ASSESSMENT OF THE SPECIES COMPOSITION OF MAJOR TROPICAL TUNAS IN PURSE SEINE CATCHES: A NEW MODELLING APPROACH FOR THE TROPICAL TUNA TREATMENT PROCESSING

Case of the French fleet in Indian Ocean

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ABSTRACT

The precise assessment of the catches by species is a major element in multi-species fisheries, such as the tropical tuna purse seine fisheries. The species composition by set is reported in the logbook, but it has been evidence of large bias mainly for the small individuals in the logbooks, which prevent the direct use of that source for catch estimates. For the major tropical tuna purse seine fisheries operating in the Indian Ocean, the species composition is estimated from sampling operations at landing and thought a statistical treatment to interpolate value for non-sampled sets. This method, called the Tropical Tunas Treatment (T3), developed by IRD and IEO in the mid-1990s has been criticized, specifically in the part on the species composition corrections. This document presents the results of a new statistical approach to handle the different shortcomings pointed out using data collected from the French fleet in the Indian ocean. Analyses specifically focus on the spatio-temporal dimension of the catches. Furthermore, the use of more information from the logbook reports are investigated and discussed.

KEYWORDS

Bias estimate, logbook reporting, sampling, spatio-temporal modelling, Thunnus albacore, Thunnus obesus, Katsuwonus pelamis

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1. Introduction

The precise assessment of the catches by species is a major element in multi-species fisheries, such as the tropical tuna purse seine fisheries. Even if the total weight is correctly estimate, as catches are weighted at landing (Duparc et al. 2018), the species composition remained a tricky issue (Lawson 2013). Indeed, the species compositions of each set, which are reported in the logbook suffered of large bias mainly for the small fishes (Fonteneau 1975; Cayré 1984; Fonteneau 2007), which prevent their use for estimations. In absence of good estimation of species composition by sets directly onboard, as it is done by observers in the Pacific Ocean (Lawson 2008), it is necessary to rely on a sampling procedure performed on a fraction of the catch at the landing site. Since 1984, the species composition is thus estimated from these samples in the Atlantic and Indian oceans. The method, called the Tropical Tunas Treatment (T3) and developed by IRD and IEO, is based on the definition of homogenous strata in terms of school type, year, quarter and spatial area, which should validate the assumption of representativeness of the samples for all sets in the sampled well. Indeed, sets are frequently mixed in the vessel wells. As samples are performed on wells at landing, the homogeneity of sets that composed each well is the key element to ensure the reliability of the extrapolation of the species composition from well to set. Finally, the species compositions of the non-sampled sets are calculated as the weighted mean of the samples on sets belonging to the same stratum and preserving the proportion of small and big fishes declared in logbooks (see Duparc et al. 2018 for details).

However, this method, was criticized, specifically with regards to the species composition corrections (Duparc et al. 2018; Herrera and Baez 2019) because several limitations were identified. First of all the spatial areas defined in 1997 (Pallarés and Petit 1998) revealed potential bias because of their large size. The main reason for such large area was the result of a compromise between the need of similarity between sets (samples homogeneity) and the necessity to keep a reasonable amount of data (samples) to reliably assess the species composition for the non-sampled sets. Indeed, catches are correlated spatially and temporally, hence an increase of the homogeneity of species composition with the spatial resolution, as it was recently confirmed in the European project RECOLAPE (MARE/2016/22, Ruiz et al. 2019). However, the higher the resolution, the lower the number of data, which could lead to a lack of data (sampled sets) in some strata and so prevent any species composition assessment. Furthermore, the use of delineate areas, i.e. categorical variable, to describe a continuous process is questionable in case of isolated catch or between catches that are geographically close but located on either side of the boundaries which separate areas. Second, no error on the catch assessment could be estimated with the actual method. Yet the knowledge of the error associated to the corrected catches is an important parameter that could greatly enhance the quality of the stock assessment.

Logbook reports, even if they are visual estimations of the crew and subjected to bias, are also the first source of a large amount of information on catches. In the last decades, the evolution of fishing practices, could have enabled an enhancement of the quality of this reporting. The reevaluation of its use as predictor to upgrade the prediction performance of the modelling of the species compositions is so a relevant question now.

Objectives of the new approach describe in this paper is double. First, we address the identified matters with the use of statistical models, specifically the spatio-temporal dimension of the catches. Second, we improve prediction accuracy by using new predictors, particularly by including more information from the logbook knowing their uncertainties and their limitations. To do so, we tested different model approaches and compared their predictive performances from simple spatio-temporal model to multivariate models including additional predictors. In particular, we investigated the bias in logbook reports with respect to the samples in terms of species detections and species compositions. Finally, we discussed implications of this study to upgrade the T3 process.

2. Materiel and methods

2.1. Data source

We focused our analyses in the 2015-2018 period on the French purse seine fishery on major tropical tuna in the Indian Ocean.

Logbook

Logbooks contain information on catch by set including date, position, fishing mode and species split in commercial categories (based on weight categories). Weights are estimated visually by the captain, the quartermaster and the chief engineer. IRD gets the logbooks the day before the purse seiners come back to ports. While in the past some logbooks were missing, nowadays the logbook coverage reaches 100%.

Samples at landing

The annual sampling plan is conducted in order to cover the wider geographical area and temporal range, for all vessels and for both free school and associated school sets. To ensure this coverage, the sampling plan is continuously updated according to strata already sampled and. As the logbook and the wells plan are communicated in advance, this enables to determine which wells (i.e. dates, positions and fishing modes) must be sampled. The sampling protocol accounts for the homogeneity of the well's content (e.g., in case of several sets in the same well, it is recommended to select a well containing a single fishing mode, as well as the shortest range in date and locations of the sets).

For each well selected, a sample of 500 individuals of tuna species in two batches (300 individuals first and 200 individuals in general selected one hour after the first batch) is randomly selected and sampled while fish is frozen. The enumerators focus on species identification and measure sizes with calipers. Small individuals, less than 70 cm fork length (FL), are measured in fork length, while larger individuals are measured in predorsal length. Fork length measurements use 1 or 2 cm size intervals, depending on species, while predorsal length measurements are performed with 0.5 cm intervals. Sometimes for a subset of the sample, individuals are weighted using a scale, at a 10 g precision.

2.2. Statistical analyses

2.2.1. Selection of pairs sample - logbook

As mentioned in the introduction section, one of the key points of the species composition assessment is the selection of wells used for modelling, which have to be composed of similar sets, wherever possible, to validate the assumption of sample representativeness. Therefore, we applied a strict pre-selection process of each well before any modelling based on following criteria: all sets should result from the same fishing mode (Associated school or free school only), made in the same area (within a maximum range of 3° lat/lon) and mixed in well with a maximum of 5 sets. We also removed the small sets (< 6t) for which samples could not be representative considering the number of fishes counted by well.

2.2.2. Logbook and sample species detection in sets

We aimed at determining the detection sensitivity of the logbook reports and the sample. To do so, we first calculated the error rate of species detection, i.e. the frequency at which species was not detected in a source (logbook or sample) but detected in the second one. We calculated this rate for mono-sets, i.e. a unique set in the sample well, and for all sets (mixed sets in well).

2.2.3. Modelling species compositions

We modelled the frequency of the major tropical tuna species separately for YFT and SKJ and for associated (FOB) and free schools (FSC), using various models (see details for each on below): simple spatio-temporal kriging (SSTK), multivariate spatio-temporal kriging (MSTK), general additive model (GAM) and random forest (RF). We then compared predictive performance of each model calculating the RMSE, MAE and coefficient of variation of MAE (CVMAE) using cross validation by k-fold method with 10 partitions. We also tested the spatial and temporal autocorrelation of the residuals to check whether the model corrected these 2 dimensions calculating Moran Index (Permutation test, nsim =999, Cliff and Ord 1981) and Autocorrelation Function (ACF, Venables and Ripley 2002) respectively.

The SSTK model was used as references and we added predictors to all other models to test for prediction improvement. We added the logbook report, as main source of information on species frequencies, and vessel ID to correct for the vessel catch specificity (technical characteristics, company fishing strategy, etc.). Month, year and their interaction were also in the model to account for temporal variation between and within years. Finally, the total catch of major tuna by set was included to correct for potential bias due to the set size.

We tested multi-collinearity in data using qr-matrix decomposition (Murphy et al. 2010). We selected for variables which maximize the prediction performance of each model (MSE, MAE and CVMAE) using backward stepwise method.

Proportion in sample and logbook were linearized with a square root transformation only for YFT on FOB. For SKJ, we removed from analyses the sets with absence of that species in the logbook because absence is well detected by crew, hence considered as a true absence (see results section).

Finally, to preserve unicity of the species composition data and considering the error rate of classification just as well as the amount of available data, frequencies of bigeye tuna in sets were estimate as 1 less the frequencies of the YFT and SKJ.

Simple and multivariate Spatio-temporal kriging (SSTK and MSTK)

The spatiotemporal kriging model (SSTK and MSTK in our case) consists in a kriging based on both the spatial and the temporal structure of the data (Gräler et al. 2016). The MSTK is the same model as SSTK, with the addition of predictors previously defined. Frequency in sets of the species of interest was the response variable.

For both models we first calculated the spatio-temporal sample variogram of species frequency in sample (cutoff = 4000 km, step = 100 km, time lag from 1 to 6 months) and fitted a spatio-temporal variogram model to it, based on minimization of the MSE value.

General additive model (GAM)

We employed simple GLM and trend-surface generalized additive models (GAM, Hastie and Tibshirani 1986), in which geographical location was fitted using splines as a trend-surface (as a two-dimensional spline on geographical coordinates). Trend surface GAM does not address the problem of spatial autocorrelation, but merely accounts for trends in the data across larger geographical distances (Cressie and Cassie 1993; Dormann et al. 2007).

Random forest (RF)

RFs are a non-parametric ensemble modeling technique that uses bagging and a random selection of covariates across numerous classification and regression trees to reconstruct nonlinear relationships and interactions of the covariates (Breiman 2001). When all trees are combined, the RF is robust to small and large sample sizes and "noisy" datasets. Bagging each new tree is fitted with a bootstrap sample of the training observations. The out-of-bag (OOB) error is the average error calculated using predictions from the trees and the remaining sample. This allows error to be computed for each tree while training the model.

As for GAM, we included longitude and latitude as covariates to account for trends in the spatial dimension and year and month for the temporal dimension. We optimized model parameter for minimizing the OOB error (MSE): Number of trees = 1000, number of variables randomly sampled at each split = 2, Number of times the OOB data are permuted per tree = 5.

2.2.4. Predict nominal catches

Prediction was done using each best selected model on the sets not used in the analyses. Regarding others (the sample sets used in analyses), we conserved the species composition from the sample. Finally, catches by sets were the sum of predicted values and sample value of the species composition weighted by the set size of major tuna. Nominal catches were sums of sets grouped by variables of interest (year, species, fishing mode). We compared best model estimations with estimations from non-corrected logbook reports (only weighted) and from the current T3 process (called hereafter 't3f', Pallarés and Petit 1998).

3. Results

3.1. Comparison of logbook reports and samples at landing

Comparison between logbook reports and samples demonstrated that samples detected more accurately species presence (**Table 1 and 2**). Thus, sample error rate was always within a short range, from 0 to 0.03, (except for BET on associated school = 0.09 and 0.11) whatever the sets considered (mono-sets or multi sets). SKJ was also accurately reported in logbooks whereas the error rate for other species could be very high. As example, in about half of the mono-sets on associated school, the absence of detection of BET, which was always the worst, was in fact an error.

Furthermore, the comparison of frequency in species reported of sample to logbook described the overall pattern of discrepancy between these two data sources, especially on associated school catches. Thus, low frequency values of species in sets reported by logbooks where lower than the value estimated from samples (see example of YFT and SKJ on associated school sets, **Figure 1**).

3.2. Estimate of species composition

The proportion of tuna in samples was autocorrelated over long distances (> 1000 km) and several months depending on the species and fishing mode (see example of YFT on FOB, **Figure 2**). The spatio-temporal variograms, commonly used for the SSTK and MSTK, were then fitted with different models also depending of the species and the fishing mode (**Table 3**, example in **Figure 3** for the YFT on FOB). Thus, models efficiently corrected, as expected, for spatial and temporal dimensions as their residuals were not autocorrelated anymore (**Figure 4**). GAM and RF models gave similar results (**Figure 5 and 6**).

Model performance varied strongly among model type, species and fishing mode (**Table 4**). The RF had always the best performance and the SSTK the worst one but close to the GAM. Thus, the addition of selected predictors was always benefit for the prediction performance. The model's performances for the SKJ on free school was twice lower than for other species and fishing mode due to the low amount of data available (65 free school sets only with a presence of SKJ).

Regarding selection of predictors, every variable has been selected but set size (for SKJ only) was the less informative for the prediction. On the contrary, logbook frequency of the species was conserved in all models confirming its importance to improve the prediction performances (**Figure 7**). However, the amount of gain in accuracy varied. Vessels selection was not constant among models but always enhance the predictions of the RF model by about 3-4% (**Table 4**).

3.3. Prediction of the nominal catches

On free schools, all models gave overall similar results despite their differences in prediction for the nominal catches (**Figure 8**). Total catches on free schools were very similar between the logbook reports, the values from the actual T3 (T3f) and the predictions of the random forest model (**Figure 9**). This result confirms the accuracy of reporting by crew members which need minor corrections.

Regarding the sets on associated schools, we observed strong differences in total catches depending on the source of data for the estimation. The main discrepancy came from the lower proportion of SKJ predicted by the RF model compared to the logbook report or the T3f estimated (**Figure 10**). This over-reporting of SKJ (10.9 ± 4.8 % on average for the study period), as predicted by the RF, was balanced by the under reporting of the YFT (-9.4 ± 6.4 %) and, to lesser extent, the BET (-1.4 ± 1.6%) compared to uncorrected logbooks reports. Discrepancy with the T3f process were lowered (as example for SKJ: 3 ± 1.4%).

4. Discussion

Modelling the species composition and comparison

We demonstrated that species composition of catches was correlated spatially and temporally. Therefore, we needed to account for this auto-correlation in the modelling of species composition. The new model approach, whereby the spatio-temporal variation of species proportion was processed in a continuous way to test for the replacement of large area currently used in T3, seems to be promising. Indeed, we found similar results using three different types of models which all converged. SKJ was over-reported in the logbook report in the associated school sets at the cost of YFT and BET. This expected pattern was also found in the West Pacific Ocean (Hampton and Williams 2011). However, and contrary to the West Pacific, we did not find major differences between logbooks and estimates from the T3f or RF for the free school composition, suggesting reliable reports by the crew member for this fishing mode.

These results could be explained by several concomitant hypotheses. The SKJ is easy to identify because of the longitudinal dark bands on its sides contrary to the small YFT and BET frequently present in associated schools (Fonteneau 1975). Crew member can then detect preferentially the SKJ pattern, leading to a visual over-estimation with regards to the two other species. This hypothesis is in agreement with our results, as we found that the error rate for absence in logbook reports was very low. Secondly, it is well known by fishers that associated schools were dominated by the SKJ (present in 99% of the associated school sets). Thus, crew member could report large amount of SKJ in the catches on associated school because this is the usual pattern. Thirdly, the error rate of absence for BET and SKJ in logbook reports led the model to correct for these 'false absences' and so increase the proportion of these two species at the cost of SKJ (in associated schools with absence or low proportion of BET and SKJ). More generally, estimation of frequency in SKJ were lower in sample than in logbook (and the opposite for YFT), which clearly lead to the predict pattern. Finally, part of the small size YFT and BET could have been reported in the same commercial class as SKJ in logbooks as they have similar market price (Bard 1986), which also increases artificially the SKJ proportion in catches.

Prediction and covariables

We also demonstrated that the addition of logbook reports as predictor in the modelling greatly improve the predictive performance. Even if we were aware of the misclassification of small YFT and BET, the proportion of species reported was correlated to the one in samples. Therefore, the report gave information on the amount of individual of each species by set. This information could enhance prediction by correcting for local variation in catches, as natural variation of catches for instance or local point not accounted in models (e.g. seamount proximity). However, we also pointed out a large discrepancy of frequency estimated from the logbook and the sample asking the question of the reliability of these two sources. Even if we clearly demonstrated the low detection ability of the logbook reporting for species in low frequency in sets, we did not really evaluate the accuracy of samples to estimate frequencies of species. Comparison with other data sources (e.g. selling note from cannery)) and experiment (super-sampling) should be done to estimate the potential bias of the sampling.

The amount of tuna catch did not improve the predictive performances. We could expect variation in species composition according to the set size but it seems to be a marginal effect. Similarly, the vessel ID did not impact all models depending of the species and the fishing mode. However, this factor should be included because it rendered an account of the specificity of the vessel and companies in term of fishing strategies.

Surprisingly catches differences found with the Indian ocean fishing data were very similar to the results observed in Atlantic ocean (Duparc et al. 2019) despite the differences in catches for local market. Indeed, the local market (also called "faux poisson"), is much more developed in Atlantic Ocean and was supposed to explained a part of the observed bias in species composition only for this ocean. These results so demonstrated the limited importance of the local market in the species composition.

Limits of the new approach

The new approach of the estimation of the species composition performed reasonably well, however several limitations remain to be addressed. First, the management of absence in logbook reports is questionable. We detected important error rate on absence reported for the YFT and BET mainly on associated school sets. The current T3 process could be challenged on this point because proportion estimates are the weighted mean of the spatio-temporal strata. This implies that absence in logbook reports are systematically replaced by the mean presence in the strata. Thus, the T3 process performs a smoothing by strata, which should not have strong incidence on the nominal catches, but could bias the spatial distribution of catches (task 2), as for instance the gradient in BET and SKJ proportion from coastal to high-sea areas (Fonteneau and Pascual-Alayón 2018a; Fonteneau and Pascual-Alayón 2018b). The new approach should better correct for the absence and low proportions because the logbook report included in the model (plus the vessel ID) enables more variability in the predicted proportion. However, total absence could not be predicted yet because the error rate of absence in logbook is not null. A solution could be to fix a threshold of proportion under which the species is considered absent as it is commonly done in spatial distribution models (Guisan and Thuiller 2005; Elith and Leathwick 2009).

Another issue for the kriging and GAM models is that they could predict impossible proportion value (<0 or >1) because the distribution was not limited (Normal distribution). Even if these out-of-range predictions are rare, they are due to the fact that we modelled species separately. Therefore, we calculated the BET as the difference between 1 and proportion of YFT and SKJ to ensure unicity. Random forest model better performed on this point and never predicted for out-of-range values. However, further investigations have to be done to model all species simultaneously using multinomial distribution or other (e.g. Dirichlet distribution). However, these models are not well implemented yet to account for spatio-temporal structure and could not also predict for 0 or 1 values.

Conclusion and perspectives

A robust estimation of the species composition of major tropical tunas remains a challenge. We proposed a new approach that deals with the spatial and temporal issues and improves prediction performance including the logbook reports. Logbook data were certainly biased for small fishes (mis-classification) and low species proportion but held information on the raw proportion of species at the sets scale and variability inherent to its fishing date and its location. Nevertheless, further research could be conducted to still upgrade estimations of the species composition. First, we selected sampled wells for analyses with the purpose of being in conformity with the assumption of representativeness of the samples. Sensitivity analyses should then be performed to test the impact of the set's mixture on the prediction performance. Similarly, the minimum number of logbook/sample pairs needed for analyses should be determined. These analyses could answer to the question about the sample size and would provide adjustment of the sampling effort.

Then, in this document, we only test fishing variables (logbook report, vessel ID and set size) which are already available. However, many other variables could be added to the model to improve the prediction performance. As an example, topographic variables, such as distance to the coast and presence of a seamounts or knolls could explain changes in the density and catchability of species. Similarly, oceanographic variables associated to tuna habitat could also play a role in the species composition of the purse seine fishery. It has been demonstrated for instance that sea surface temperature gradients, dissolved oxygen and mixed layer depth are important cues in the catchability of yellowfin (Block et al. 1997) .

Finally, we focused in this document only on the nominal catches. As models predicted the species composition at the set scales, the task 2, i.e. catches by cells of 1-degree square, could easily be calculated. By accounting for spatio-temporal structure of the fishery, the model should indeed better estimate the spatial variation in the species composition. Such investigation could be useful in testing the validity of our approach.

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TABLES

Table 1: Number of mono-sets used in analyses with the proportion of set reporting absence of the species (Prop_absence) in the logbook and detected error in presence/absence. Error rate LB: proportion of absence reported in logbook but detected in sample. Error rate Sample: proportion of absence reported in sample but detected in logbook.

Fishing mode	Species	Number of Set	p_abs_LB	Error rate LB	Error rate Sample
Associated school	BET	151	**0.47**	**0.40**	0.01
Associated school	SKJ	151	0.01	0.00	0.03
Associated school	YFT	151	0.08	0.08	0.00
Free school	BET	123	**0.54**	**0.12**	**0.11**
Free school	SKJ	123	**0.81**	0.00	0.03
Free school	YFT	123	0.06	0.03	0.01

Table 2: Total number of sets used in analyses (mono and multi-sets) with the proportion of set reporting absence of the species (Prop_absence) in the logbook and detected error in presence/absence. Error rate LB: proportion of absence reported in logbook but detected in sample. Error rate Sample: proportion of absence reported in sample but detected in logbook.

Fishing mode	Species	Number of Set	Prop_absence	Error rate LB	Error rate Sample
Associated school	BET	970	**0.60**	**0.55**	0.01
Associated school	SKJ	970	0.01	0.00	0.01
Associated school	YFT	970	**0.12**	**0.12**	0.00
Free school	BET	340	**0.57**	**0.22**	0.09
Free school	SKJ	340	**0.81**	0.04	0.03
Free school	YFT	340	0.07	0.05	0.01

Table 3: Spatio-temporal structure selected for kriging on proportion in samples by species and fishing mode

Species	Fishing mode	ST model structure	Spatial variogram Nugget	psill	range	sill	MSE
YFT	FOB	sum metric (gau)	0.01134542	0.5278769	20000	NA	6.47E-05
YFT	FSC	sum metric (exp)	0.01840857	0.02732192	700	NA	1.63E-03
SKJ	FOB	sum metric (sph)	0.009834259	0.019244144	200	NA	4.35E-05
SKJ	FSC	separable (Exp)	0	1	600	0.12	1.32E-02

Species	Fishing mode	ST model structure	Temporal variogram Nugget	psill	range
YFT	FOB	sum metric (gau)	0	0.009820686	6.15
YFT	FSC	sum metric (exp)	0.009408573	0.007867881	10.08
SKJ	FOB	sum metric (sph)	0.000834259	0.002686324	10.00
SKJ	FSC	separate	0	1	5.19

Table 4: Model selection and predictive performance for the SSTK, MSTK, GAM and RF model based on k-fold method (k=10) by species and fishing mode. In bold: best model selected.

YFT (square root transfomed) on associated school

Name	Model	RMSE	MAE	CVMAE
SSTK	1	0.1429	0.1103	0.1834
MSTK 1	SSTK + LB	0.1268	0.1002	0.1666
MSTK 2	MSTK 1 + year	0.1232	0.0971	0.1626
MSTK3	MSTK2 + set size	0.1222	0.0961	0.1611
MSTK4	MSTK 3 + vessel	0.1218	0.0953	0.1597
MSTK5	**MSTK 4 + month**	**0.1214**	**0.0950**	**0.1592**
GAM3	**GAM2 + setsize**	**0.1242**	**0.0966**	**0.1608**
GAM2	GAM1 + vessel	0.1247	0.0967	0.1611
GAM1	GAM0 + LB	0.1255	0.0979	0.1629
GAM0	1	0.1412	0.1071	0.1783
RF3	RF2 + setsize	0.0506	0.0383	0.0638
RF2	**RF1 + vessel**	**0.0500**	**0.0379**	**0.0631**
RF1	RF0 + LB	0.0718	0.0559	0.0931
RF0	1	0.0849	0.0656	0.1091

Name	Model	RMSE	MAE	CVMAE
SSTK	1	0.23590	0.1795	0.2265
MSTK 1	SSTK + LB	0.19106	0.1337	0.1674
MSTK 2	**MSTK 1 + year**	**0.18728**	**0.1323**	**0.1656**
MSTK3	MSTK 2 + month	0.18634	0.1326	0.1660
MSTK4	MSTK3 + vessel	0.18806	0.1362	0.1706
MSTK5	MSTK4 + setsize	0.18886	0.1375	0.1721
GAM3	GAM2 + setsize	0.20530	0.1503	0.1893
GAM2	GAM1 + vessel	0.20391	0.1488	0.1875
GAM1	**GAM0 + LB**	**0.20227**	**0.1437**	**0.1821**
GAM0	1	0.25084	0.1813	0.2289
RF3	**RF2 + setsize**	**0.07697**	**0.0539**	**0.0682**
RF2	RF1 + vessel	0.07842	0.0542	0.0687
RF1	RF0 + LB	0.11576	0.0836	0.1059
RF0	1	0.15485	0.1121	0.1420

Name	Model	RMSE	MAE	CVMAE
SSTK	1	0.1534	0.1195	0.2130
MSTK 1	SSTK + LB	0.1410	0.1109	0.1978
MSTK 2	MSTK 1 + year	0.1396	0.1090	0.1945
MSTK3	**MSTK2 + set size**	**0.1387**	**0.1072**	**0.1911**
MSTK4	MSTK 3 + vessel	0.1388	0.1074	0.1915
MSTK5	MSTK 4 + month	0.1389	0.1075	0.1917
GAM3	**GAM2 + setsize**	**0.1532**	**0.1185**	**0.2108**
GAM2	GAM1 + vessel	0.1546	0.1194	0.2125
GAM1	GAM0 + LB	0.1545	0.1208	0.2152
GAM0	1	0.1755	0.1346	0.2398
RF3	RF2 + setsize	0.0625	0.0475	0.0846
RF2	**RF1 + vessel**	**0.0621**	**0.0469**	**0.0835**
RF1	RF0 + LB	0.0892	0.0700	0.1246
RF0	1	0.1042	0.0821	0.1461

Name	Model	RMSE	MAE	CVMAE
SSTK	1	0.2815	0.2093	0.4295
MSTK 1	**SSTK + LB**	**0.2801**	**0.2108**	**0.3921**
MSTK 2	MSTK 1 + year	0.2869	0.2183	0.4005
MSTK3	MSTK 2 + month	0.3214	0.2502	0.4682
MSTK4	MSTK3 + setsize	0.3169	0.2501	0.4699
MSTK5	MSTK4 + vessel	0.4095	0.3100	0.6820
GAM3	GAM2 + vessel	not enougth data		
GAM2	GAM1 + setsize	0.2229	0.1821	0.3424
GAM1	**GAM0 + LB**	**0.2218**	**0.1836**	**0.3422**
GAM0	1	0.2767	0.2075	0.3895
RF3	RF2 + setsize	0.1083	0.0856	0.1748
RF2	**RF1 + vessel**	**0.1105**	**0.0850**	**0.1723**
RF1	RF0 + LB	0.1318	0.1049	0.2149
RF0	1	0.1578	0.1201	0.2455

FIGURES

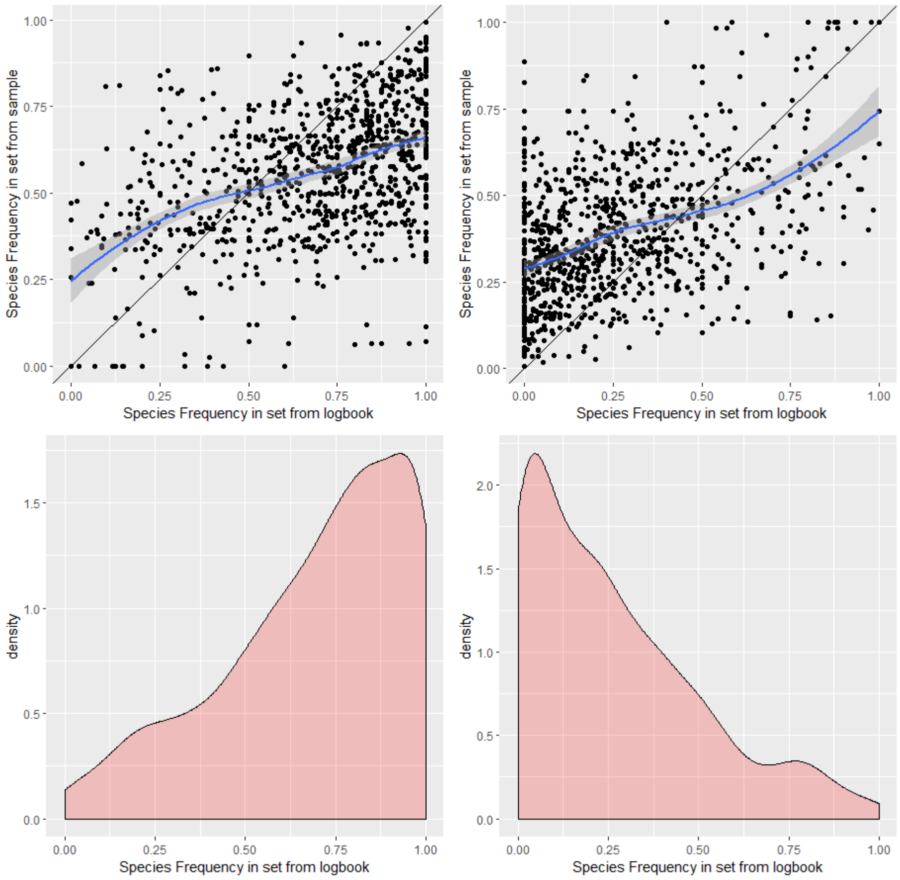

Figure 1: Relationship between species frequency in set reported from sample and from logbook (Top panels) and the data distribution in logbook (Bottom panels) for skipjack and yellowfin tunas (left and right panels respectively). Blue line and grey polygons represent fitted value and se from a local polynomial regression fitting (loess). Dark straight line represents the perfect fitting (slope=1, intercept = 0).

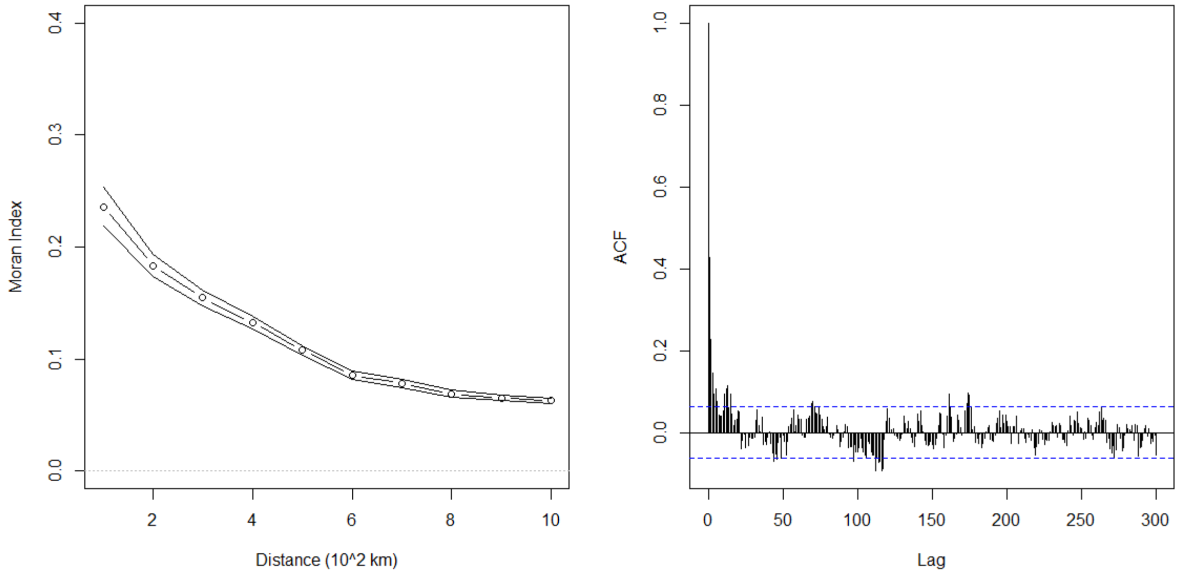

Figure 2: Spatial and temporal autocorrelation of YFT frequency (square root transformed) in sample on associated school calculated separately. Left panel: Mean and SD of Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

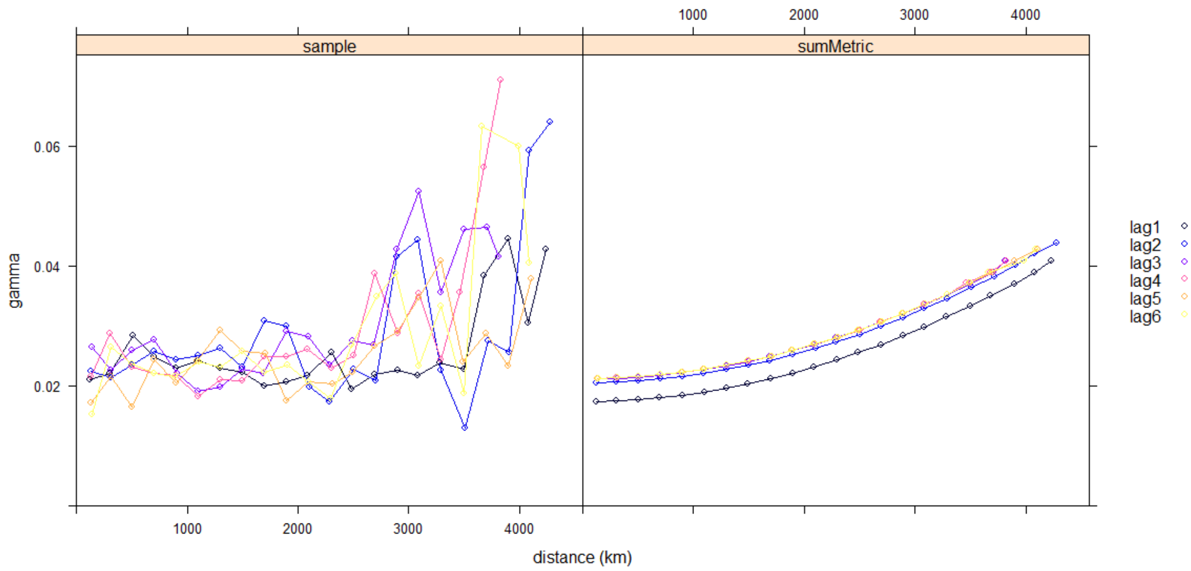

Figure 3: Left panel: Spatio-temporal variogram on YFT frequency in sample on associated school. Lag 1 to 6 represents 1 to 6 months' time lags. Right panel: Fit of the best Spatio-temporal variogram model. (product sum metric type, MSE =6.47e-05)

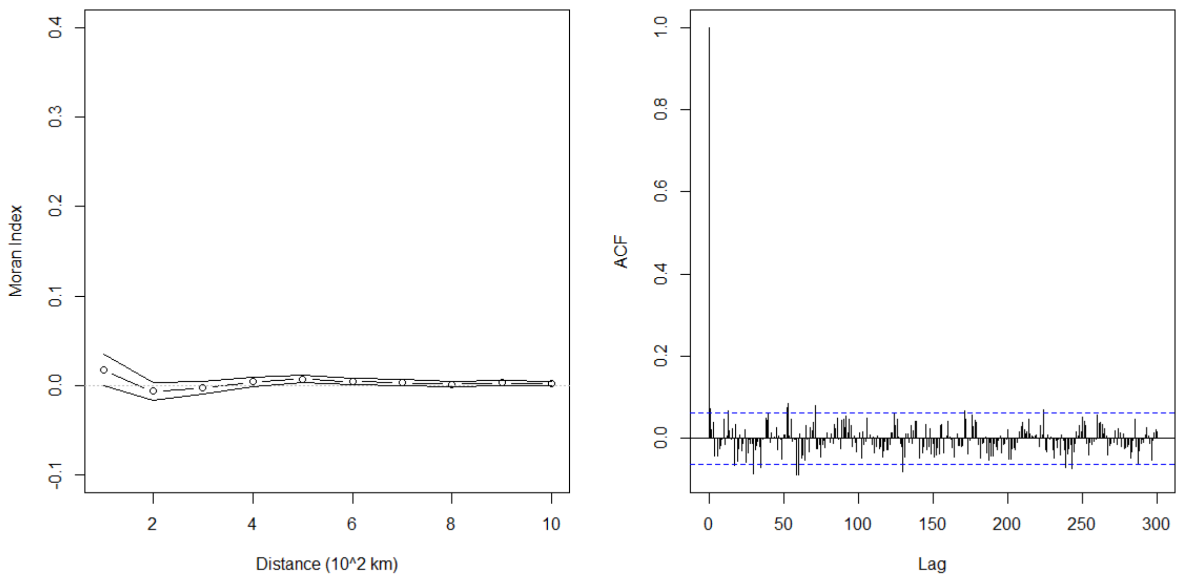

Figure 4: Spatial and temporal autocorrelation of residuals of the MSTK on associated school calculated separately. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

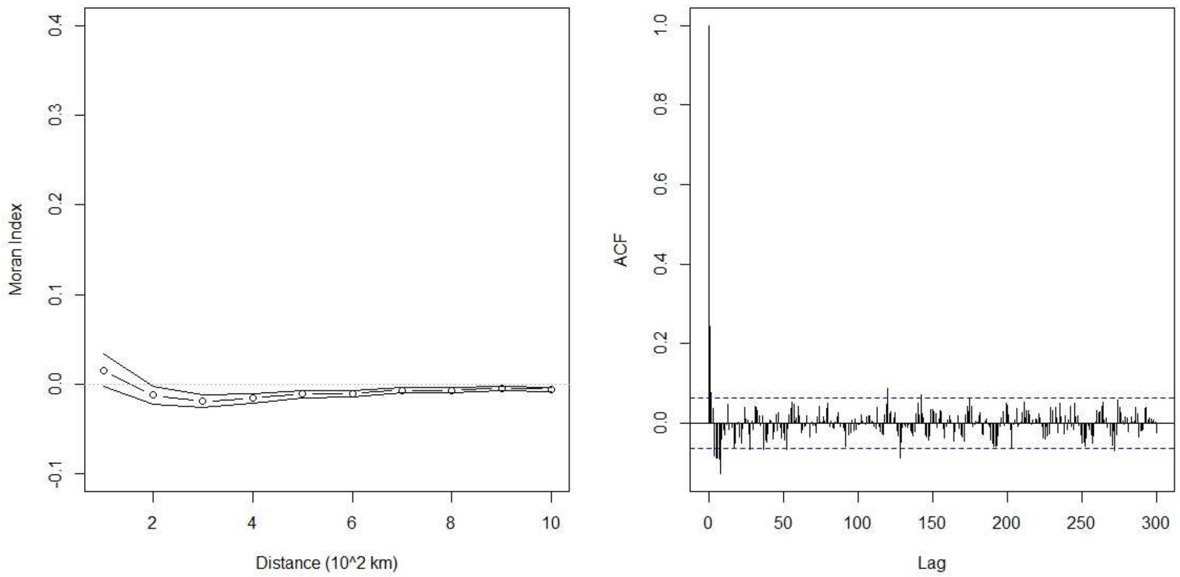

Figure 5: Spatial and temporal autocorrelation of residuals of GAM on associated school calculated separately. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

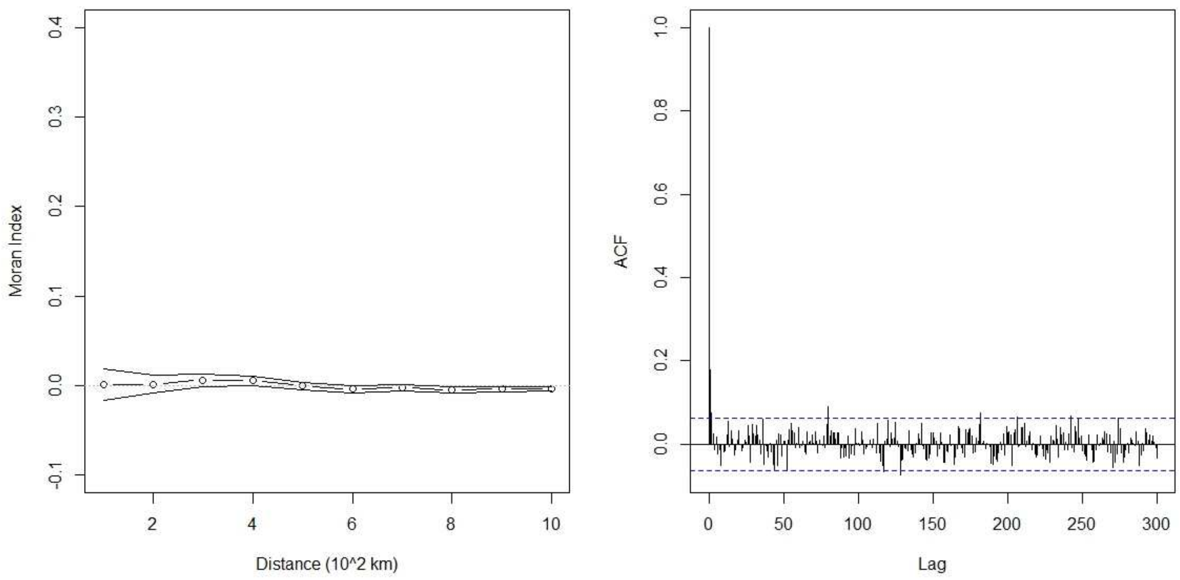

Figure 6: Spatial and temporal autocorrelation of residuals from best random forest model on associated school. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

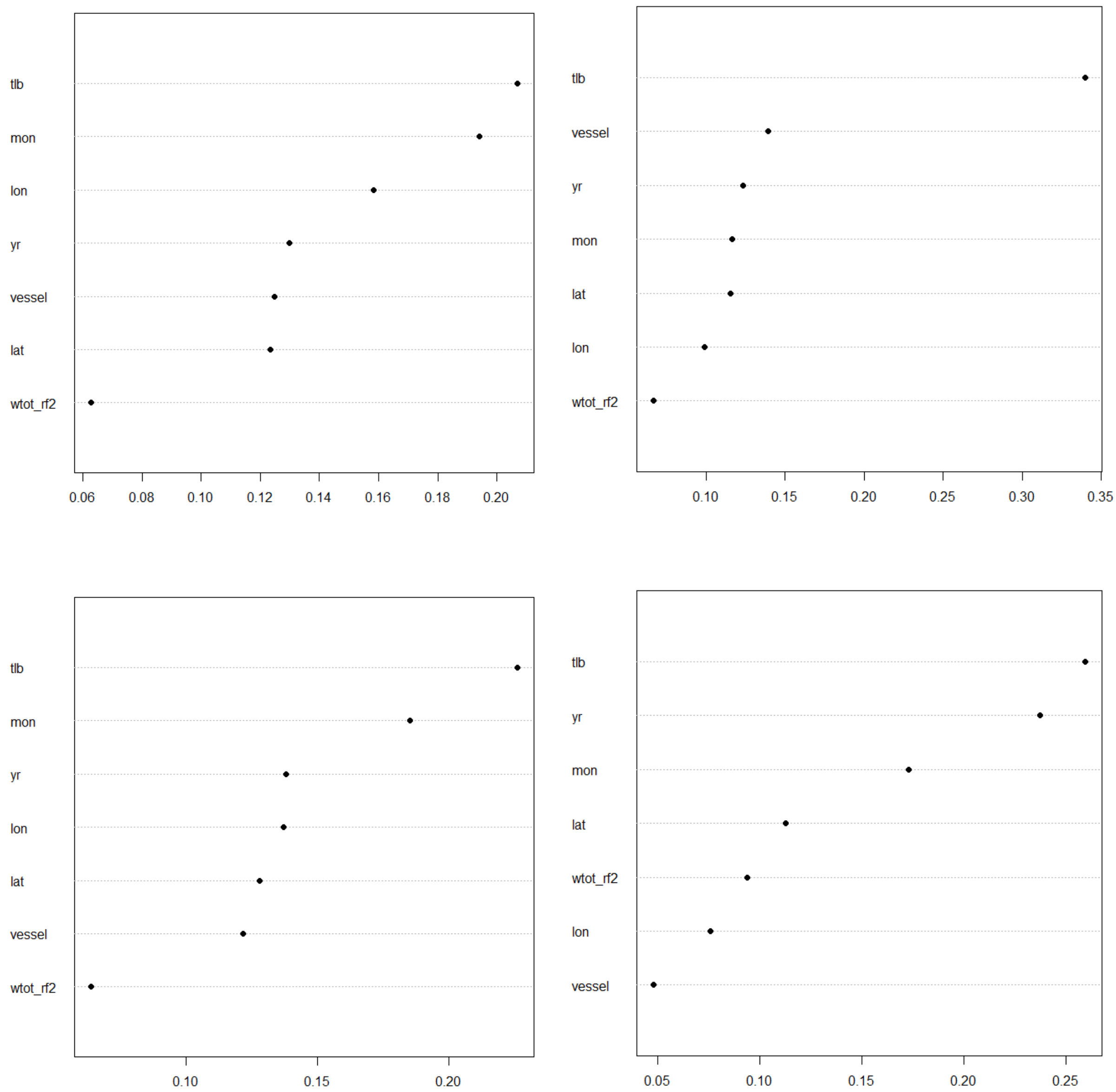

Figure 7: Standardized error variable importance of variables in random forest model, Top: on YFT frequency (square root transformed) in FOB and FSC, Bottom: on SKJ in FOB and FSC

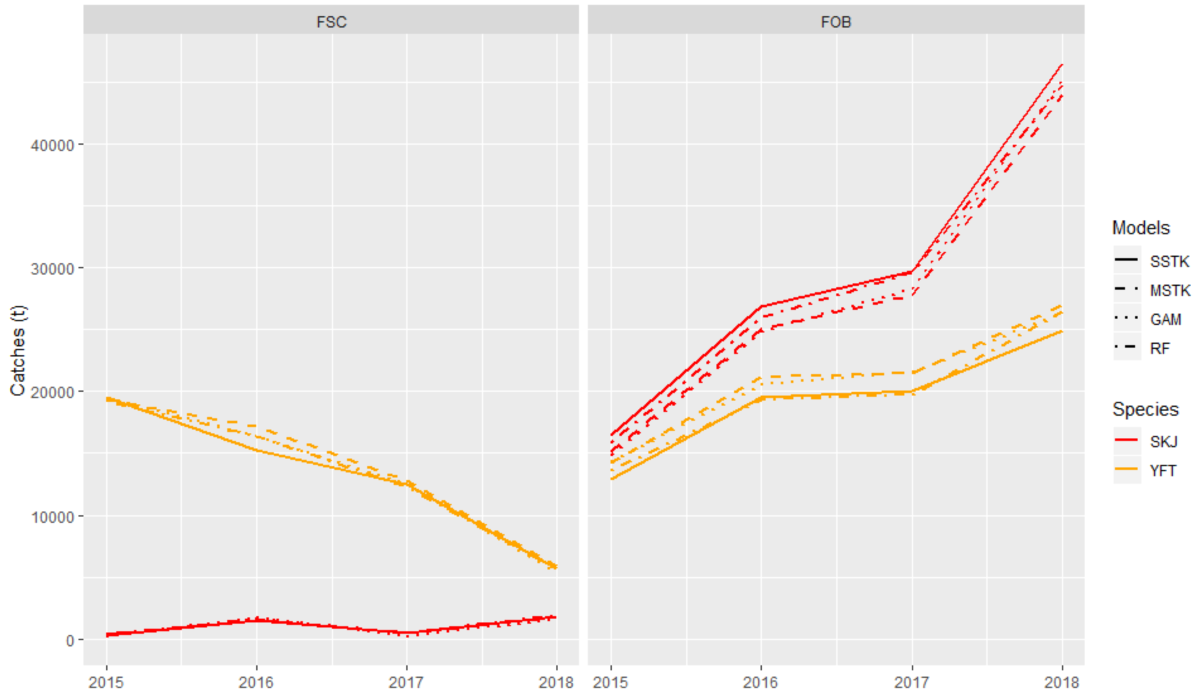

Figure 8: Total catches by tuna species and fishing mode according to 4 estimation methods for the 2010-2018 period.

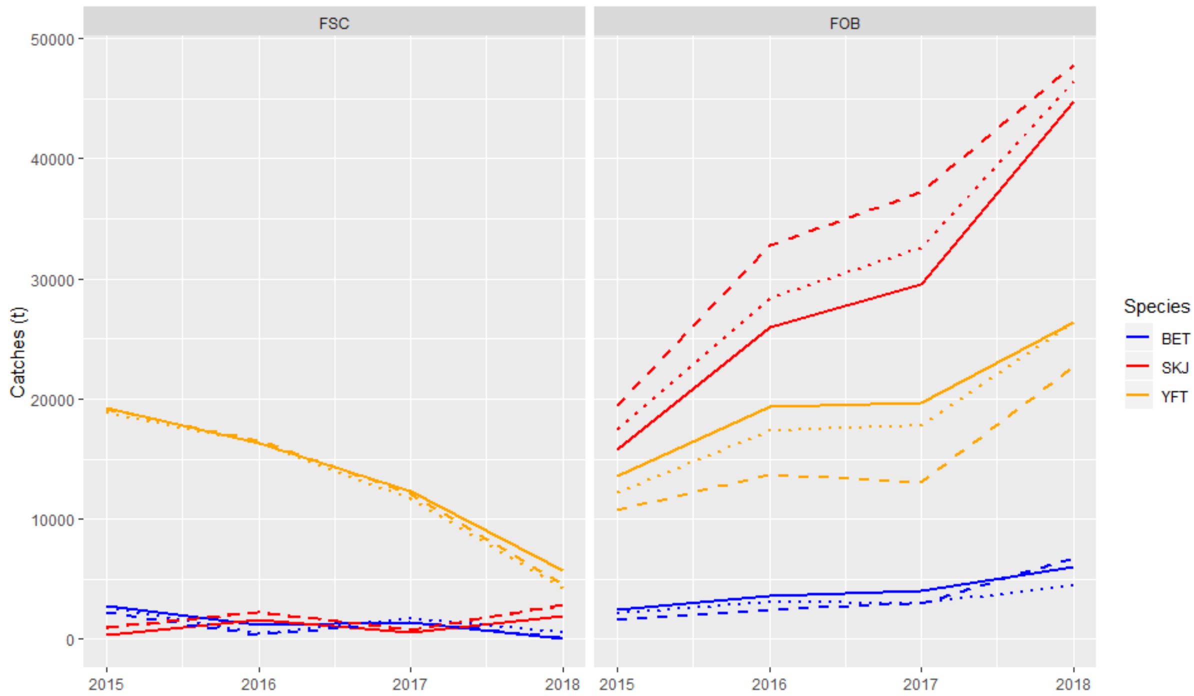

Figure 9: Total catches by tuna species and fishing mode according to three estimation methods for the 2010-2018 period. Logbook report: dashed line, T3f: dotted line and RF: solid line.

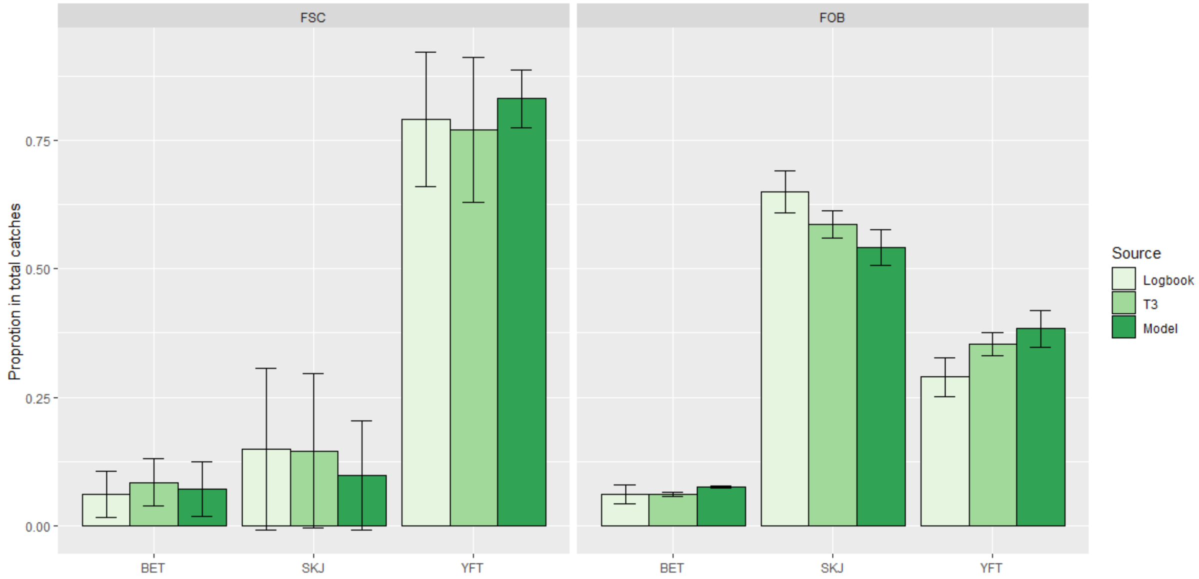

Figure 10: Mean ± SD of proportion of total catches by tuna species and fishing mode according to three estimation methods for the 2010-2018 period.

APPENDIX 1: OUTPUTS OF MODELS FOR THE YELLOWFIN (YFT) ON ASSOCIATED SCHOOL

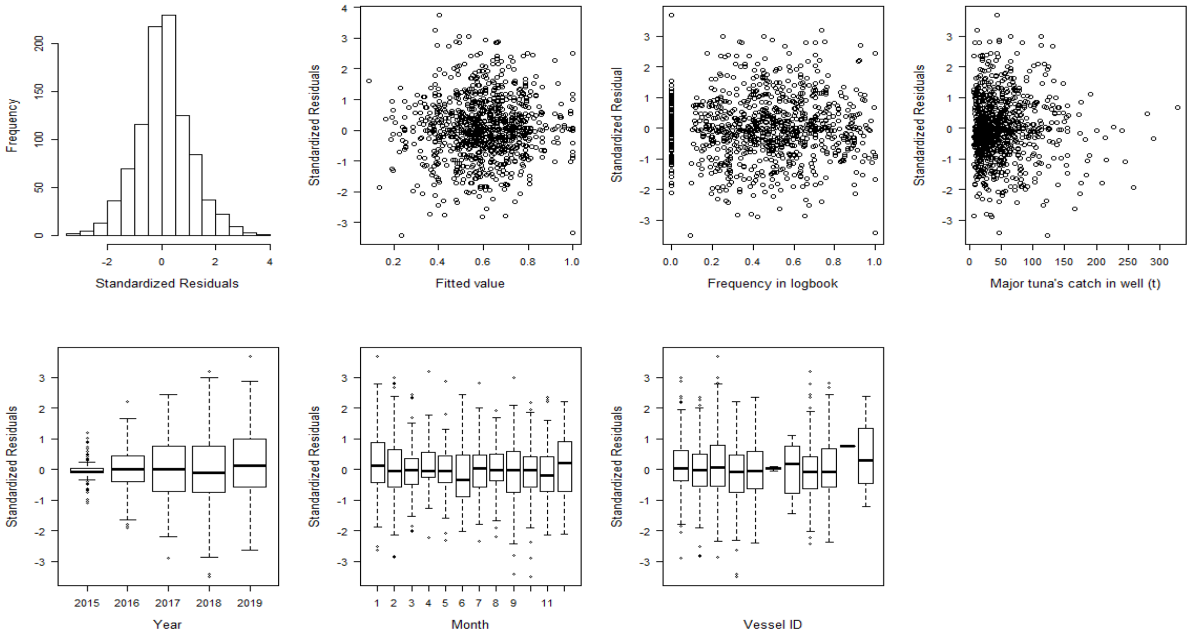

Figure A1-1: Model diagnostic of MSTK on YFT in FOB

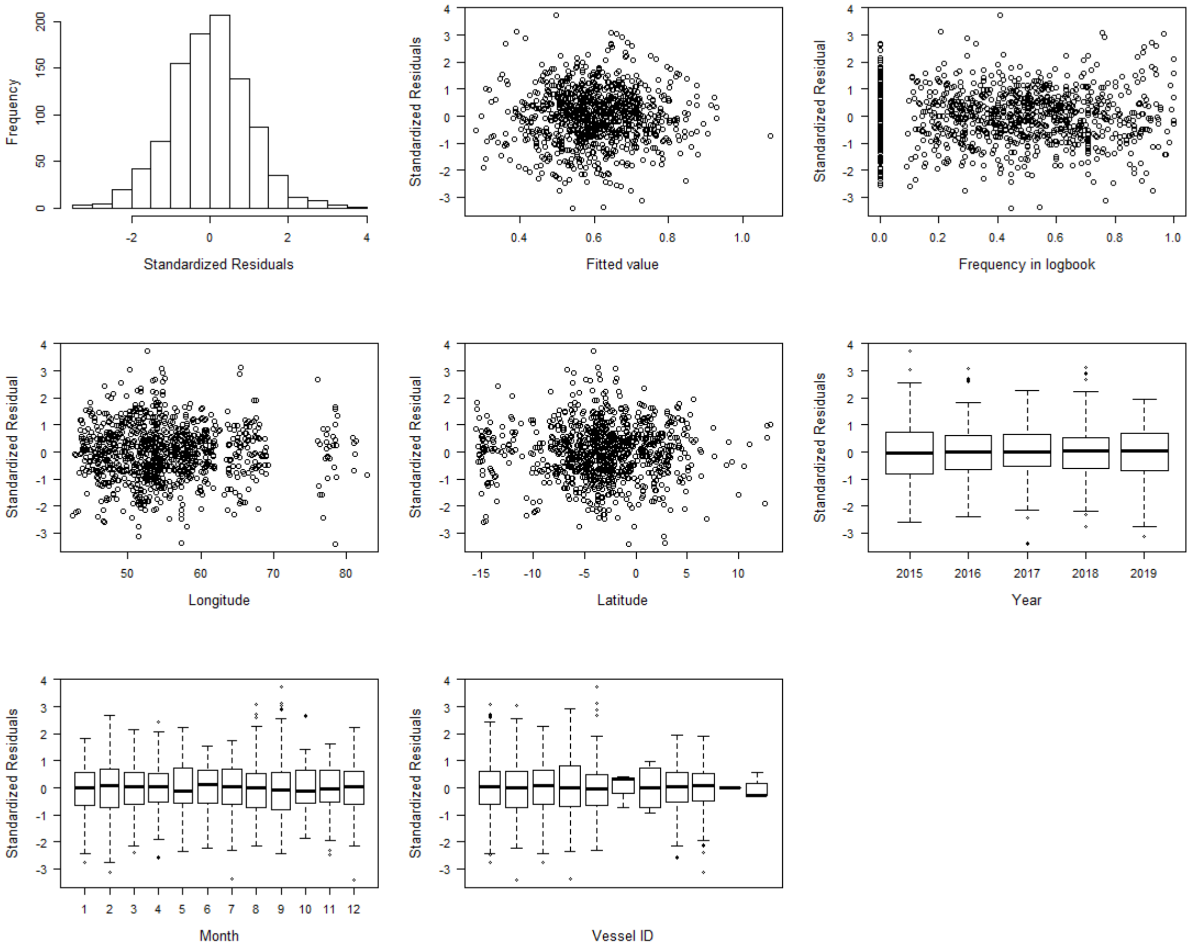

Figure A1-2: Model diagnostic of GAM on YFT in FOB

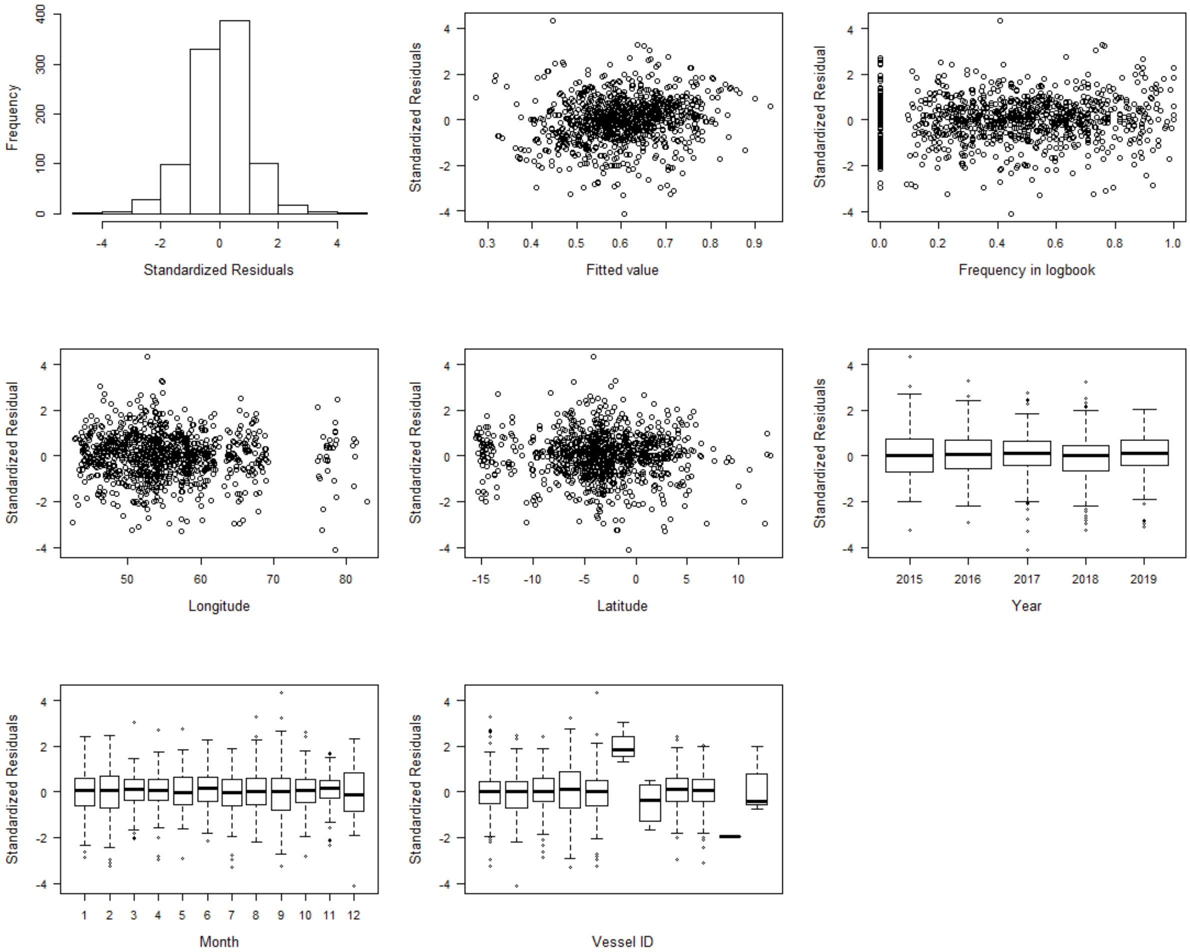

Figure A1-3: Model diagnostic of RF on YFT in FOB

APPENDIX 2: OUTPUTS OF MODELS FOR THE YELLOWFIN (YFT) ON FREE SCHOOL

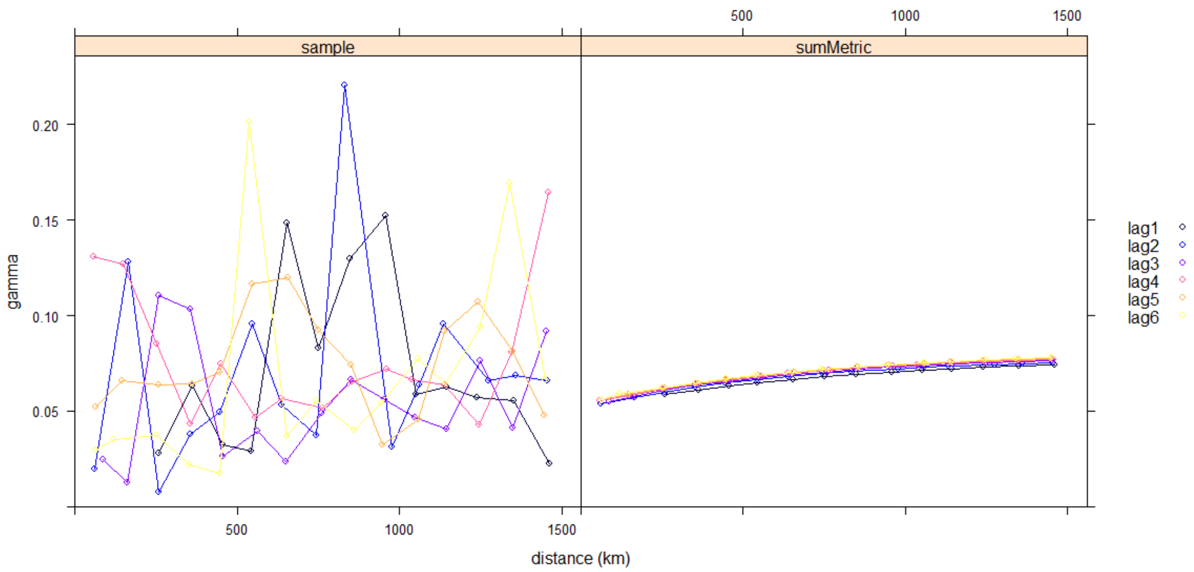

Figure A2-1: Left panel: Spatio-temporal variogram on YFT frequency in sample on free school. Lag 1 to 6 represents 1 to 6 months' time laps. Right panel: Fit of the best Spatio-temporal variogram model. (product sum metric type, MSE =3.22e-03)

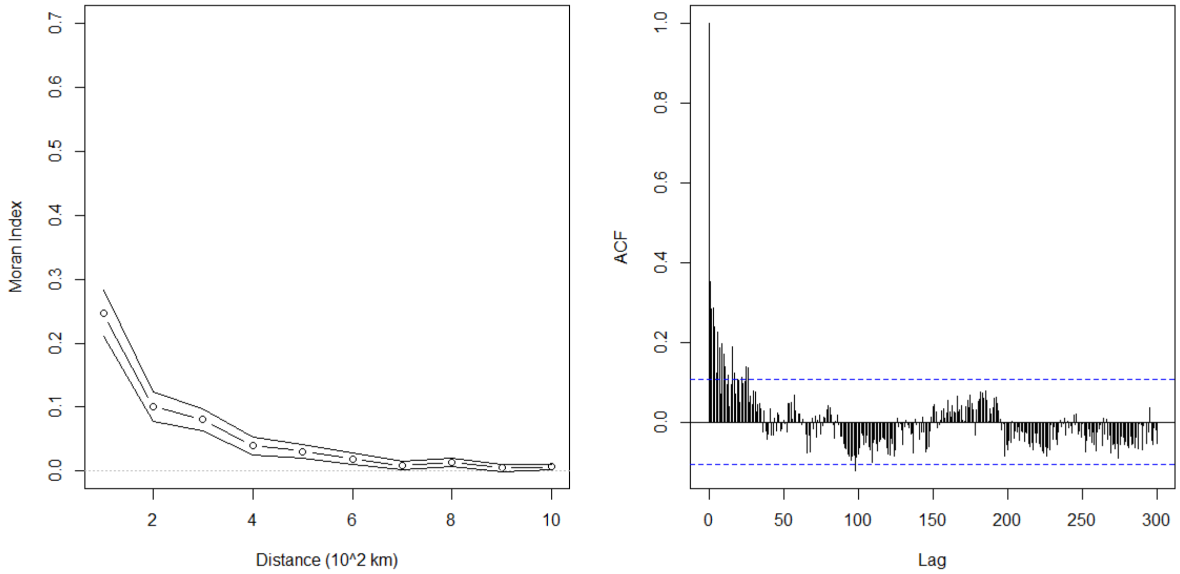

Figure A2-2: Spatial and temporal autocorrelation of YFT frequency in sample on free school calculated separately. Left panel: Mean and SD of Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

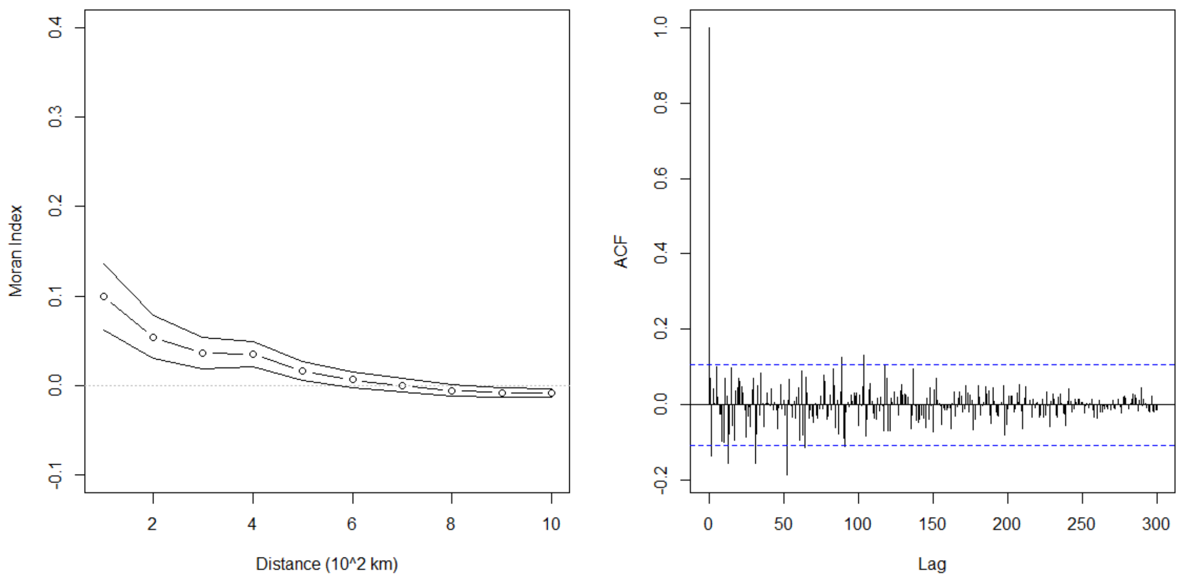

Figure A2-3: Spatial and temporal autocorrelation of residuals of the MSTK on associated school calculated separately. Left panel : Moran Index. Right panel : Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

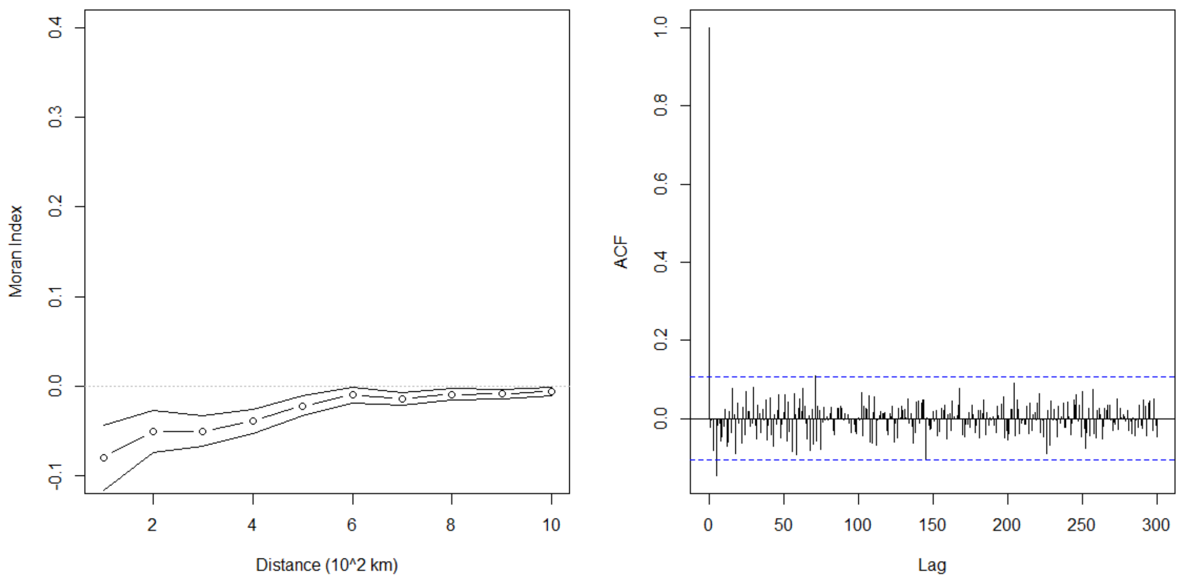

Figure A2-4: Spatial and temporal autocorrelation of residuals of GAM on free school calculated separately. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

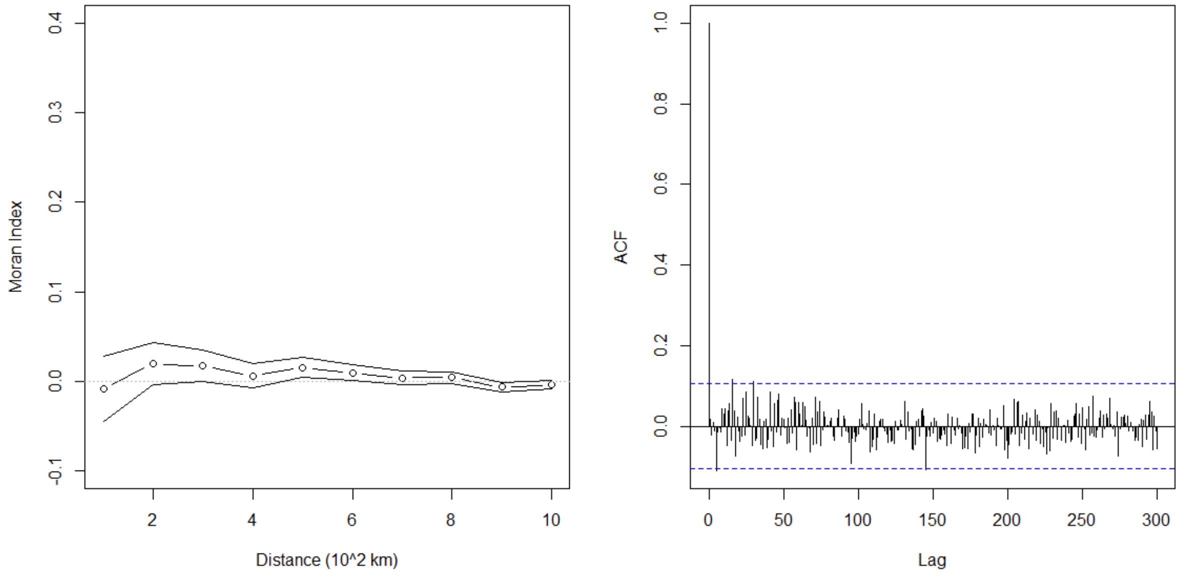

Figure A2-5: Spatial and temporal autocorrelation of residuals from best random forest model on free school. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

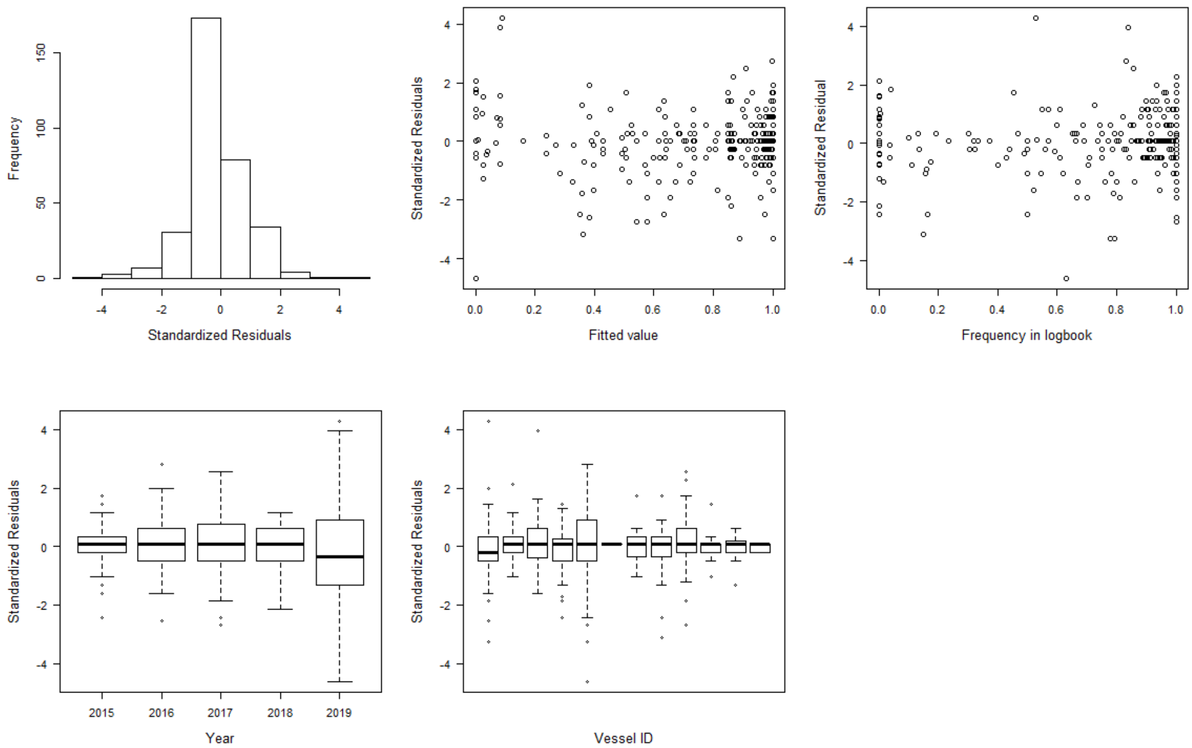

Figure A2-6: Model diagnostic of MSTK on YFT in FSC

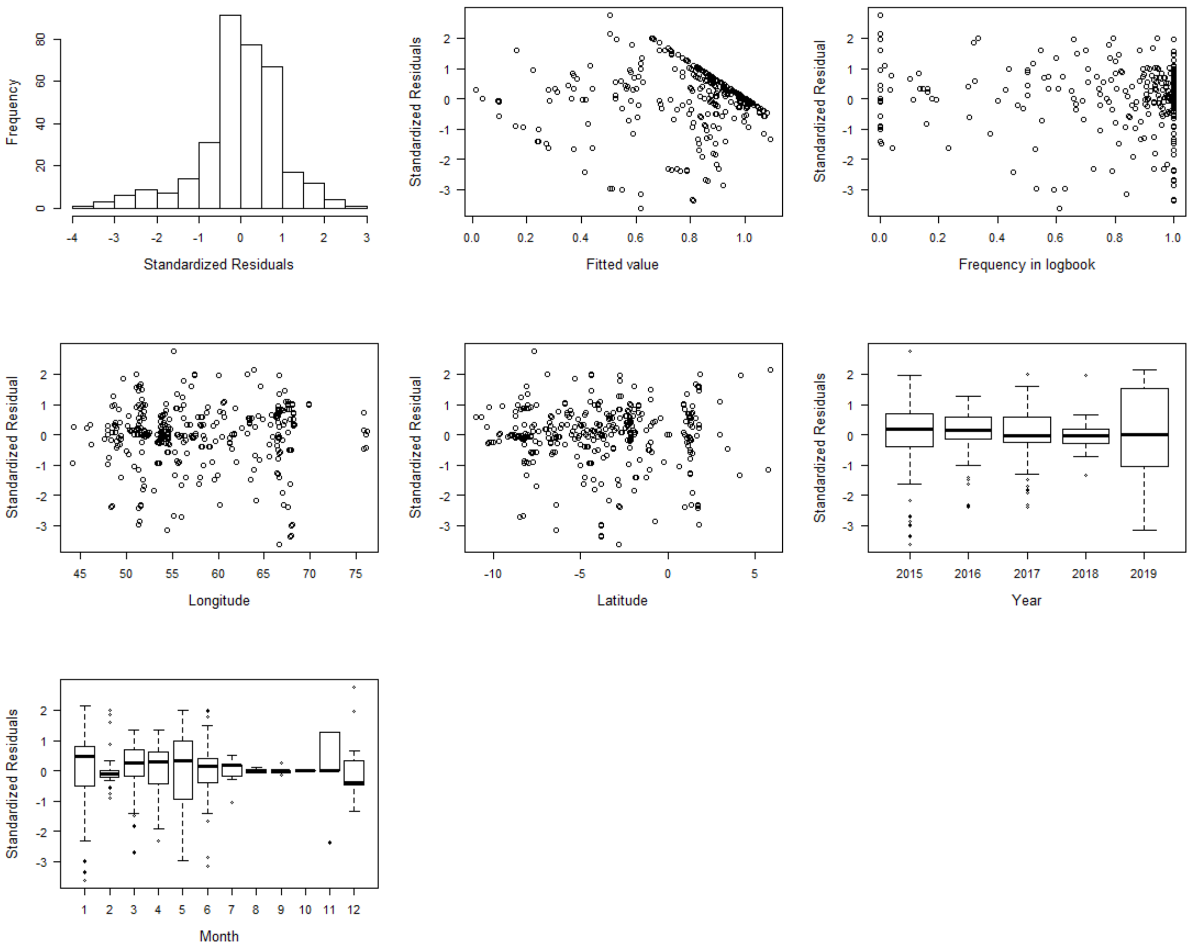

Figure A2-7: Model diagnostic of GAM on YFT in FSC

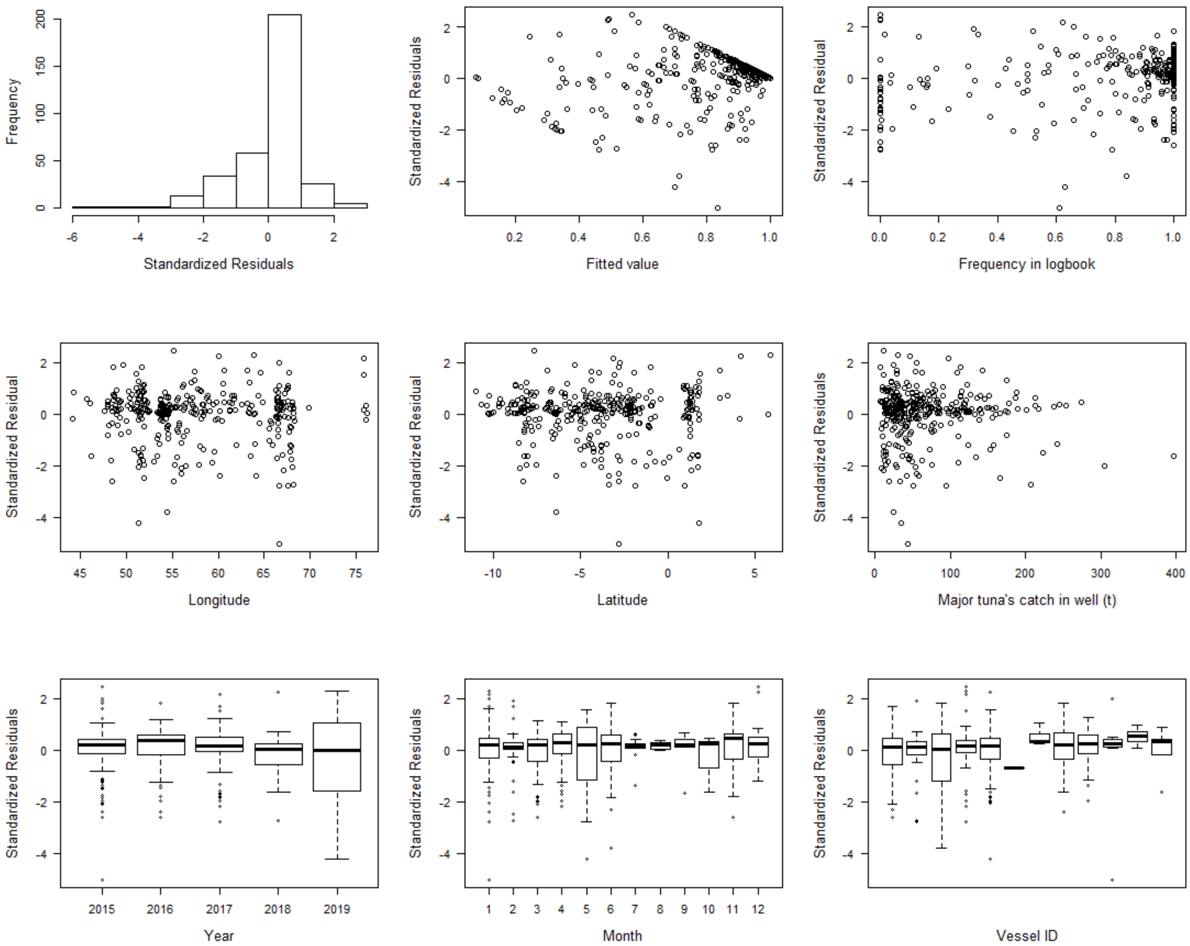

Figure A2-8: Model diagnostic of RF on YFT in FSC

APPENDIX 3: OUTPUTS OF MODELS FOR THE SKIPJACK (SKJ) ON ASSOCIATED SCHOOL

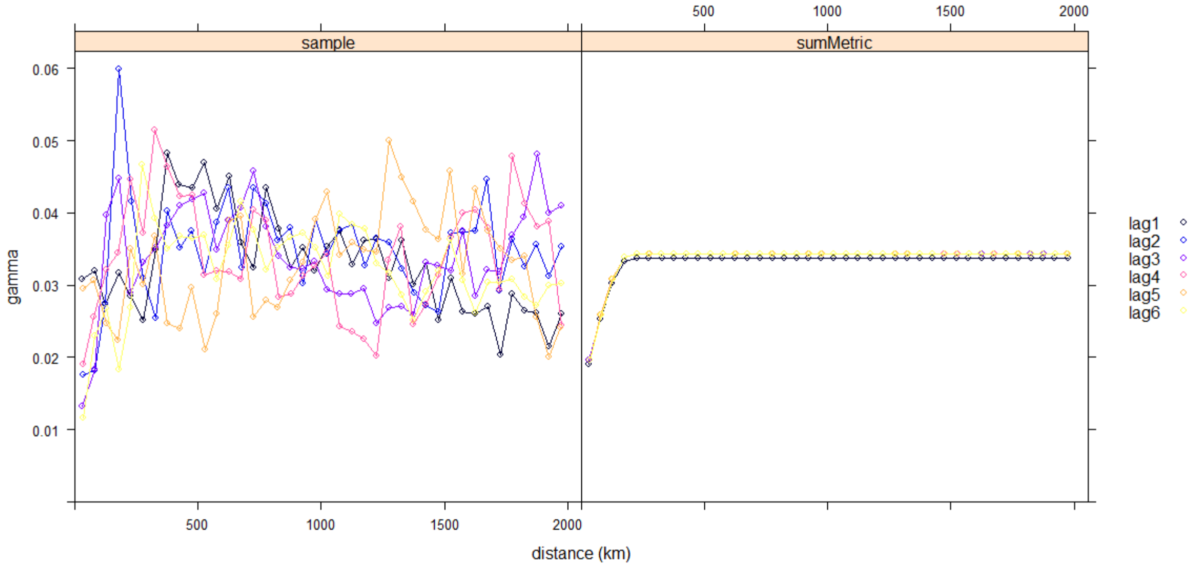

Figure A3-1: Left panel: Spatio-temporal variogram on SKJ frequency in sample on associated school. Lag 1 to 6 represents 1 to 6 months' time laps. Right panel: Fit of the best Spatio-temporal variogram model. (product sum metric type, MSE =1.39e-04)

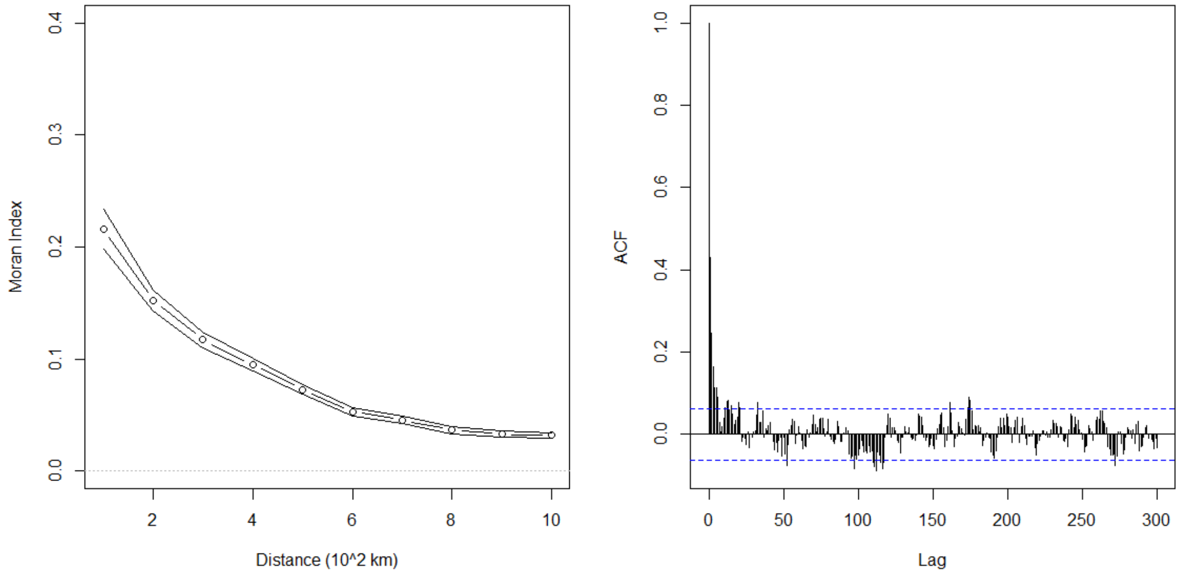

Figure A3-2: Spatial and temporal autocorrelation of SKJ frequency (square root transformed) in sample on associated school calculated separately. Left panel: Mean and SD of Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

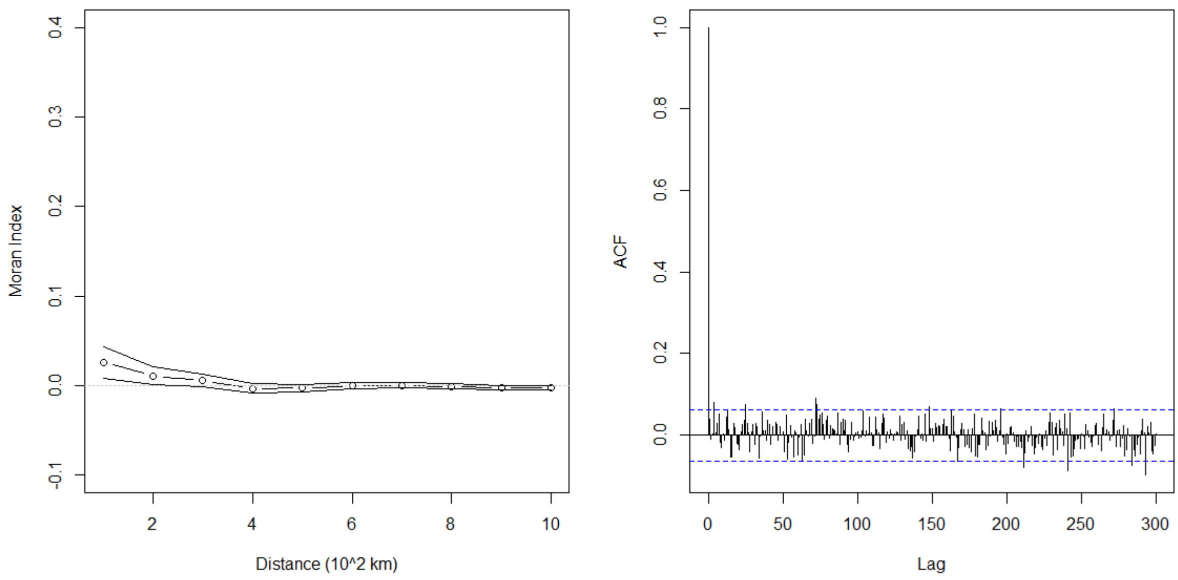

Figure A3-3: Spatial and temporal autocorrelation of residuals of the MSTK on SKJ in associated school calculated separately. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

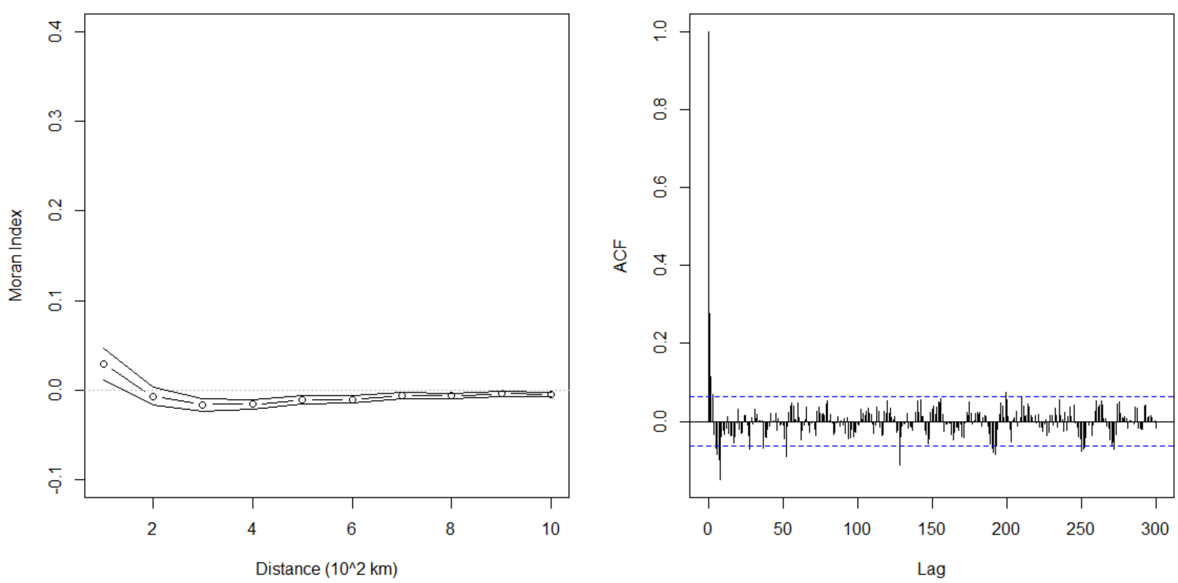

Figure A3-4: Spatial and temporal autocorrelation of residuals of GAM on associated school calculated separately. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

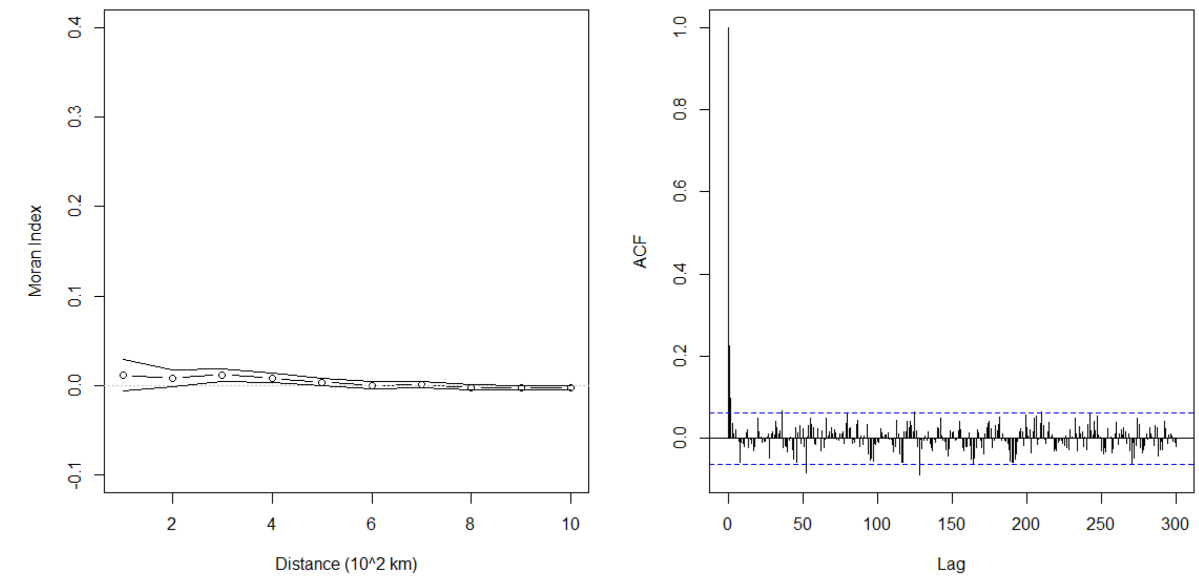

Figure A3-5: Spatial and temporal autocorrelation of residuals from best random forest model on associated school. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

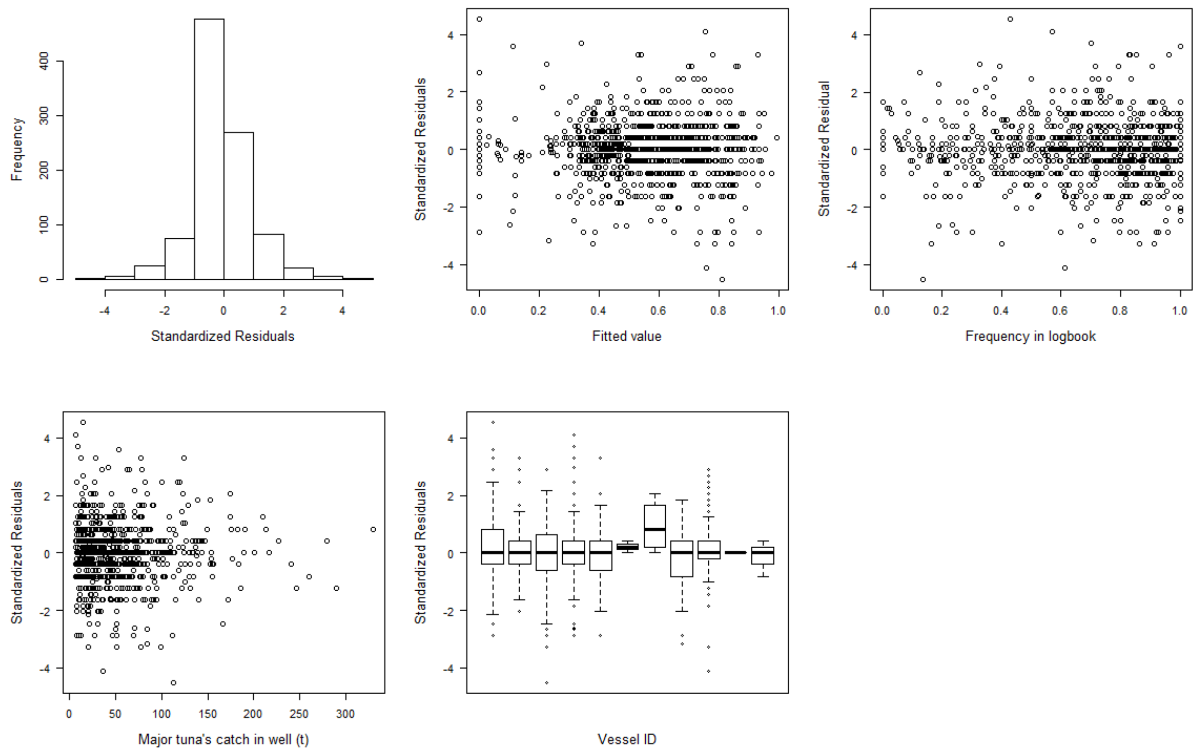

Figure A3-6: Model diagnostic of MSTK on SKJ in FOB

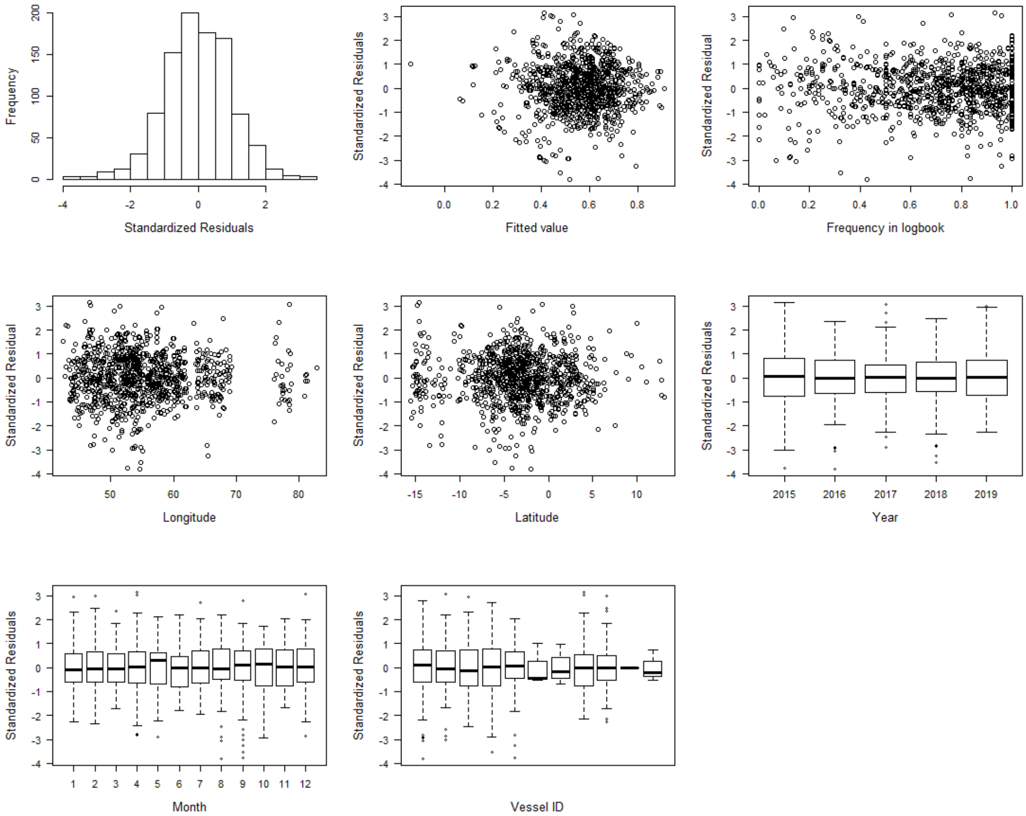

Figure A3-7: Model diagnostic of GAM on SKJ in FOB

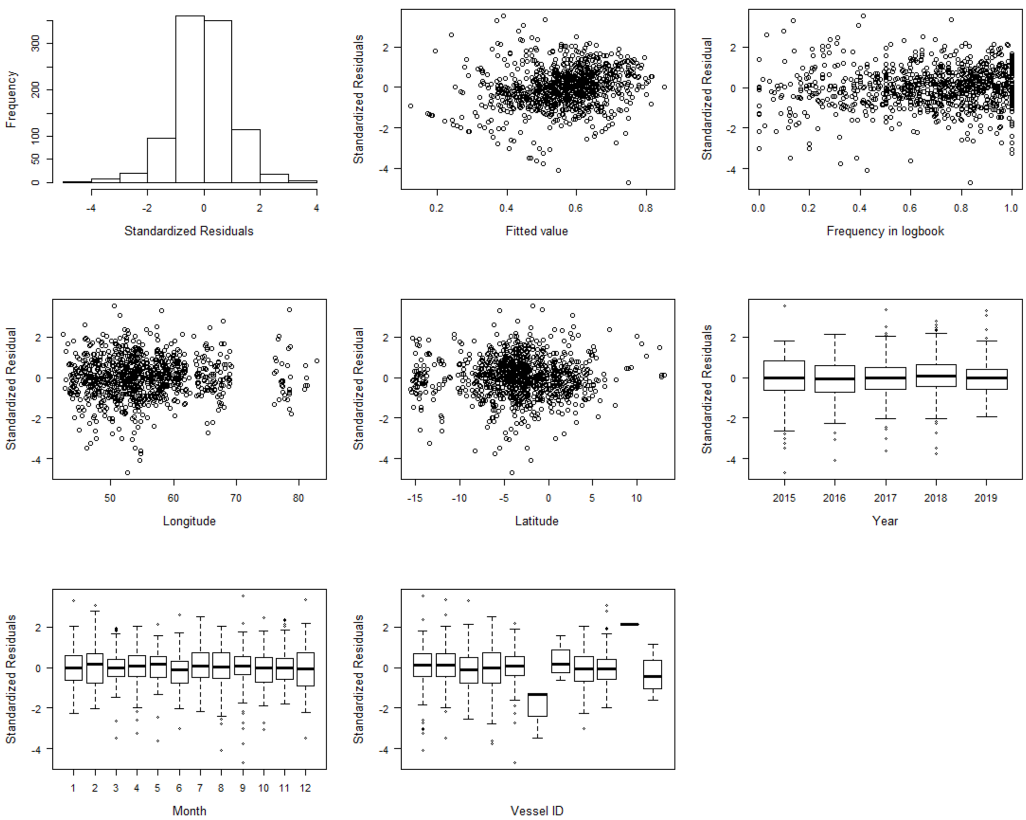

Figure A1-1: Model diagnostic of RF on SKJ in FOB

APPENDICES 4: OUTPUTS OF MODELS FOR THE SKIPJACK (SKJ) ON FREE SCHOOL

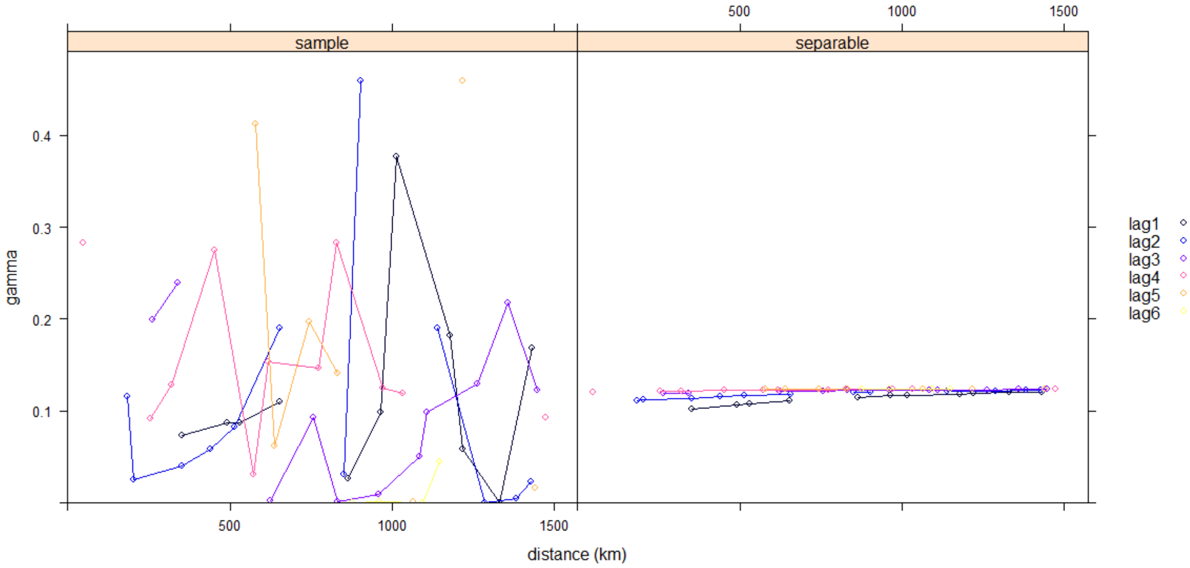

Figure A4-1: Variogram and the fitted model of SKJ frequency in sample on free school

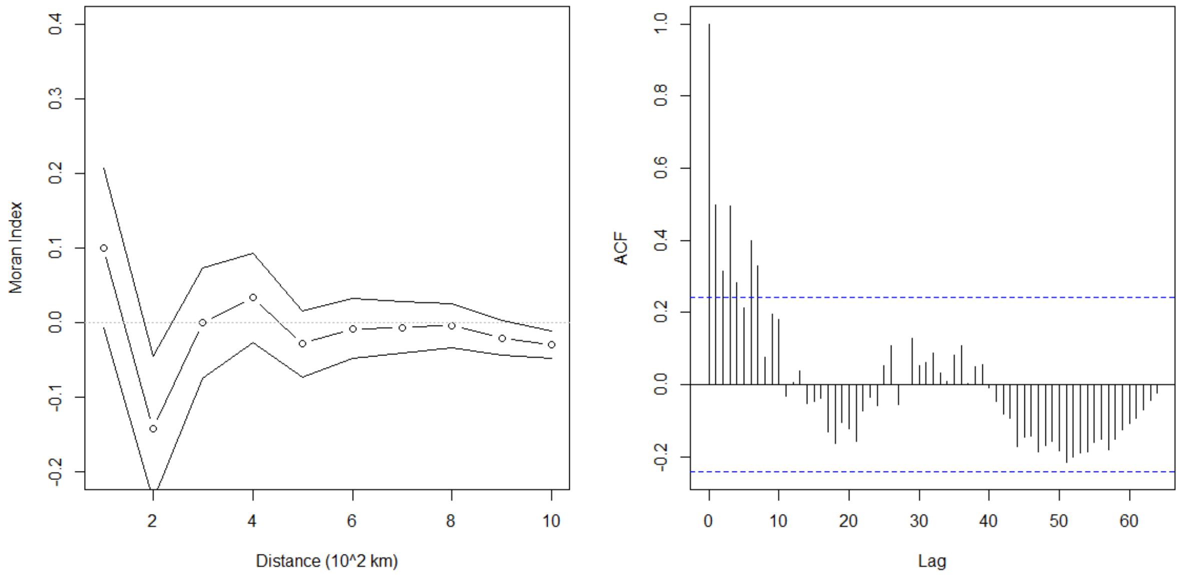

Figure A4-2: Spatial and temporal autocorrelation of SKJ frequency in sample on free school calculated separately. Left panel: Mean and SD of Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

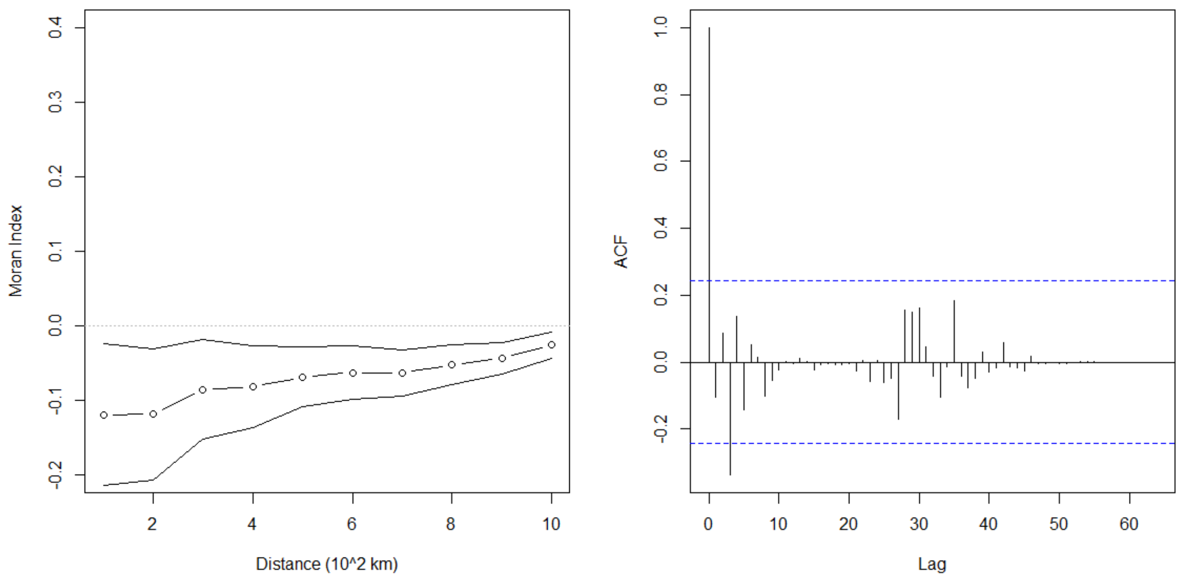

Figure A4-3: Spatial and temporal autocorrelation of residuals of the MSTK on SKJ in free school calculated sets. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

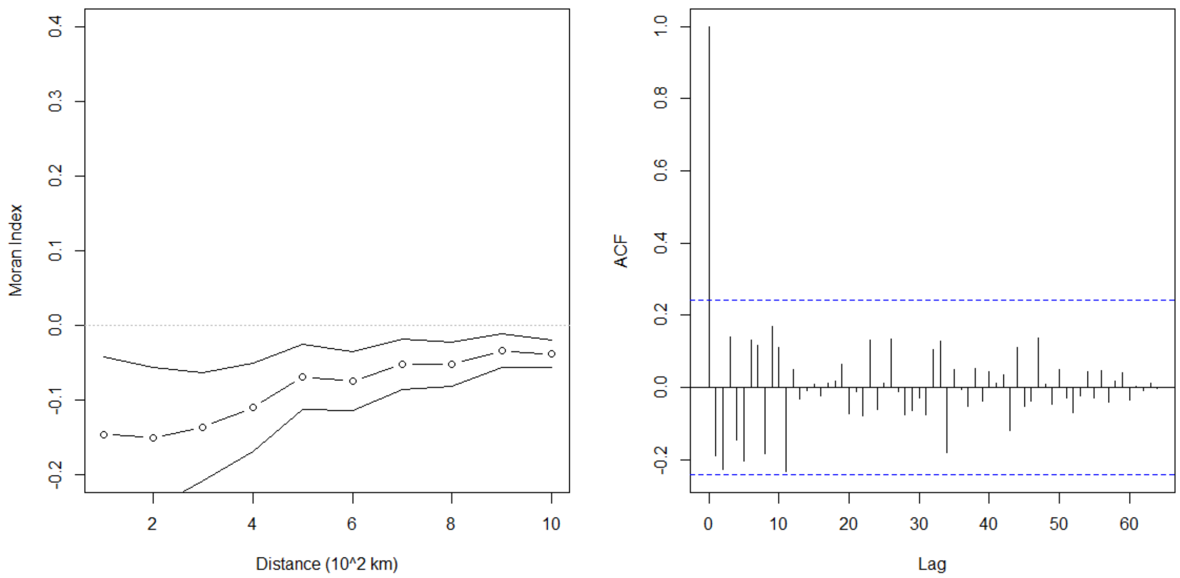

Figure A4-4: Spatial and temporal autocorrelation of residuals of GAM on associated school calculated separately. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

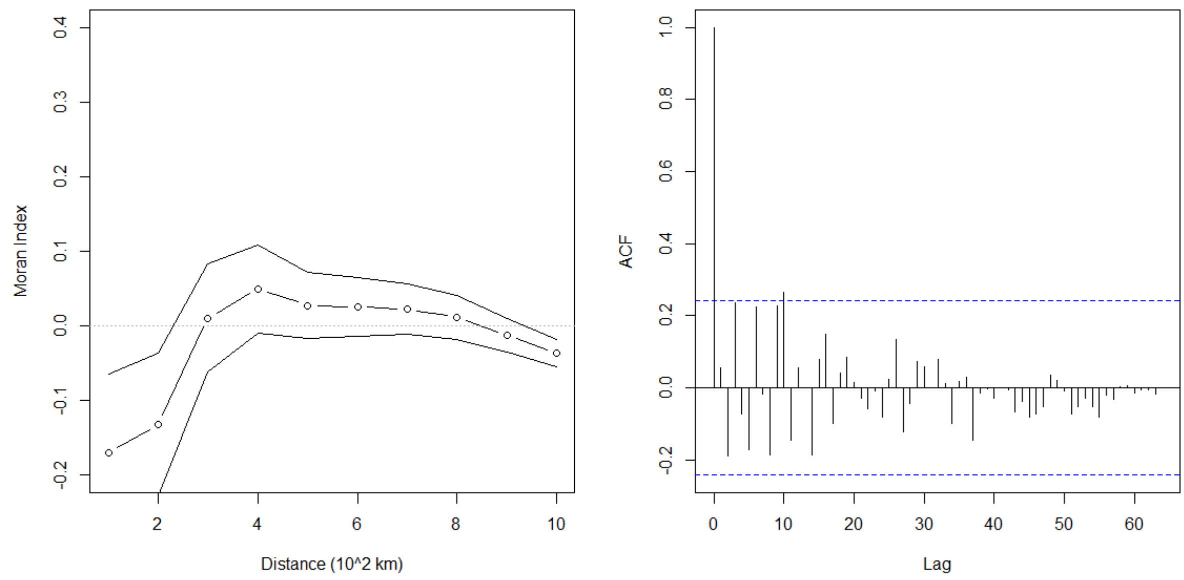

Figure A4-5: Spatial and temporal autocorrelation of residuals from best random forest model on associated school. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

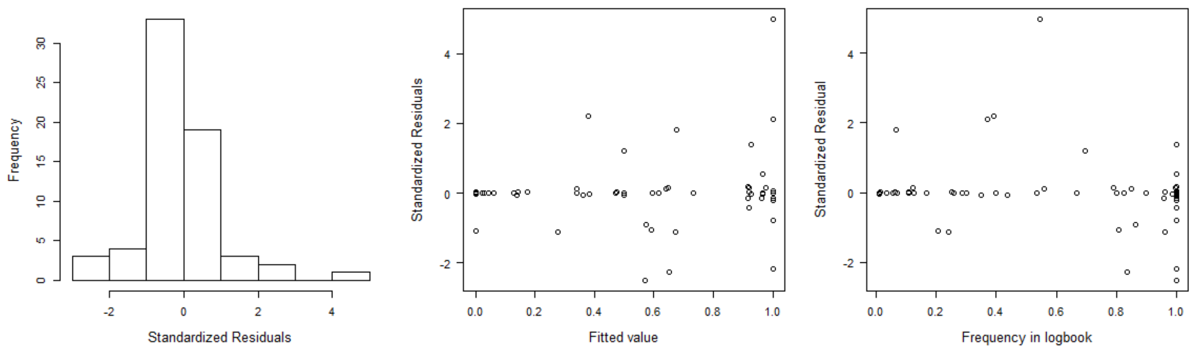

Figure A4-6: Model diagnostic of MSTK on SKJ in FSC

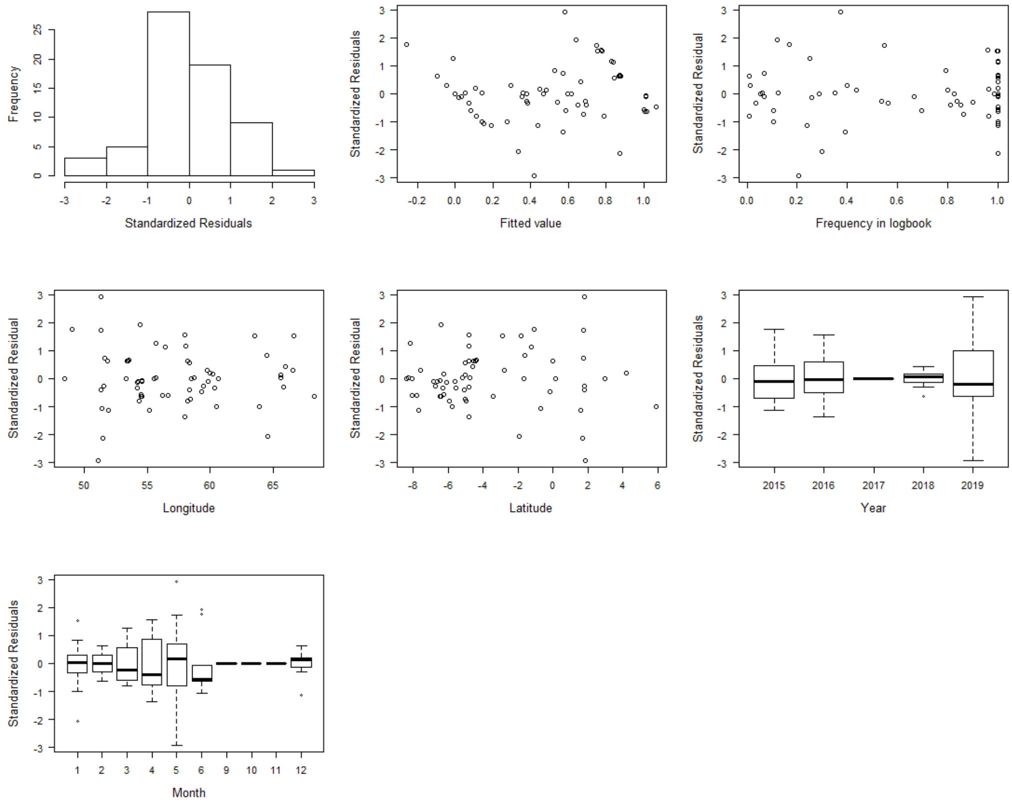

Figure A4-7: Model diagnostic of GAM on SKJ in FSC

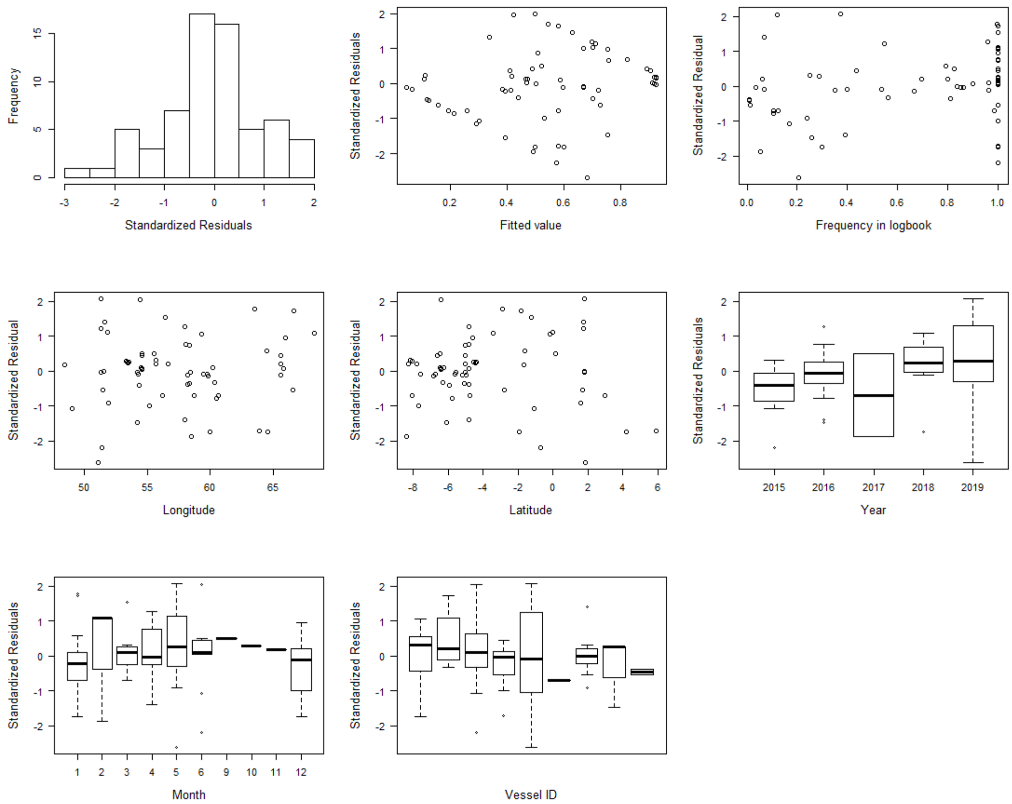

Figure A4-8: Model diagnostic of RF on SKJ in FSC