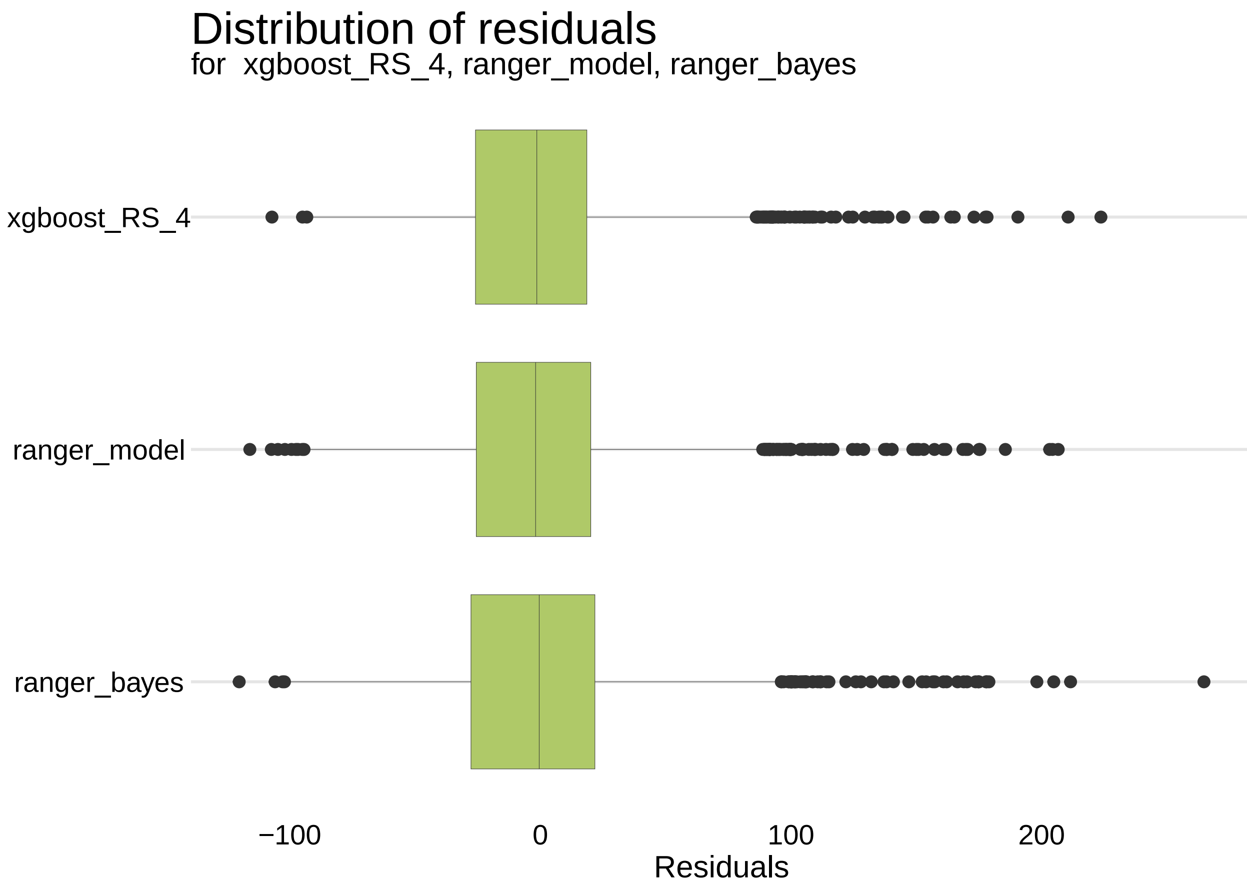
no.	name	rmse	mse	r2	mae
1	ranger_model	38.5783	1488.286	0.4411	28.0719
19	xgboost_RS_4	38.6979	1497.527	0.4376	27.7701
56	ranger_bayes	38.7590	1502.261	0.4358	28.2413
8	ranger_RS_3	38.8394	1508.499	0.4335	28.4305
7	ranger_RS_2	39.0735	1526.739	0.4266	28.7080
2	xgboost_model	39.4755	1558.319	0.4148	29.0375
6	ranger_RS_1	39.4809	1558.740	0.4146	29.0126
60	catboost_bayes	39.8859	1590.887	0.4026	28.1163
11	ranger_RS_6	40.1946	1615.605	0.3933	29.6485
10	ranger_RS_5	40.2040	1616.359	0.3930	29.6709

Model comparison

Residuals

The residual boxplot indicates whether the model generally fits well to the data or not. Ideally, the residuals are all close to 0, relative to the scale of the response variable (the larger true values, the larger residuals are considered small). It means, that when the box representing the interquantile range (IQR) is around 0, the model is well-fit. The dots on the plot represent the outliers of the model, which are incomparably large to other observations. Large amounts of the outliers might indicate, that the model doesn't fit well to the data.

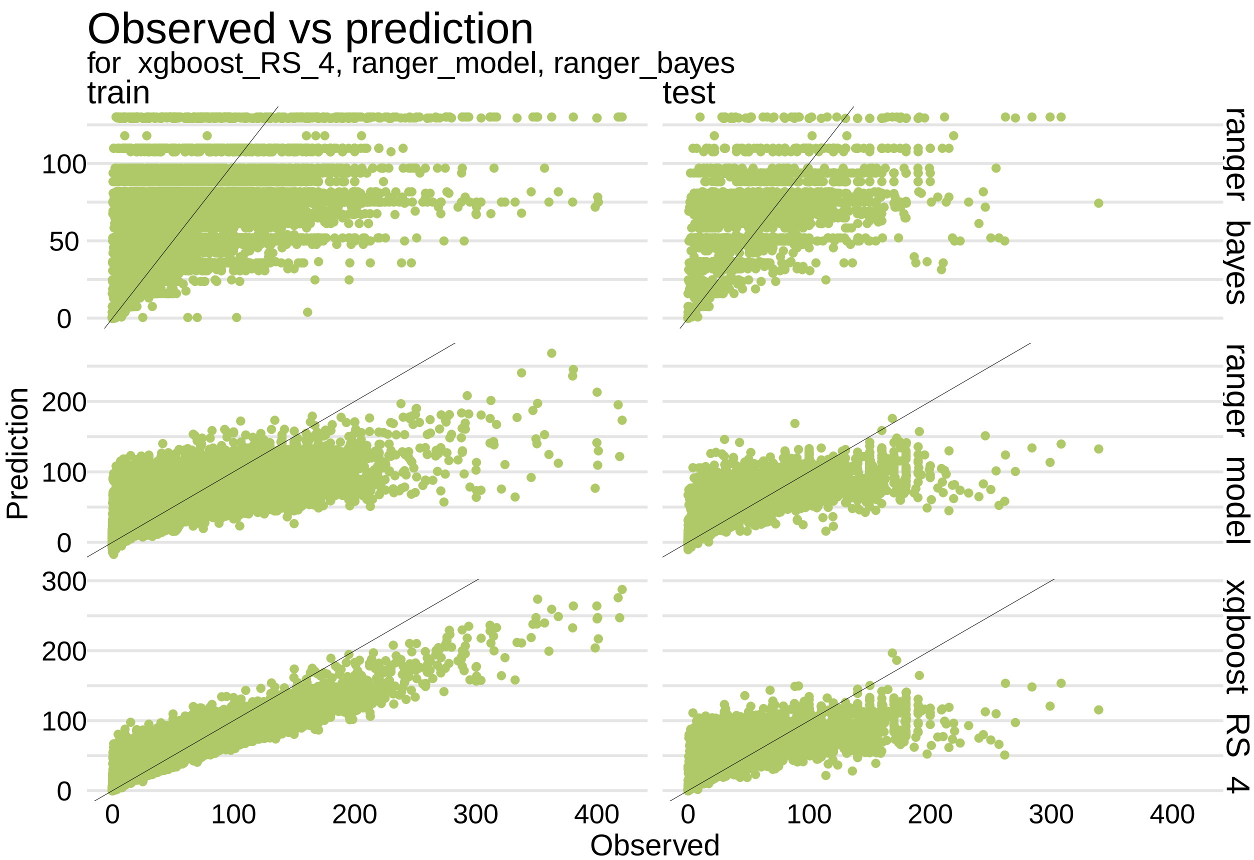
With the usage of this plot we can evaluate if best models fit well to the presented task (residuals close to 0, only a few outliers), and compare them between each other in order to choose the best one. We can suspect that the model with residuals closer to 0 (or a narrower IQR (box)) performs better.



Observed vs prediction

This scatter plot on the x axis presents us the observed values of the dataset, whereas the y axis corresponds to models predictions. The line drawn on the plot represents the estimated 'fit-line' where x = y. In this case we want particular observations (dots) to be close to each other (to estimated line). The further from the line an observation is, the worse the quality of this prediction is.

In this case we say that the model where observations are closer to each other is better. This visualization lets us also check if the model overfits or not. If predicted values for the train subplot are close to the line, whereas, for the train subplot are far from it, it suggests that the model might be overfitted, so it generalizes poorly for the unseen data.



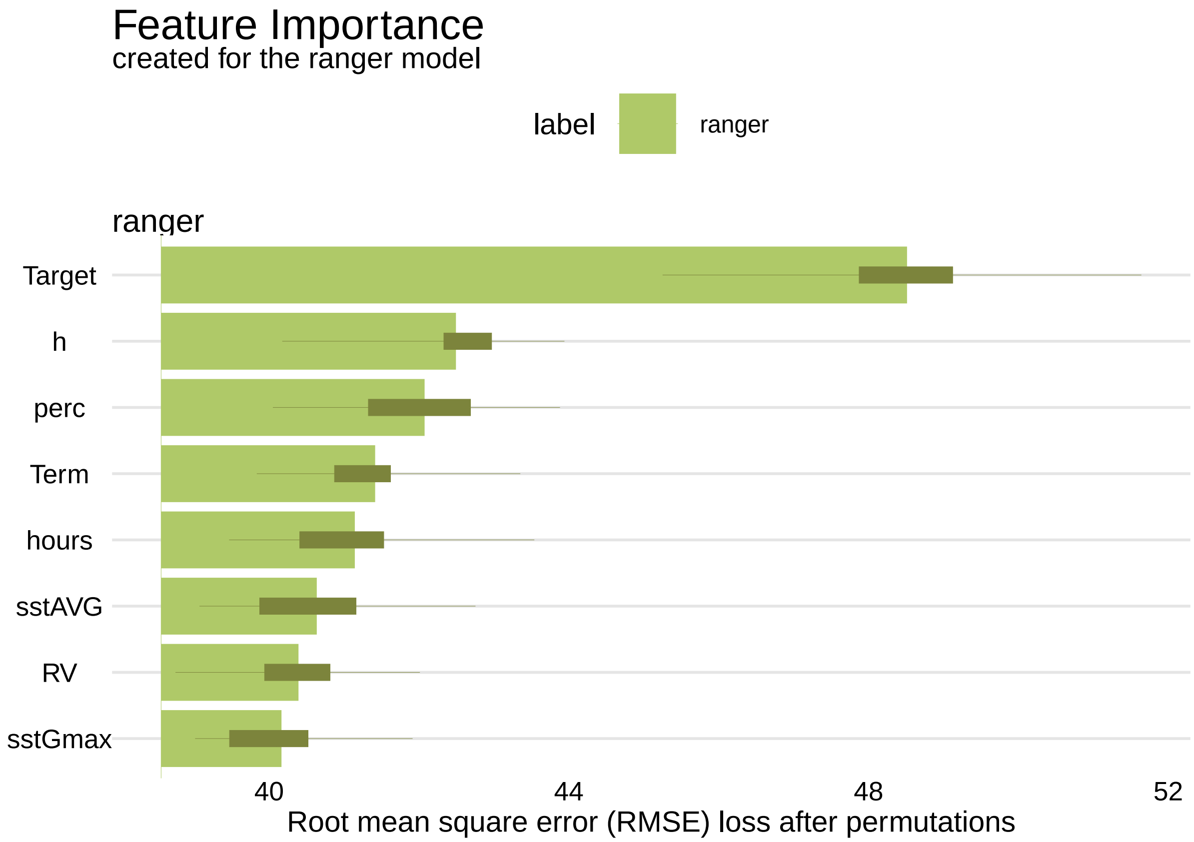
Train vs test plot

This scatter plot tackles the issue of the overfitting, and compares large amounts of models at once. On the x axis we provide the metrics value evaluated on the training dataset, whereas on the y axis we have the same for the testing dataset. Models performance is assessed in two ways. Firstly, we want the model to have as small value as possible on the testing dataset (so we want it to be lower than other models). Secondly, we want to choose the model which is close to the x = y line, because it means that the model is not overfitted, so it generalizes better. In most cases we want to chose the model that is less overfitted, even though it has worse performance.

Plots for the best model

Feature Importance

The final visualization presents us with the feature importance plot which lets us understand what's happening inside the best model evaluated on validation set. Feature Importance (FI) shows us the most important variables for the model, and the bigger the absolute value, the more important a variable is. Large FI values for a feature indicate that if we permute the values for the column randomly, it changes the final outcomes drastically.



Details about data

——————— **CHECK DATA REPORT** ———————

The dataset has 26195 observations and 12 columns which names are:

y; h; RV; Target; perc; Term; hours; geartype; sstAVG; sstGmax; sssDavg; msDavg;

With the target described by a column y.

No static columns.

No duplicate columns.

No target values are missing.

No predictor values are missing.

No issues with dimensionality.

No strongly correlated, by Spearman rank, pairs of numerical values.

No strongly correlated, by Crammer's V rank, pairs of categorical values.

There are more than 50 possible outliers in the data set, so we are not printing them. They are returned in the output as a vector.

Target data is not evenly distributed with quantile bins: 0.25 0.31 0.18 0.27

Columns names suggest that none of them are IDs.

Columns data suggest that none of them are IDs.

——————— **CHECK DATA REPORT END** ———————

Appendix IV. Parameter estimates and errors from GLM No 18

Term	mu	se	t	Pr(>|t|)
YM.2015.07	0.562	0.525	1.070	0.285
YM.2016.07	0.891	0.435	2.050	0.040
YM.2016.08	1.077	0.426	2.529	0.011
YM.2016.09	0.967	0.423	2.287	0.022
YM.2016.10	0.243	0.476	0.511	0.609
YM.2017.06	-0.769	0.931	-0.825	0.409
YM.2017.07	-1.577	0.227	-6.951	0.000
YM.2017.08	-1.163	0.175	-6.660	0.000
YM.2017.09	-0.770	0.165	-4.676	0.000
YM.2017.10	-0.975	0.164	-5.952	0.000
YM.2017.11	-0.888	0.215	-4.126	0.000
YM.2018.06	-0.526	0.430	-1.223	0.221
YM.2018.07	-0.747	0.153	-4.892	0.000
YM.2018.08	-0.626	0.149	-4.215	0.000
YM.2018.09	-0.221	0.134	-1.649	0.099
YM.2018.10	-0.342	0.133	-2.563	0.010
YM.2018.11	-0.549	0.141	-3.886	0.000
YM.2019.06	0.773	0.283	2.734	0.006
YM.2019.07	0.412	0.131	3.153	0.002
YM.2019.08	0.681	0.114	5.983	0.000
YM.2019.09	0.542	0.111	4.888	0.000
YM.2019.10	0.662	0.107	6.177	0.000
YM.2019.11	-0.138	0.107	-1.284	0.199
YM.2020.04	-4.591	0.479	-9.591	0.000
YM.2020.05	0.368	0.259	1.421	0.155
YM.2020.06	-0.109	0.137	-0.802	0.423
YM.2020.07	0.058	0.126	0.461	0.645
YM.2020.08	0.311	0.124	2.504	0.012
YM.2020.09	0.248	0.122	2.037	0.042
YM.2020.10	0.466	0.118	3.937	0.000
YM.2020.11	0.189	0.122	1.551	0.121
YM.2021.01	-0.389	0.156	-2.492	0.013
YM.2021.02	0.033	0.219	0.149	0.881
YM.2021.05	-0.464	0.183	-2.540	0.011
YM.2021.06	-1.398	0.209	-6.700	0.000
YM.2021.07	-0.239	0.127	-1.878	0.060
YM.2021.08	-0.559	0.118	-4.752	0.000
YM.2021.09	-0.755	0.111	-6.794	0.000
YM.2021.10	-0.536	0.107	-4.996	0.000
YM.2021.11	-0.236	0.113	-2.094	0.036
YM.2022.01	1.204	0.155	7.761	0.000
YM.2022.02	1.215	0.133	9.107	0.000
YM.2022.03	1.487	0.234	6.357	0.000
YM.2022.05	0.729	0.153	4.761	0.000
YM.2022.06	0.498	0.134	3.718	0.000
YM.2022.07	0.074	0.111	0.668	0.504
YM.2022.08	-0.104	0.101	-1.030	0.303
YM.2022.09	0.146	0.091	1.608	0.108
YM.2022.10	0.368	0.089	4.113	0.000
YM.2022.11	0.770	0.091	8.483	0.000
YM.2023.01	0.001	0.154	0.006	0.995
YM.2023.02	0.151	0.292	0.517	0.605
YM.2023.04	-0.613	0.651	-0.941	0.347
YM.2023.05	0.115	0.110	1.044	0.296
YM.2023.06	-0.117	0.091	-1.285	0.199
YM.2023.07	-0.251	0.097	-2.597	0.009
YM.2023.08	-0.229	0.083	-2.760	0.006
YM.2023.09	0.027	0.075	0.361	0.718
YM.2023.10	0.348	0.075	4.645	0.000
YM.2023.11	0.416	0.077	5.429	0.000
YM.2024.01	-0.432	0.418	-1.034	0.301
YM.2024.04	-0.550	0.169	-3.261	0.001
YM.2024.05	-0.224	0.100	-2.228	0.026
YM.2024.06	0.211	0.095	2.224	0.026
YM.2024.07	0.033	0.100	0.329	0.742
YM.2024.08	-0.006	0.102	-0.057	0.955
YM.2024.09	0.334	0.095	3.523	0.000
YM.2024.10	0.482	0.091	5.311	0.000
YM.2024.11	0.297	0.093	3.204	0.001
YM.2025.05	0.942	0.192	4.901	0.000

Term	mu	se	t	Pr(>|t|)
YM.2025.06	0.080	0.178	0.451	0.652
YM.2025.07	0.018	0.340	0.053	0.958
YM.2025.09	-1.301	0.250	-5.213	0.000
YM.2025.10	-2.037	0.396	-5.136	0.000
YM.2025.11	-0.303	0.198	-1.532	0.125
Idves10116	-4.215	0.538	-7.839	0.000
Idves10183	0.629	0.118	5.313	0.000
Idves10184	0.641	0.098	6.539	0.000
Idves10203	-0.616	0.104	-5.928	0.000
Idves10204	-0.618	0.105	-5.896	0.000
Idves10209	0.687	0.110	6.251	0.000
Idves10237	-1.420	0.145	-9.821	0.000
Idves10239	0.012	0.112	0.104	0.917
Idves10256	-0.138	0.474	-0.292	0.771
Idves10274	-1.529	0.242	-6.320	0.000
Idves10408	-4.178	0.320	-13.042	0.000
Idves10409	-0.268	0.173	-1.545	0.122
Idves10412	0.145	0.184	0.792	0.428
Idves10414	-3.175	0.207	-15.346	0.000
Idves10419	-0.477	0.188	-2.534	0.011
Idves10452	-0.911	0.107	-8.495	0.000
Idves10518	0.611	0.096	6.333	0.000
Idves10520	-2.724	0.220	-12.371	0.000
Idves10524	-2.666	0.159	-16.774	0.000
Idves10531	-2.623	0.207	-12.677	0.000
Idves10552	-0.595	0.183	-3.242	0.001
Idves10563	-1.905	0.138	-13.797	0.000
Idves10564	-2.428	0.280	-8.660	0.000
Idves10640	-1.239	0.305	-4.064	0.000
Idves10663	-3.738	0.655	-5.707	0.000
Idves10671	-1.755	0.163	-10.790	0.000
Idves10686	-2.095	0.186	-11.264	0.000
Idves10689	-1.062	0.655	-1.622	0.105
Idves10694	-1.244	0.272	-4.571	0.000
Idves10697	-1.041	0.361	-2.883	0.004
Idves10700	-3.453	0.228	-15.126	0.000
Idves10721	1.001	0.095	10.552	0.000

Term	mu	se	t	Pr(>|t|)
Idves10822	-0.029	0.098	-0.301	0.764
Idves10823	-2.999	0.308	-9.721	0.000
Idves10827	-0.605	0.172	-3.511	0.000
Idves10846	-0.208	0.101	-2.057	0.040
Idves10852	-2.779	0.270	-10.306	0.000
Idves10854	-0.256	0.111	-2.312	0.021
Idves10909	-0.685	0.236	-2.903	0.004
Idves10932	-0.243	0.117	-2.068	0.039
Idves10968	-3.089	0.401	-7.696	0.000
Idves10981	-1.309	0.114	-11.430	0.000
Idves10987	-0.959	0.206	-4.664	0.000
Idves11015	-1.021	0.125	-8.193	0.000
Idves11116	-0.752	0.245	-3.067	0.002
Idves11200	-0.835	0.129	-6.471	0.000
Idves11275	-3.212	0.468	-6.865	0.000
Idves11285	-0.455	0.161	-2.829	0.005
Idves11298	-1.144	0.658	-1.739	0.082
Idves11310	-1.647	0.226	-7.301	0.000
Idves11317	-0.795	0.267	-2.982	0.003
Idves11318	-0.586	0.164	-3.577	0.000
Idves11411	0.115	0.191	0.601	0.548
Idves11417	-0.808	0.322	-2.510	0.012
Idves11429	-1.624	0.118	-13.757	0.000
Idves11517	-1.712	0.337	-5.073	0.000
Idves11535	-1.279	0.305	-4.195	0.000
Idves11673	-4.144	0.241	-17.208	0.000
Idves11738	-0.798	0.222	-3.593	0.000
Idves11762	-2.973	0.150	-19.807	0.000
Idves11767	-0.681	0.242	-2.810	0.005
Idves11768	-3.613	0.491	-7.356	0.000
Idves11781	-2.284	0.549	-4.162	0.000
Idves11817	-2.942	0.142	-20.761	0.000
Idves11818	-2.643	0.674	-3.920	0.000
Idves11819	-3.501	0.491	-7.127	0.000
Idves11820	-0.967	0.224	-4.316	0.000
Idves11948	-4.252	0.660	-6.441	0.000
Idves12019	-1.453	0.106	-13.673	0.000

Term	mu	se	t	Pr(>|t|)
Idves12042	-3.046	0.173	-17.598	0.000
Idves12097	-0.595	0.138	-4.324	0.000
Idves12114	-0.829	0.125	-6.618	0.000
Idves12123	-0.726	0.539	-1.346	0.178
Idves12125	-3.416	0.137	-25.021	0.000
Idves12129	-3.345	0.320	-10.454	0.000
Idves12297	-1.985	0.362	-5.481	0.000
Idves12464	-3.283	0.541	-6.065	0.000
Idves13013	-0.165	0.114	-1.439	0.150
Idves13048	-0.749	0.147	-5.079	0.000
Idves13049	-1.703	0.332	-5.129	0.000
Idves13102	-0.471	0.339	-1.389	0.165
Idves13200	-1.183	0.126	-9.381	0.000
Idves13495	-1.357	0.155	-8.752	0.000
Idves13496	-0.708	0.111	-6.365	0.000
Idves13832	-1.991	0.166	-11.992	0.000
Idves13841	-1.403	0.116	-12.114	0.000
Idves13853	-1.695	0.115	-14.780	0.000
Idves13866	-2.256	0.126	-17.890	0.000
Idves13953	-3.184	0.171	-18.656	0.000
Idves13954	-2.023	0.216	-9.361	0.000
Idves18006	-0.084	0.126	-0.667	0.505
Idves18017	0.437	0.100	4.382	0.000
Idves18233	-4.713	0.385	-12.227	0.000
Idves20074	-1.356	0.107	-12.694	0.000
Idves20206	-1.050	0.185	-5.670	0.000
Idves20434	-0.229	0.126	-1.815	0.070
Idves20483	-0.722	0.206	-3.507	0.000
Idves20601	-1.381	0.375	-3.682	0.000
Idves20604	-0.376	0.130	-2.890	0.004
Idves22103	-0.373	0.124	-3.004	0.003
Idves22528	0.131	0.128	1.026	0.305
Idves27467	0.772	0.099	7.796	0.000
Idves27493	-0.841	0.426	-1.975	0.048
Idves27520	0.513	0.165	3.104	0.002
Idves27565	-0.279	1.132	-0.247	0.805
Idves27623	0.508	0.100	5.068	0.000

Term	mu	se	t	Pr(>|t|)
dves27662	-0.949	0.132	-7.178	0.000
Idves27745	0.425	0.229	1.859	0.063
Idves27760	0.685	0.100	6.864	0.000
Idves27770	-0.475	0.105	-4.516	0.000
Idves27832	0.153	0.128	1.190	0.234
Idves27894	0.222	0.109	2.035	0.042
Idves27898	0.002	0.969	0.002	0.998
Idves28028	-0.308	0.130	-2.361	0.018
Idves28032	0.226	0.218	1.039	0.299
Idves28140	0.536	0.116	4.636	0.000
Idves28376	0.007	0.125	0.057	0.954
Idves28473	-0.015	0.110	-0.138	0.891
Idves28531	-0.952	0.214	-4.455	0.000
Idves28588	-0.285	0.191	-1.494	0.135
Idves28617	0.514	0.176	2.926	0.003
Idves30605	-0.317	0.304	-1.041	0.298
Idves46103	-3.683	0.959	-3.840	0.000
Idves46241	-1.744	0.159	-10.984	0.000
Idves46271	-2.742	0.282	-9.725	0.000
Idves46294	-1.763	0.120	-14.692	0.000
Idves46323	-2.734	0.152	-18.030	0.000
Idves46324	-3.039	0.219	-13.906	0.000
Idves46329	-2.668	0.132	-20.204	0.000
Idves46330	-2.804	0.181	-15.487	0.000
Idves46339	-0.165	0.123	-1.336	0.182
Idves46343	-0.477	1.204	-0.396	0.692
Idves46344	-2.142	1.193	-1.795	0.073
Idves46350	-0.735	0.136	-5.411	0.000
Idves46360	0.032	0.111	0.287	0.774
Idves46361	-0.047	0.114	-0.413	0.680
Idves46376	-0.501	0.186	-2.696	0.007
Idves46383	0.292	0.128	2.285	0.022

Appendix V. Checklist for the CPUE standardization protocol

No.	Step-by-step protocols	yes/no	Note
1	Provide a description of the type of data (logbook, observer, survey, etc.), and the "resolution" of the data (aggregated, set-by-set etc.). This description should also include the representativeness of the data in two tables: (1st table) Number of observations, % Coverage of CPUE fleet (catch), % Coverage of CPUE fleet (effort), Total Catch CPUE fleet (mt), Total Effort CPUE fleet, Percentage of overall catch by member (across all fleets/gears); and (2nd table) Number of records remaining, Number removed, Number of records with chub mackerel catch >0;	yes	See *2.1* (p. 2-3) and Tables 4-5, (p. 3)
2	Conduct a thorough literature review to identify potential explanatory variables (i.e., spatial, temporal, environmental, and fisheries variables) that may influence CPUE values;	yes	See 1. Background (p. 1-2)
3	Plot annual/monthly spatial catch, effort and nominal CPUE distributions and determine temporal and spatial resolution for CPUE standardization;	yes	See Figs 3,4,7, p. 6, 12, and **Appendix I**
4	Make scatter plots (for continuous variables) and/or box plots (for categorical variables) and present correlation matrix, if possible, to evaluate correlations between each pair of those variables;	yes	See Figs 5-6, p. 9-10
5	Describe selected explanatory variables based on (2)-(4) to develop full model for the CPUE standardization;	yes	Tables 6-7, p. 7-8
6	Specify model type and software (packages) and fit the data to the assumed statistical models (i.e., GLM, GAM, Delta-lognormal GLM, Neural Networks, Regression Trees, Habitat based models, and Statistical habitat based models);	yes	See *2.2.,* p. 11-12
7	Evaluate and select the best model(s) using methods such as likelihood ratio test, information criterions, cross validation etc.;	yes	See Table 8, p. 12
8	Provide diagnostic plots to support the chosen model is appropriate and assumption are met (QQ plot and residual plots along with predicted values and important explanatory variables, etc.);	yes	Figs 8-15, p. 13-18
9	Present estimated values of parameters and uncertainty in the parameters in table;	yes	See Tables 11-12, p. 20-21, and **Appendix IV**

10	Present relationship between dependent variable and independent variables. Check whether it is interpretable.	yes	See Fig. 16, p. 19
11	Extract yearly standardized CPUE and standard error by a method that can account for spatial heterogeneity of effort, such as least squares mean or expanded grid. If the model includes area and the size of spatial strata differs or the model includes interactions between time and area, then standardized CPUE should be calculated with area weighting for each time step. Model with interactions between area and season or month requires careful consideration on a case by case basis. Provide details on how the CPUE index was extracted.	yes	See *2.3.* p. 13
12	Calculate uncertainty (SD, CV, CI) for standardized CPUE for each year. Provide detailed explanation on how the uncertainty was calculated;	yes	See Tables 13-14, p. 13 and Figs 17-18, p. 22
13	Provide a table and a plot of nominal and standardized CPUEs over time. When the trends between nominal and standardized CPUE are largely different, explain the reasons (e.g. spatial shift of fishing efforts), whenever possible.	yes	