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# 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 ATLANTIC OCEAN)*

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*SUMMARY*

*The precise estimate 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 evidenced that logbooks suffered of large bias mainly for the small individuals, which prevent their direct use for catch estimates. For the major tropical tuna purse seine fisheries operating in the Atlantic 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 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. Analyses specifically focus on the spatio-temporal dimension of the catches. Furthermore, the use of more information from the logbook declaration are investigated and discussed.*

*RÉSUMÉ*

*L'estimation précise des captures par espèce est un élément majeur dans les pêcheries plurispécifiques, telles que les pêcheries de senneurs ciblant les thonidés tropicaux. La composition par espèces par opération est consignée dans le carnet de pêche, mais il a été démontré que les carnets de pêche contenaient des biais importants, principalement en ce qui concerne les petits spécimens, ce qui empêche leur utilisation directe pour les estimations des prises. Pour les principales pêcheries senneurs ciblant les thonidés tropicaux qui opèrent dans l'océan Atlantique, la composition par espèce est estimée à partir des opérations d'échantillonnage au débarquement et d'un traitement statistique pour interpoler la valeur des opérations non échantillonnées. Cette méthode, appelée Traitement des thons tropicaux (T3), développée par l'IRD au milieu des années 1990 a été critiquée, notamment dans la partie sur les corrections de la composition par espèce. Ce document présente les résultats d'une nouvelle approche statistique pour traiter les différentes lacunes signalées. Les analyses portent spécifiquement sur la dimension spatio-temporelle des captures. En outre, l'utilisation d'informations supplémentaires consignée dans les carnets de pêche est étudiée et discutée.*

*RESUMEN*

*La estimación precisa de las capturas por especies es un elemento principal en las pesquerías de varias especies, como las pesquerías de cerco de túnidos tropicales. La composición por especies por lance se consigna en el cuaderno de pesca, pero se ha demostrado que los cuadernos de pesca sufren grandes sesgos para los individuos pequeños, lo que impide su uso directo para las estimaciones de captura. Para las principales pesquerías de cerco dirigidas a los túnidos tropicales que operan en el Atlántico, la composición por especies se estima a partir de operaciones de muestreo en el desembarque y mediante un tratamiento estadístico para interpolar valores para los lances no muestreados. Este método, denominado Tratamiento de Túnidos Tropicales (T3), desarrollado por el IRD a mediados de los 90, ha sido criticado, de manera específica por la parte sobre las correcciones de la composición por especies. Este documento presenta los resultados de un nuevo enfoque estadístico para manejar los diferentes fallos señalados. El análisis se centra específicamente en la dimensión espacio temporal de las capturas. Además, se investiga y discute el uso de más información de los cuadernos de pesca.*

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*KEYWORDS*
*Spatio-temporal modelling, logbook declaration, bias estimate, sampling,*
*Katsuwonus pelamis, Thunnus albacares, Thunnus obesus*

## 1. Introduction

The precise estimate 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, although species compositions of each set are reported in the logbook, these lasts 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 Pacific Ocean (Lawson 2008), it is necessary to rely on a sampling in a part of the load at landing. Since 1984, the species compositions are thus estimated from these samples in Atlantic and Indian oceans. The method, called the Tropical Tunas Treatment (T3) and developed by IRD, is founded on the definition of homogenous strata in term 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 were stores and 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 the part on the species composition corrections (Duparc et al. 2018; Herrera and Baez 2019) because several limits 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 minimum amount of data (samples) to reliably assess the species composition for the non-sampled sets. Indeed, catches are correlated spatially and temporally, and so the homogeneity of species composition increase with the spatial resolution, as it was recently confirmed in the European project RECOLAPE (MARE/2016/22, Ruiz et al. 2019). However, higher the resolution increase, lower the number of data, which could lead to a lake 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 geographically close but 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 stock assessment.

Logbook declarations, even if they are visual estimations of the crew subjected to bias, are also the first source of a large amount of information on catches. In these last decades, the evolution of the fishing practices, could have enable 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 so double. First, address the identified matters with the use of statistical models, specifically the spatio-temporal dimension of the catches. Second, improve prediction accuracy by the use of new predictors, particularly the use of more information from the logbook knowing their uncertainties and their limits. To do so, we tested for different model approaches and compare their predictive performances from simple spatio-temporal model to multivariate models including additional predictors. In particular, we investigated the logbook declaration bias compare to the samples in terms of species detections and species compositions. Finally, we discussed implications of this study in the upgrade of the T3 process.

## 2. Materiel and methods

### *2.1. Data source*

We focused our analyses in the 2010-2018 period on the French purse seine fishery on major tropical tuna in the Atlantic Ocean.

#### 2.1.1. Logbook

Logbooks contain information on catch data by set including date, position, fishing mode and species split in commercial categories (define by a weight range). Weights are estimated visually by the captain, the bosco and the chief engineer. IRD get 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%.

#### 2.1.2. 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 the annual objective. 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 take into account 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 limited dates and spatial 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. Sampling team focuses on species identification and size measures with callipers. Small individuals, less than 70 cm fork length (FL), are measured in fork length, while larger individuals are measured in predorsal length. Fork length measures use 1 cm and 2 cm length classes steps, according to species, while predorsal length are performed with 0.5 cm steps. Sometimes for a subset of the sample, individuals are weighted using a scale, currently insuring 10 g precision.

### 2.2. Statistical analyses

#### 2.2.1. Selection of pairs sample – logbook

As we see 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, as much as possible to validate the assumption of sample representativeness. Therefore, we applied strict pre-selection process of each well before any modelling based on following criteria: all sets were of the same fishing mode (Associated school or free school only), caught in the same area (at a distance of 3° maximum) and composed of 5 sets maximum. We also remove for 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 determined the detection sensitivity of the logbook declaration 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).

Furthermore, we assessed the probability of detection in logbook according to the proportion measured in samples, making the assumption that these last were more sensitive to detect species than the first one (see results section for validation). We so modelized probability of detection, coding 1 when species was declared from logbook in a well (at least in one set of the well) else 0. We then performed a general additive model (GAM) with binomial distribution, where the probability of detection was the dependent variable and the proportion of the species in the sample (between 0 and 1) the predictor. Finally, we estimated quantile confidence interval (0.025,0.975) using bootstrap method (nsim = 999)

#### 2.2.3. Modelling species compositions

We modelled 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 for 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 declaration, 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 and year and their interaction were also in the model to take into account for temporal variation between and within years. Finally, the total catch of major tuna by set were included to correct for potential bias of the set size.

We Tested for 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 sets with absence declared in the logbook and prediction because absence was well detected by crew a so considered as true absence (see results section).

*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 = 200 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 = 4, Number of times the OOB data are permuted per tree = 5.

*2.2.4. Predict catches for task 1*

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. Total catches for the task 1 were sums of sets grouped by variables of interest (year, species, fishing mode). We compared best model estimations with estimations from logbook declaration not corrected (only weighted) and from the current T3 process (T3f).

## 3. Results

### *3.1. Comparison of logbook declaration and samples at landing*

Comparison between declaration in logbook and sample demonstrated that samples detected for species presence more accurately (**Table 1 and 2**). Thus, sample error rate was always under ranged from 0 to 0.04, (except for BET on associated school = 0.055) whatever the sets considered (mono-sets or multi sets). SKJ was also accurately detected in logbook but 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.

These results were confirmed regarding the modelling of probability of detection in logbook according to the proportion of species in sample. SKJ, with lowest error rate, had the highest probability of detection, about 80% when proportion was 0.25 in samples (**Table 3** and **Figure 1**). BET and YFT were less detected with a probability of detection of 0.63 and 0.55 respectively for proportion of 0.25 in samples.

### *3.2. Estimate of species composition*

Proportion of tuna in samples were autocorrelated in long distance (> 1000 km) and several months depending of the species and the fishing mode (see example of YFT on FOB, **Figure 2**). The spatio-temporal variograms, commonly use for the SSTK and MSTK, were so fitted with different models also depending of the species and the fishing mode (**Table 4**, example in **Figure 3** for the YFT on FOB). Thus, models efficiently corrected, as expected, for spatial and temporal dimensions as their residuals were note autocorrelated anymore (**Figure 4**). GAM and RF models gave similar results but residuals remained autocorrelated in some case for the short distances despite Moran index close to 0 (**Figure 5 and 6**).

Model performance varied strongly among model type, species and fishing mode (**Table 5**). RF had always the best performance and the SSTK the worst one but close to the GAM.

Regarding selection of predictors, every variable has been selected but set size (for SKJ only) and vessel were the less informative for the prediction. On the contrary, logbook frequency of the species and year were conserved in all models confirming their importance to improve the prediction performances (**Figure 7**). However, the amount of gain in accuracy varied.

### *3.3. Prediction of the task 1*

All models give similar results on average despite their differences in prediction performance (**Figure 8**). Total catches in free school were very similar between the logbook declarations, the values from the actual T3 (T3f) and the predictions of the random forest model (**Figure 9**). This result confirms the accuracy of declarations by crew members which so need minor corrections.

Regarding the sets on associated school, we observed strong differences in total catches between the source of data for the estimation. The main discrepancy came from the lower proportion of SKJ predicted by the RF model compare to the logbook declaration or the T3f estimated (**Figure 10**). This over-reporting of SKJ (9.2 ± 1.7 % on average for the study period), predict by the RF was balanced by the under reporting of the YFT (-7.1 ± 1.4 %) and, to lesser extent, the BET (-2.1 ± 1.0%).

## 4. Discussion

### *4.1. 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, in which 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 3 different types of model and all converged. SKJ was over-reported in the logbook declaration in the associated school sets to the detrimental of YFT and BET. This pattern was also found in the West Pacific Ocean (Hampton and Williams 2011). However, and contrary to the study in the West Pacific, we did not found differences (or minor) between logbook and estimates from the T3f or RF for the free school, suggesting a quite good declaration by the crew member for this fishing mode.

These results could be explained by several concomitant hypotheses. The SKJ is a species easy to identify because of the longitudinal dark bands on its sides contrary to the small YFT and BET frequently present in associated school either (Fonteneau 1975). Crew member so can detect preferentially the motif of SKJ leading to a visual over-estimation. This hypothesis is in agreement with our results, as we found that the error rate for absence in logbook declaration 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 so declare for large amount of SKJ in the catches on associated school because this is the usual pattern. Thirdly, the error rate of absence in declaration for BET and SKJ led the model to correct for these ‘false absences’ and so increase the proportion of these 2 species to the detrimental of the SKJ (in associated school with absence or low proportion f BET and SKJ). Finally, Part of the small YFT and BET could have been declared in the same commercial class as SKJ in logbook as they have similar market price (Bard 1986), which also increase artificially the SKJ proportion in catches.

Besides, one bias occurs in the sampling that could temper the observed differences. Indeed, samples concerned only the tunas sold to the canneries (almost) omitting individuals landed towards the local market. In the other side, logbook should account for the all tunas including individual destined for the local market. Yet, the SKJ is the most frequent major tuna in the local market, relatively to YFT and BET (Chavance et al. 2015). The species composition of the local market so could counter-balance the over-reporting in the model predictions. However, first estimations of tuna catches destined to the local market tend to show that it could not compensate all the observed discrepancy, as it represents only 4.4 ± 0.7% on average of the trip catches in major tunas (average on 234 trips between 2014 and 2019). In all case, the improvement of the catch estimations destined to the local market and its integration in the T3 process should be done to address this matter.

### *4.2. Prediction and covariables*

We also demonstrated that the addition of logbook declaration 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 on species declared was correlated to the one in samples. Therefore, the declaration 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 for instance, that departed from the spatio-temporal autocorrelation structure.

The amount of tuna catch did not improve a lot the predictive performance. 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.

### *4.3. Limits of the new approach*

The new approach of the estimation of the species composition well performed but several limits remained to address. First, the management of absence in declaration is questioning. We detected important error rate on absence declared for the YFT and BET mainly on associated school sets. The T3 process could criticize on this point because proportion estimates are the weighted mean of the spatio-temporal strata which imply absence in logbook declaration are systemically replace by the mean presence of the strata. Thus, the T3 process performs a smoothing by strata, which should not have strong incidence on the total catches (Task 1), but could bias the spatial repartition 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 declaration included in the model (plus the vessel ID) enable more variability in the predict proportion. However, total absence could not be predicted yet because of 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 for impossible proportion value (<0 or >1) because the distribution was not limited (Normal distribution). Even if these out-ranged predictions were rare, they are due to the fact that we modelized 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-ranged value. However, further investigations have to be done to model all species simultaneously using multinomial distribution or other (e.g. Dirichlet distribution). But these models are not well implemented yet to account for spatio-temporal structure and could not also predict for 0 or 1 values.

## 5. Conclusion and perspectives

A robust estimation of the species composition of major tropical tunas remains a challenge. We proposed new approach that deals with the spatial and temporal issues and improves prediction performance including the logbook declarations. These last 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 researches could be conduct to still upgrade estimations of the species composition. First, we selected sampled wells for analyses with the purpose to be conform to the assumption of representativeness of the samples. Sensitivity analyses should so be performed to test for the impact of the set's mixture on the prediction performance. Similarly, the minimum number of couple logbook/sample needed for analyses should be determined. These analyses could answer to the question about the sample size and bring to an adjustment of the sampling effort.

Then, we only test in this document for fishing variables (logbook declaration, vessel ID and set size) which are already available. However, many other variables could be added to the model to test for the improvement of the prediction performance. As an example, topographic variables, such as distance to the coast, presence of a seamounts or Guyots could explain a local increase or decrease in the presence and catchability of species. Similarly, oceanographical variables could also play a role in the species composition of the purse seine fishery. It has been demonstrated for instance the sea surface temperature, the dissolve oxygen and the mixt layer depth could improve the catchability of Yellowfin (Block et al. 1997) .

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

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**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 | Prop_absence | Error rate LB | Error rate Sample |
|---|---|---|---|---|---|
| Associated school | BET | 201 | **0.60** | **0.46** | 0.055 |
| Associated school | SKJ | 201 | 0.01 | 0.00 | 0.000 |
| Associated school | YFT | 201 | **0.32** | **0.29** | 0.005 |
| Free school | BET | 177 | **0.79** | **0.17** | 0.040 |
| Free school | SKJ | 177 | **0.75** | 0.01 | 0.011 |
| Free school | YFT | 177 | 0.10 | 0.07 | 0.000 |

**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 | 1372 | **0.66** | **0.57** | 0.025 |
| Associated school | SKJ | 1372 | 0.01 | 0.01 | 0.000 |
| Associated school | YFT | 1372 | **0.30** | **0.30** | 0.001 |
| Free school | BET | 1434 | **0.81** | **0.29** | 0.031 |
| Free school | SKJ | 1434 | **0.84** | 0.06 | 0.008 |
| Free school | YFT | 1434 | 0.05 | 0.04 | 0.000 |

**Table 3**: Fitted value and quantile interval of probability of detection in logbook according to proportion in sample by species from GAM model.

| Proportion in sample | Species | Probability of detection | Q025 | Q975 |
|---|---|---|---|---|
| 0.25 | BET | 0.627 | 0.609 | 0.65 |
| 0.50 | BET | 0.9 | 0.893 | 0.909 |
| 0.75 | BET | 0.962 | 0.958 | 0.966 |
| 0.90 | BET | 0.974 | 0.969 | 0.978 |
| 0.25 | SKJ | 0.793 | 0.775 | 0.812 |
| 0.50 | SKJ | 0.979 | 0.975 | 0.982 |
| 0.75 | SKJ | 0.987 | 0.986 | 0.989 |
| 0.90 | SKJ | 0.982 | 0.979 | 0.985 |
| 0.25 | YFT | 0.549 | 0.536 | 0.559 |
| 0.50 | YFT | 0.847 | 0.837 | 0.855 |
| 0.75 | YFT | 0.954 | 0.95 | 0.957 |
| 0.90 | YFT | 0.977 | 0.975 | 0.979 |

**Table 4**: Spatio-temporal structure selected for kriging on proportion in samples by species and fishing mode

| Species | Fishing mode | ST model structure | Spatial variogram | | | k |
|---|---|---|---|---|---|---|
| | | | Nugget | psill | range | |
| YFT | BO | product sum (Exp) | 0.0136 | 0.354 | 1570 | 1 |
| YFT | BL | separable (Gau) | 0.043 | 0.96 | 6773.4 | sill = 0.43 |
| SKJ | BO | product sum (Exp) | 0.0204 | 0.445 | 2902.7 | 1 |
| SKJ | BL | product sum (Sph) | 0.0278 | 0.103 | 900 | 1 |

| Species | Fishing mode | ST model structure | Temporal variogram | | | MSE |
|---|---|---|---|---|---|---|
| | | | Nugget | psill | range | |
| YFT | BO | product sum (Exp) | 0 | 0 | 5.35 | 1.93E-05 |
| YFT | BL | separable (Gau) | 0.043 | 0.96 | 238783.3 | 3.22E-03 |
| SKJ | BO | product sum (Exp) | 0 | 0 | 5.35 | 1.39E-04 |
| SKJ | BL | product sum (Sph) | 0 | 0 | 5 | 1.47E-02 |

**Table 5**: 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 | 0.1491 | 0.1178 | 0.2146 |
| MSTK 1 | SSTK + LB | 0.1428 | 0.1126 | 0.2050 |
| MSTK 2 | MSTK 1 + year | 0.1382 | 0.1090 | 0.1985 |
| **MSTK3** | **MSTK2 + set size** | **0.1373** | **0.1081** | **0.1968** |
| MSTK4 | MSTK 3 + vessel | 0.1379 | 0.1083 | 0.1979 |
| MSTK5 | MSTK 4 + mon | 0.1374 | 0.1087 | 0.1978 |
| **GAM3** | **GAM2 + setsize** | **0.1377** | **0.1086** | **0.1979** |
| GAM2 | GAM1 + vessel | 0.1380 | 0.1087 | 0.1981 |
| GAM1 | GAM0 + LB | 0.1389 | 0.1099 | 0.2005 |
| GAM0 | 1 | 0.1435 | 0.1134 | 0.2067 |
| RF3 | RF2 + setsize | 0.0535 | 0.0414 | 0.0755 |
| **RF2** | **RF1 + vessel** | **0.0534** | **0.0408** | **0.0745** |
| RF1 | RF0 + LB | 0.0783 | 0.0783 | 0.1134 |
| RF0 | 1 | 0.0865 | 0.0692 | 0.1262 |

YFT on free school

| Name | Model | RMSE | MAE | CVMAE |
|---|---|---|---|---|
| SSTK | 1 | 0.16507 | 0.1011 | 0.1162 |
| MSTK 1 | SSTK + LB | 0.12395 | 0.0714 | 0.0821 |
| **MSTK 2** | **MSTK 1 + year** | **0.12387** | **0.0717** | **0.0824** |
| MSTK3 | MSTK 2 + mon | 0.12391 | 0.0719 | 0.0827 |
| MSTK4 | MSTK3 + vessel | 0.12397 | 0.0721 | 0.0829 |
| MSTK5 | MSTK4 + setsize | 0.12400 | 0.0721 | 0.0829 |
| GAM3 | GAM2 + setsize | 0.11895 | 0.0753 | 0.0864 |
| GAM2 | GAM1 + vessel | 0.11878 | 0.0752 | 0.0863 |
| **GAM1** | **GAM0 + LB** | **0.11851** | **0.0725** | **0.0832** |
| GAM0 | 1 | 0.01610 | 0.0069 | 0.0082 |
| RF3 | RF2 + setsize | 0.04871 | 0.0264 | 0.0303 |
| **RF2** | **RF1 + vessel** | **0.04964** | **0.0263** | **0.0302** |
| RF1 | RF0 + LB | 0.06803 | 0.0383 | 0.0439 |
| RF0 | 1 | 0.08840 | 0.0514 | 0.0590 |

SKJ on associated school

| Name | Model | RMSE | MAE | CVMAE |
|---|---|---|---|---|
| SSTK | 1 | 0.1661 | 0.1341 | 0.2273 |
| MSTK 1 | SSTK + LB | 0.1584 | 0.1271 | 0.2154 |
| MSTK 2 | MSTK 1 + year | 0.1559 | 0.1253 | 0.2123 |
| MSTK3 | MSTK2 + set size | 0.1548 | 0.1242 | 0.2104 |
| **MSTK4** | **MSTK 3 + vessel** | **0.1547** | **0.1238** | **0.2097** |
| MSTK5 | MSTK 4 + mon | 0.1552 | 0.1240 | 0.2101 |
| **GAM3** | **GAM2 + setsize** | **0.1512** | **0.1188** | **0.2013** |
| GAM2 | GAM1 + vessel | 0.1520 | 0.1197 | 0.2028 |
| GAM1 | GAM0 + LB | 0.1526 | 0.1203 | 0.2038 |
| GAM0 | 1 | 0.1607 | 0.1261 | 0.2136 |
| **RF3** | **RF2 + setsize** | **0.0623** | **0.0492** | **0.0833** |
| RF2 | RF1 + vessel | 0.0633 | 0.0494 | 0.0837 |
| RF1 | RF0 + LB | 0.0867 | 0.0700 | 0.1185 |
| RF0 | 1 | 0.0999 | 0.0808 | 0.1369 |

SKJ on free school

| Name | Model | RMSE | MAE | CVMAE |
|---|---|---|---|---|
| SSTK | 1 | 0.2448 | 0.1965 | 0.4157 |
| MSTK 1 | SSTK + LB | 0.2032 | 0.3424 | 0.0199 |
| MSTK 2 | MSTK 1 + year | 0.1916 | 0.1506 | 0.3194 |
| **MSTK3** | **MSTK 2 + mon** | **0.1877** | **0.1431** | **0.2966** |
| MSTK4 | MSTK3 + setsize | 0.1879 | 0.1473 | 0.2986 |
| MSTK5 | MSTK4 + vessel | 0.1898 | 0.1480 | 0.3000 |
| **GAM3** | **GAM2 + vessel** | **0.1776** | **0.1302** | **0.2634** |
| GAM2 | GAM1 + setsize | 0.1789 | 0.1347 | 0.2885 |
| GAM1 | GAM0 + LB | 0.1797 | 0.1347 | 0.2887 |
| GAM0 | 1 | 0.2039 | 0.1551 | 0.3315 |
| **RF3** | **RF2 + setsize** | **0.0774** | **0.0590** | **0.1258** |
| RF2 | RF1 + vessel | 0.0777 | 0.0594 | 0.1266 |
| RF1 | RF0 + LB | 0.0977 | 0.0777 | 0.1653 |
| RF0 | 1 | 0.1134 | 0.0905 | 0.1926 |

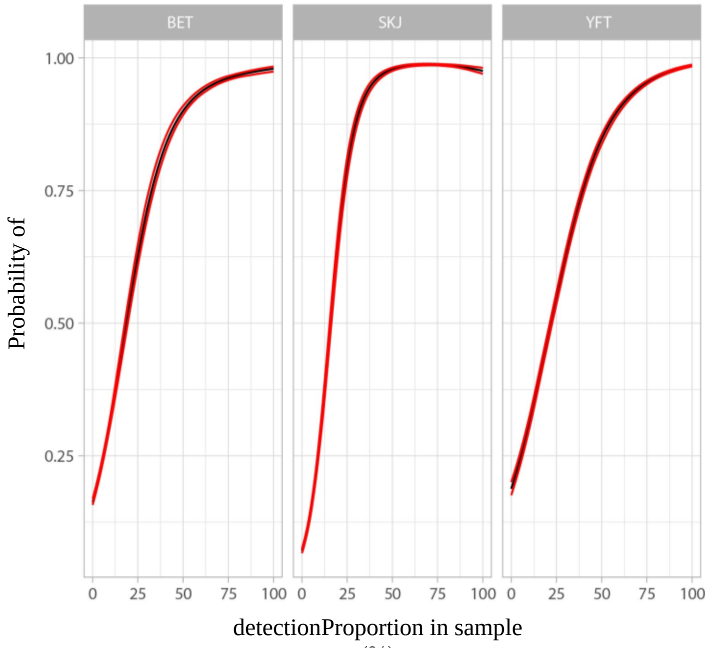


**Figure 1**: fitted value (straight line) and quantiles interval (0.025-0.975, red polygon) of the probability of detection a species in logbook against its proportion in sample by species.

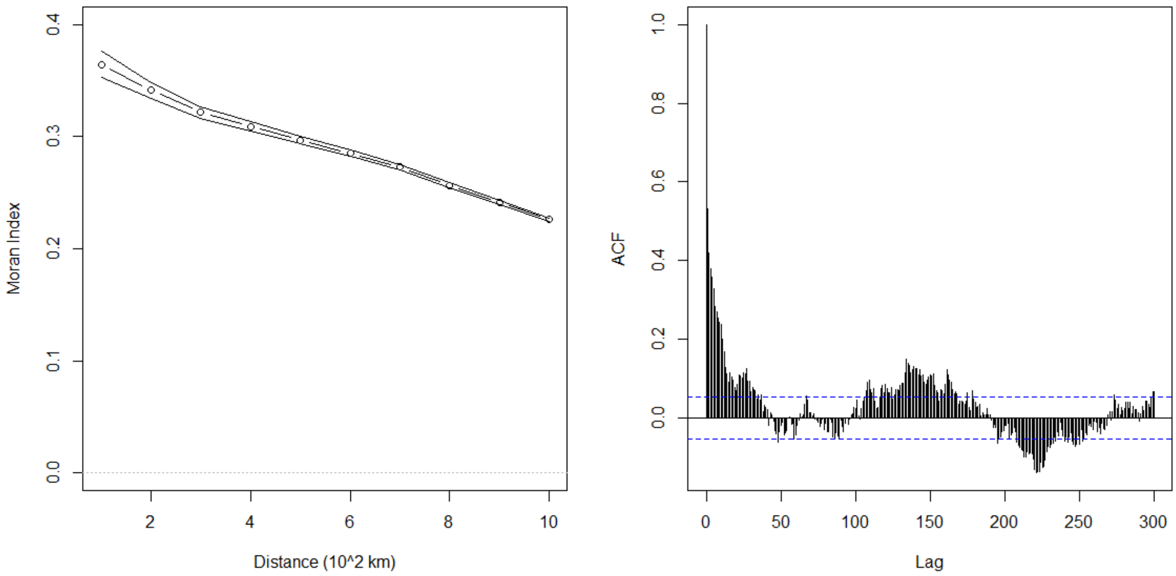


**Figure 2**: Spatial and temporal autocorrelation of YFT frequency (square root transformed) in sample on associated school calculated separately. Left panel: Mean and SD of Moran Index. Right panel: Autocorrelation Function. Dashed lines represent significant threshold for autocorrelation (p-value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

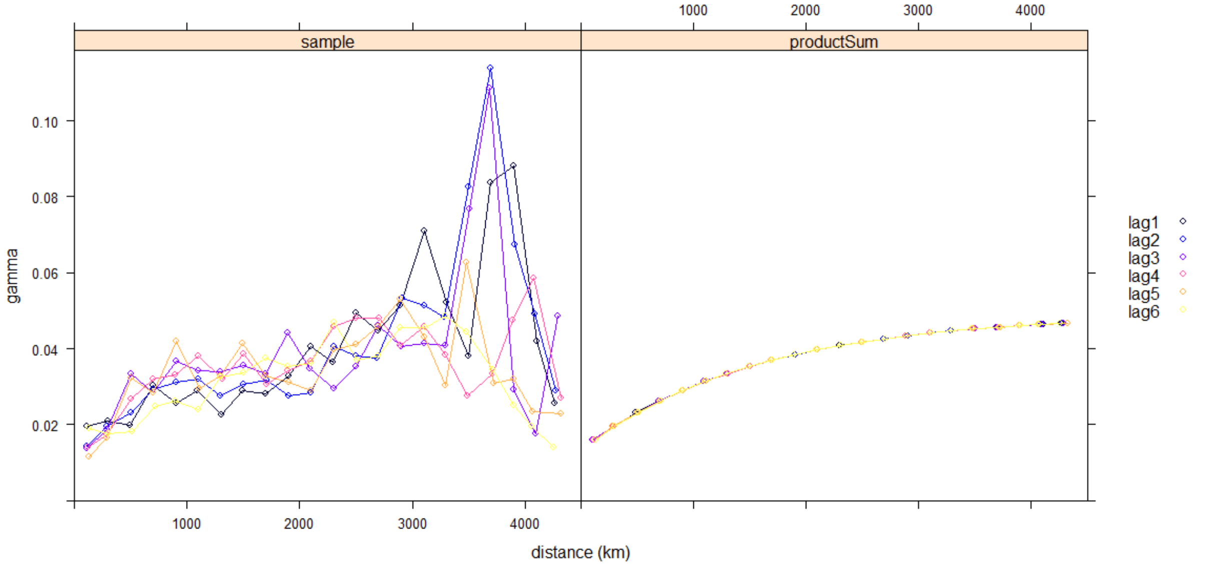


**Figure 3**: Left panel: Spatio-temporal variogram on YFT frequency in sample on associated school. Lag 1 to 6 represents 1 to 6 months' time laps. Right panel: Best Spatio-temporal variogram. (product sum metric type, MSE =1.93e-04)

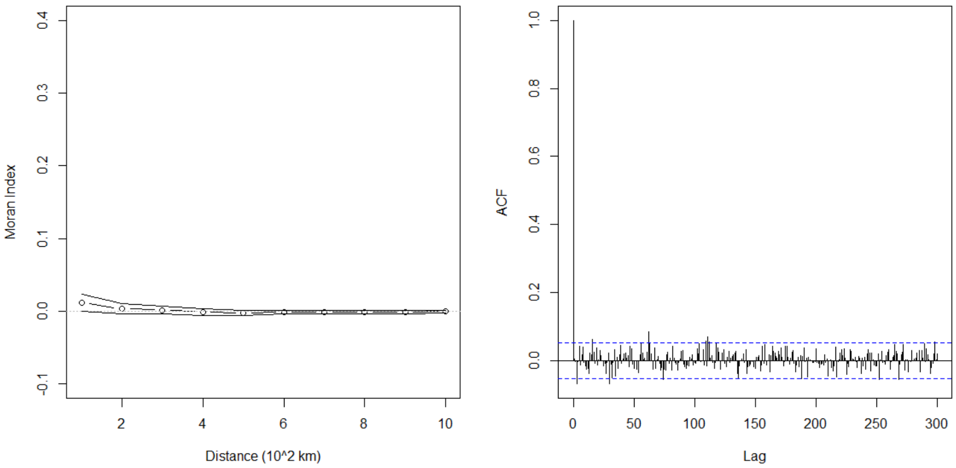


**Figure 4**: Spatial and temporal autocorrelation of residuals of the MSTK on associated school calculated separately. Left panel : Moran Index. Right panel : Autocorrelation Function. Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

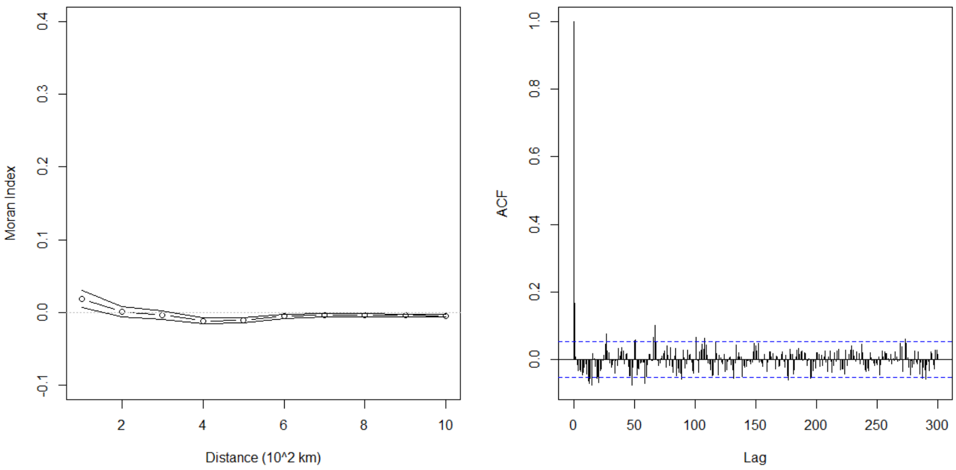


**Figure 5**: Spatial and temporal autocorrelation of residuals of GAM on associated school calculated separately. Left panel: Moran Index. Right panel: Autocorrelation Function. Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

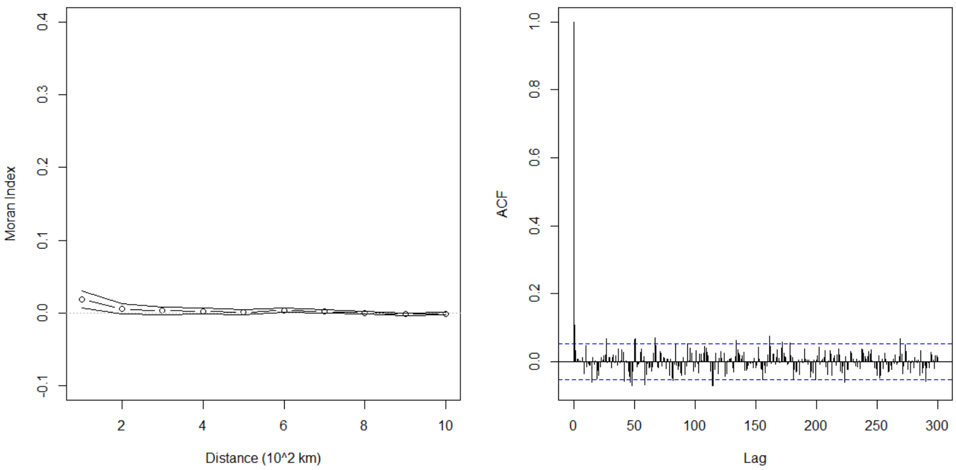


**Figure 6**: Spatial and temporal autocorrelation of residuals from best random forest model on associated school. Left panel: Moran Index. Right panel: Autocorrelation Function. Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

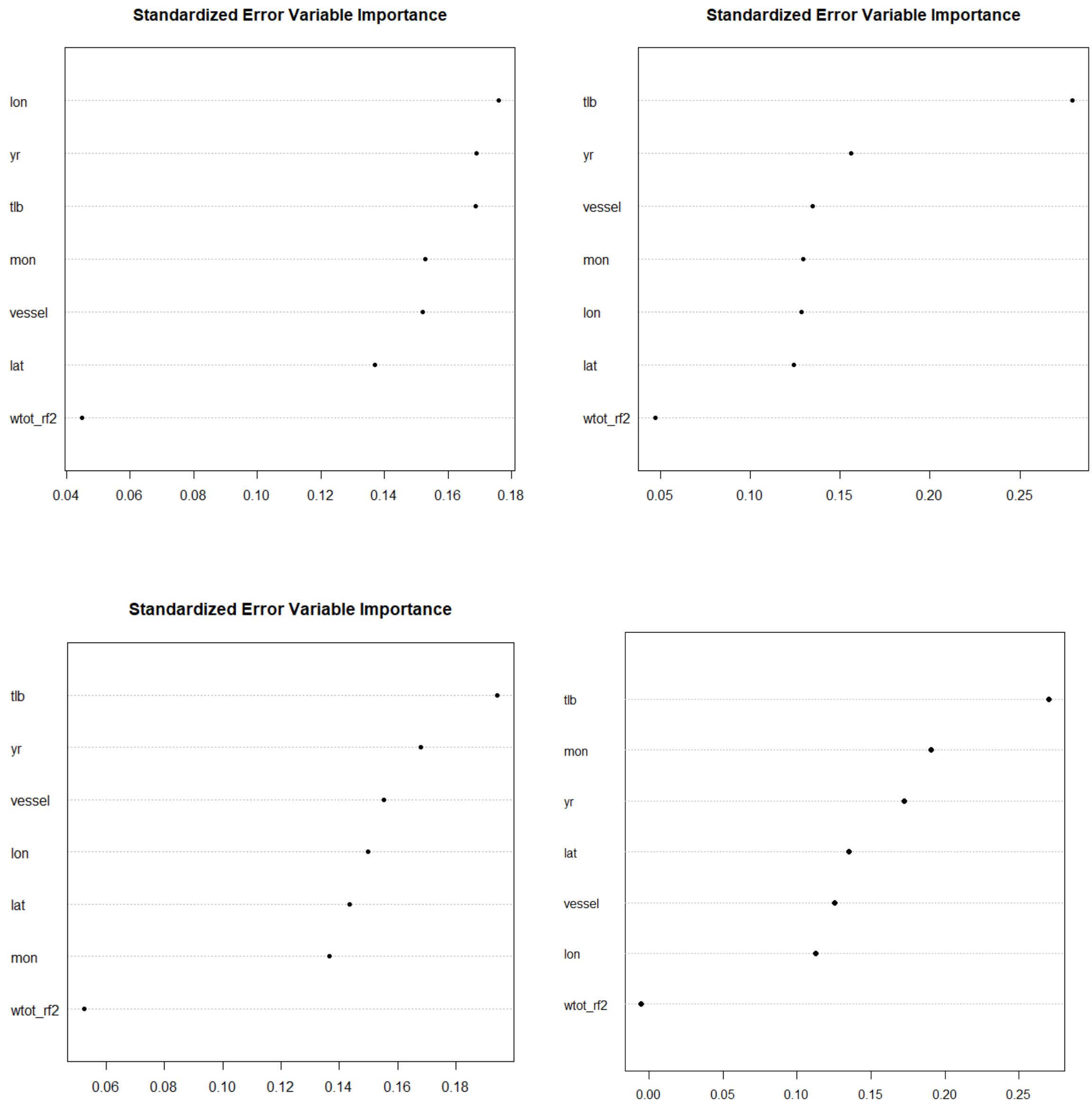


**Figure 7**: Variable importance of variables in random forest model, Top: on YFT frequency (square root transformed) in FOB and FSC, Bottom: on SKJ in FOB and FSC

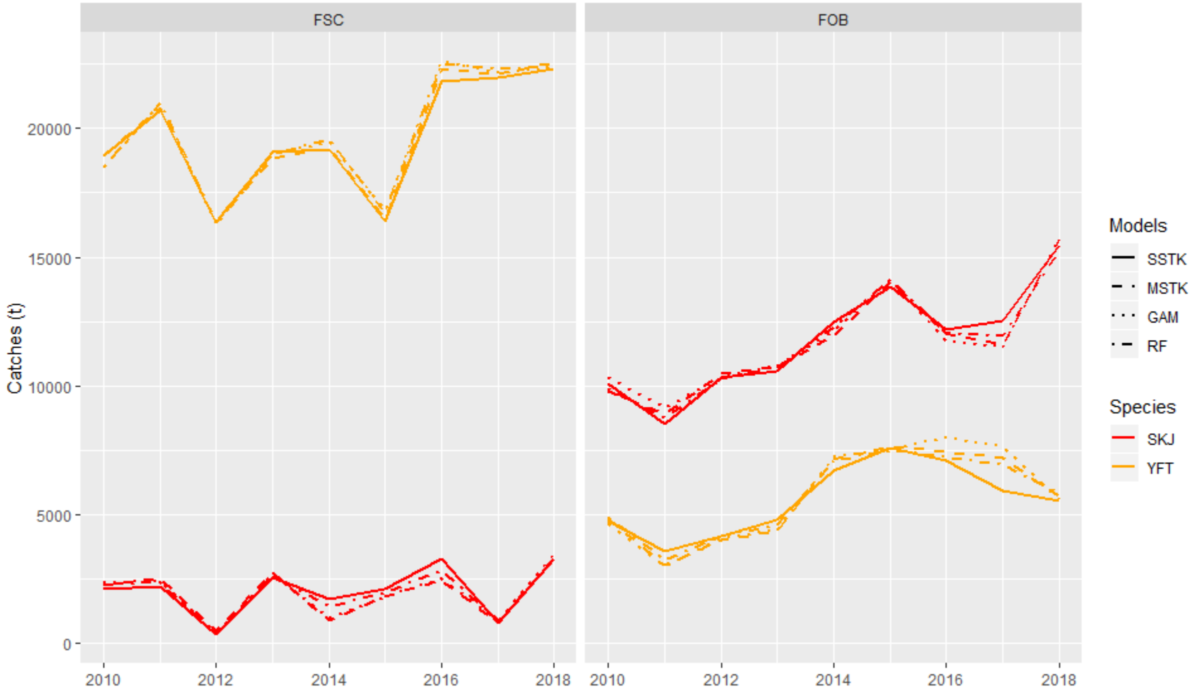


**Figure 8**: Total catches by tuna species and fishing mode according to 4 estimation methods for the 2010-2018 period.

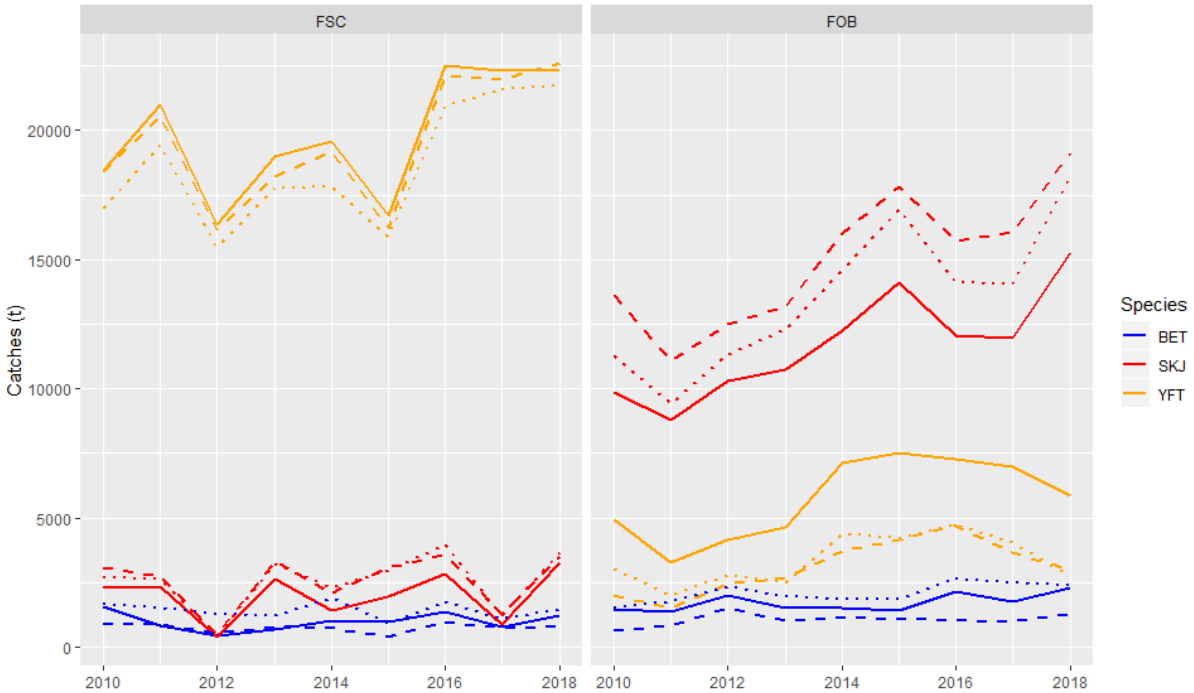


**Figure 9**: Total catches by tuna species and fishing mode according to 3 estimation methods for the 2010-2018 period. Logbook declaration: dashed line, T3f: dotted line and RF: solid line.

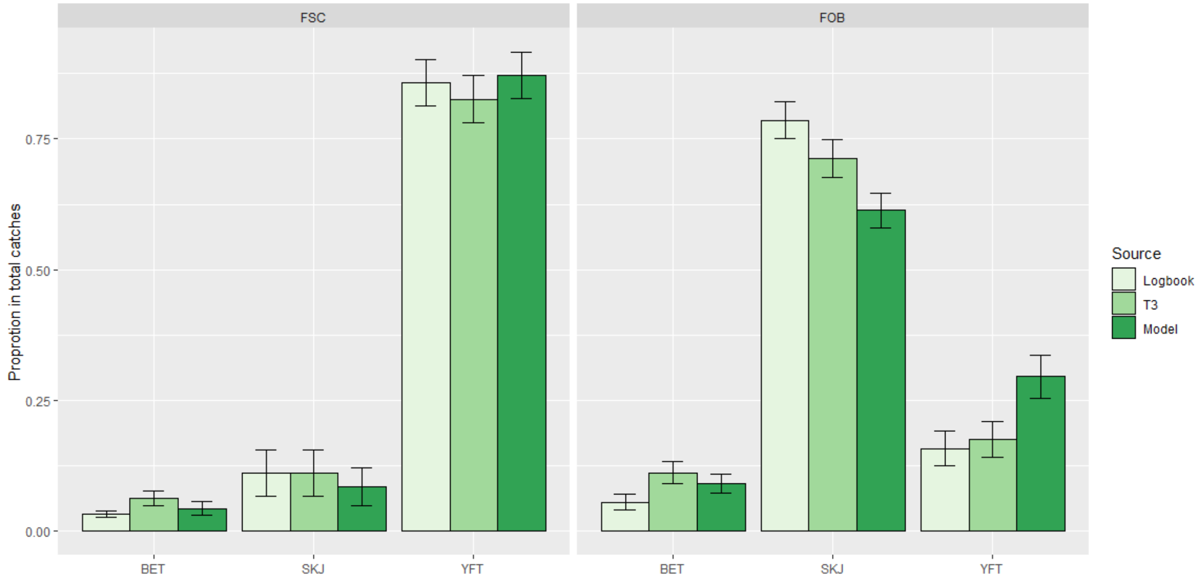


**Figure 10**: Mean ± SD of proportion of total catches by tuna species and fishing mode according to 3 estimation methods for the 2010-2018 period.

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

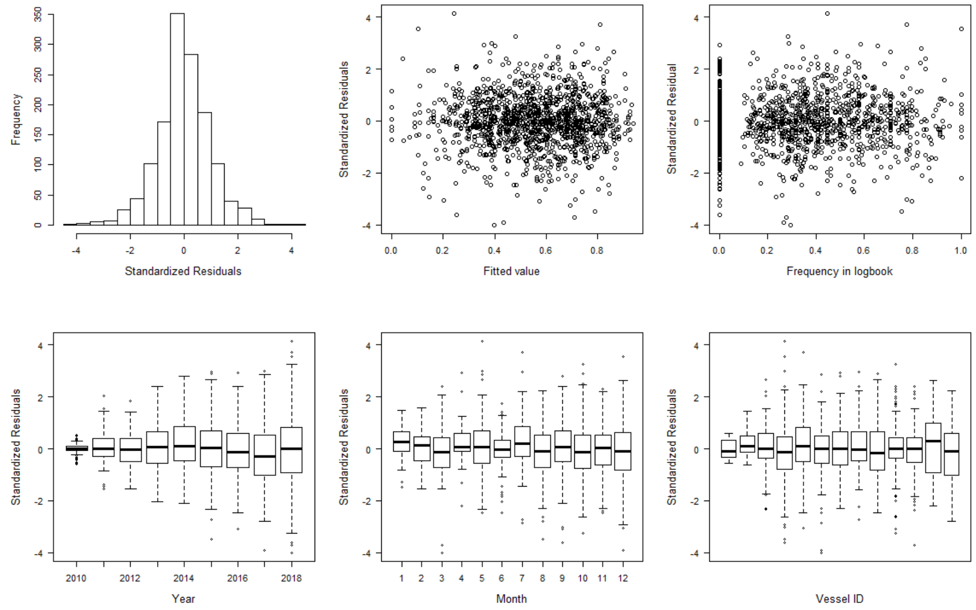


Figure A1-1: Model diagnostic of MSTK on YFT in FOB

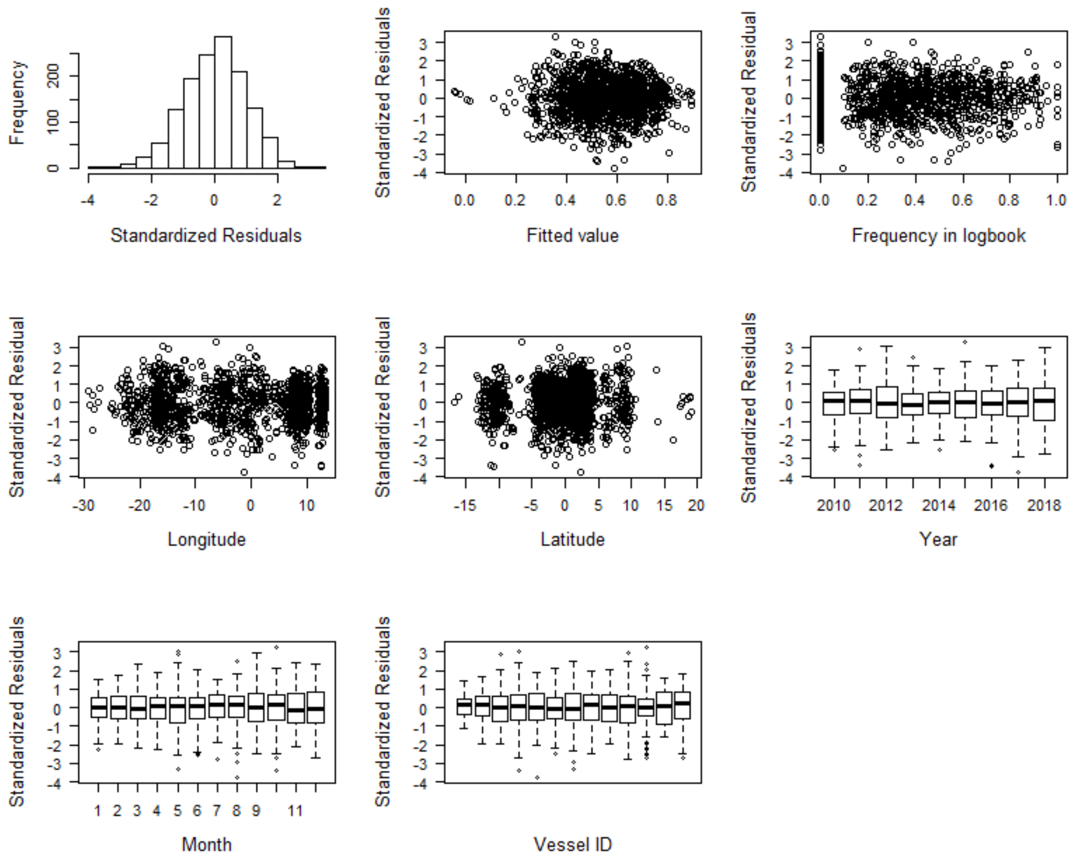


Figure A1-2: Model diagnostic of GAM on YFT in FOB

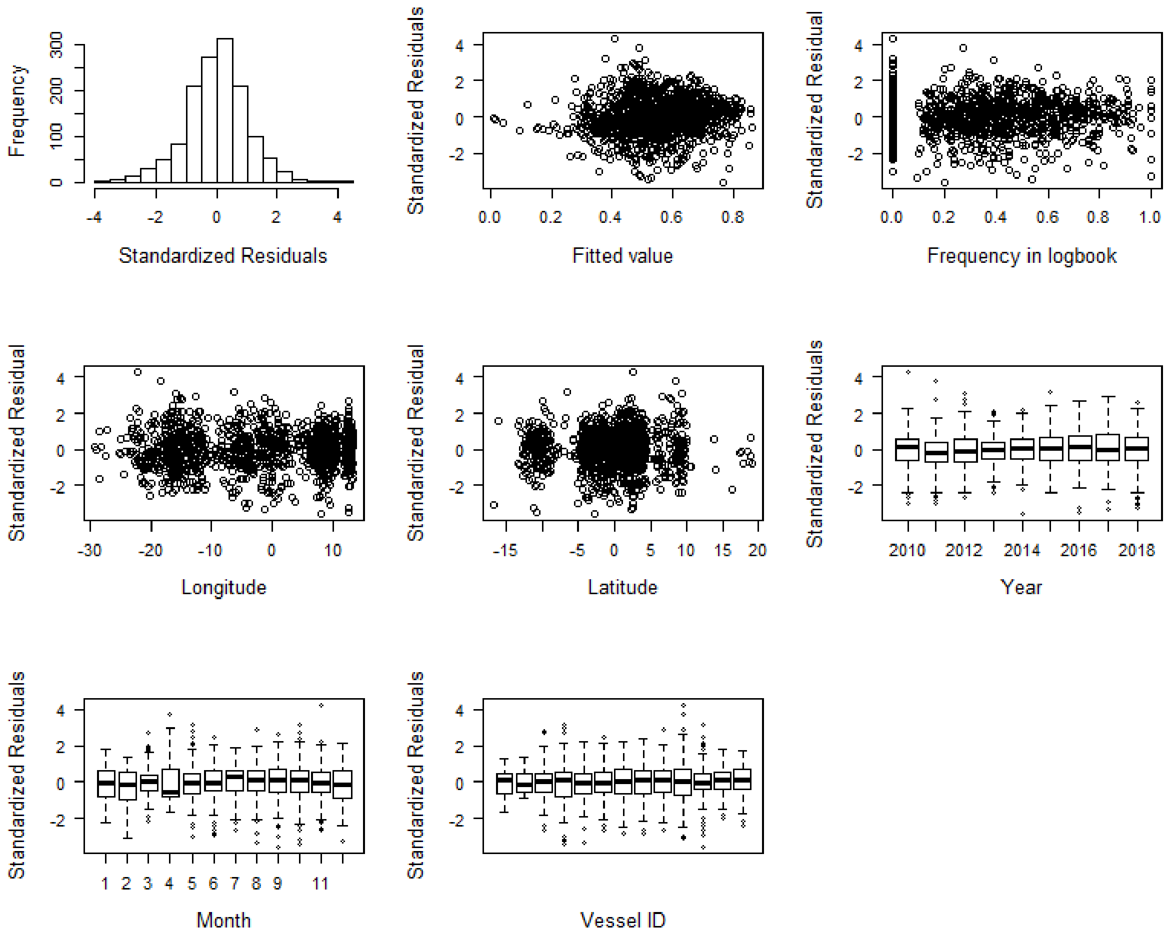


Figure A1-3: Model diagnostic of RF on YFT in FOB

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

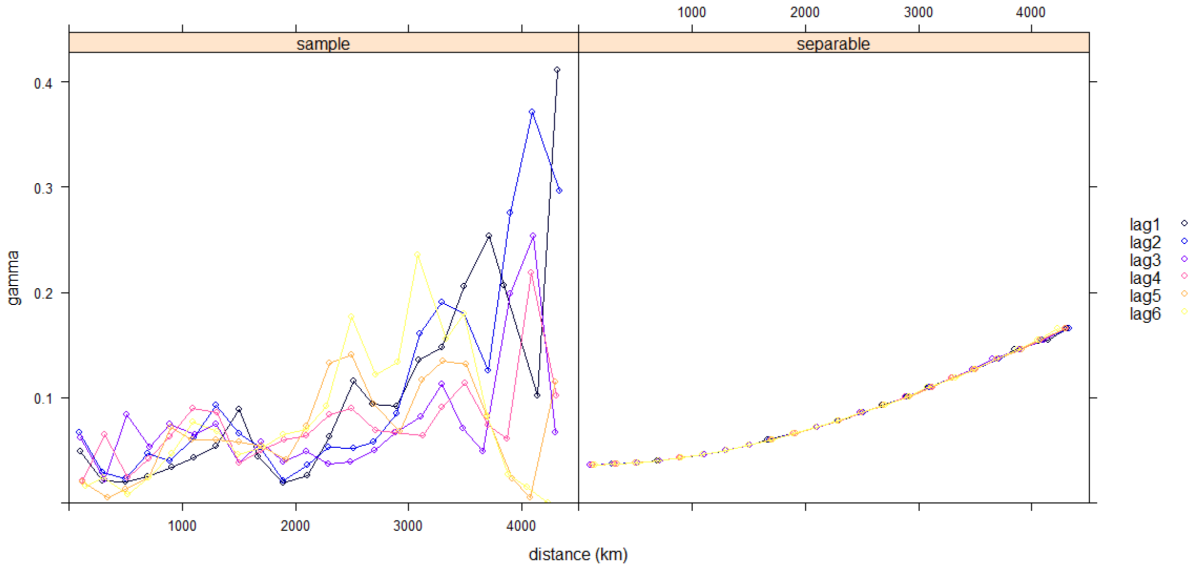


Figure A2-1: Left panel: Spatio-temporal variogram on YFT frequency in sample on free school. Lag 1 to 6 represents 1 to 6 months' time laps. Right panel: Best Spatio-temporal variogram. (separable sum type, MSE =3.22e-03)

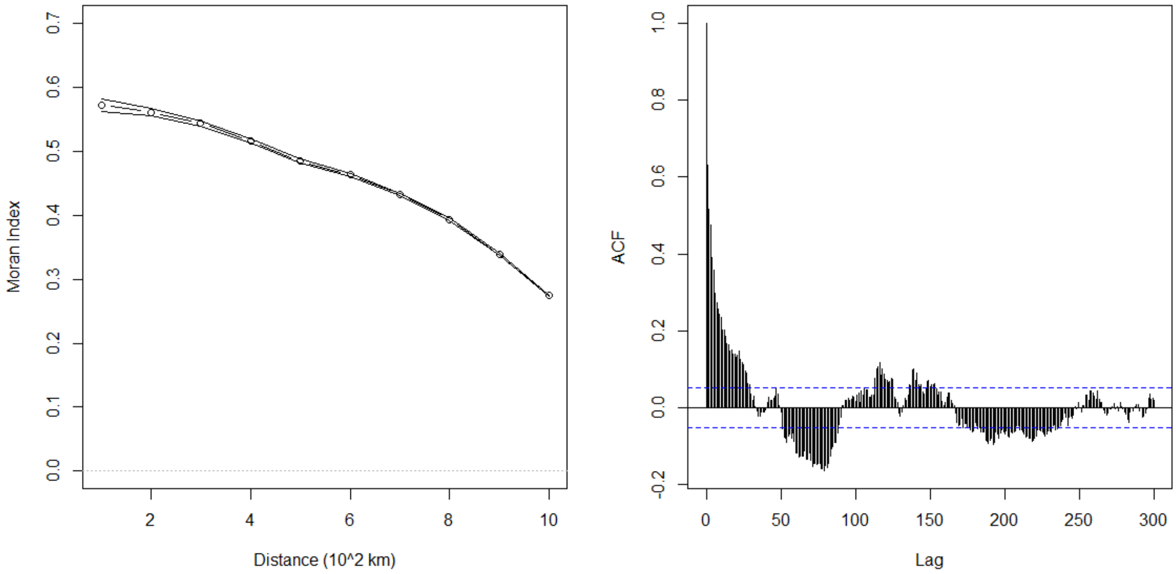


Figure A2-2: Spatial and temporal autocorrelation of YFT frequency in samples on free school calculated separately. Left panel: Mean and SD of Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

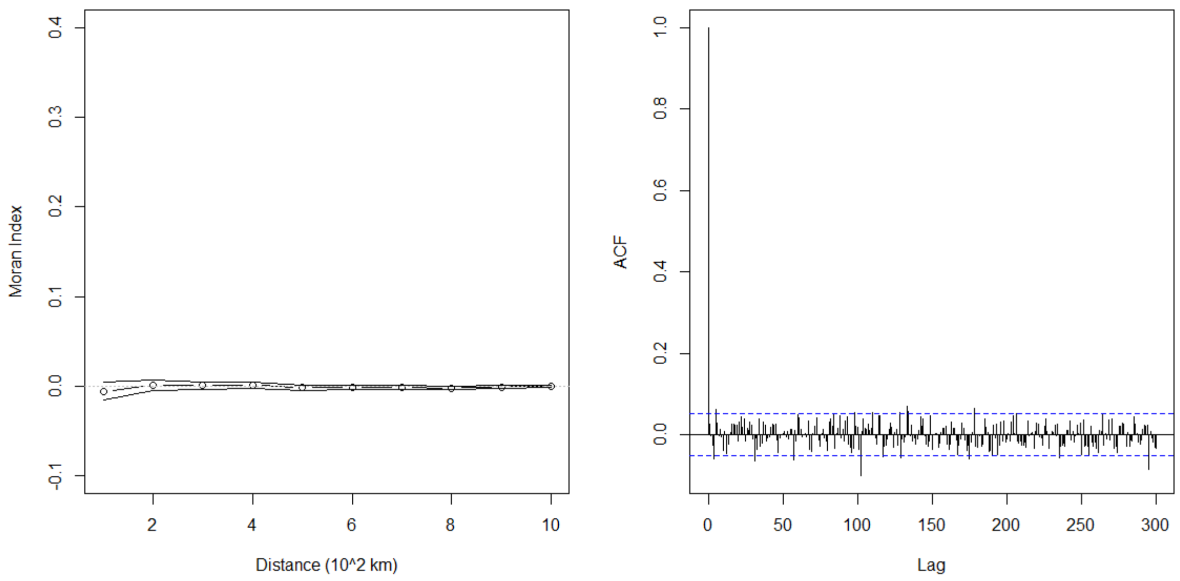


Figure A2-3: Spatial and temporal autocorrelation of residuals of the MSTK on associated school calculated separately. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

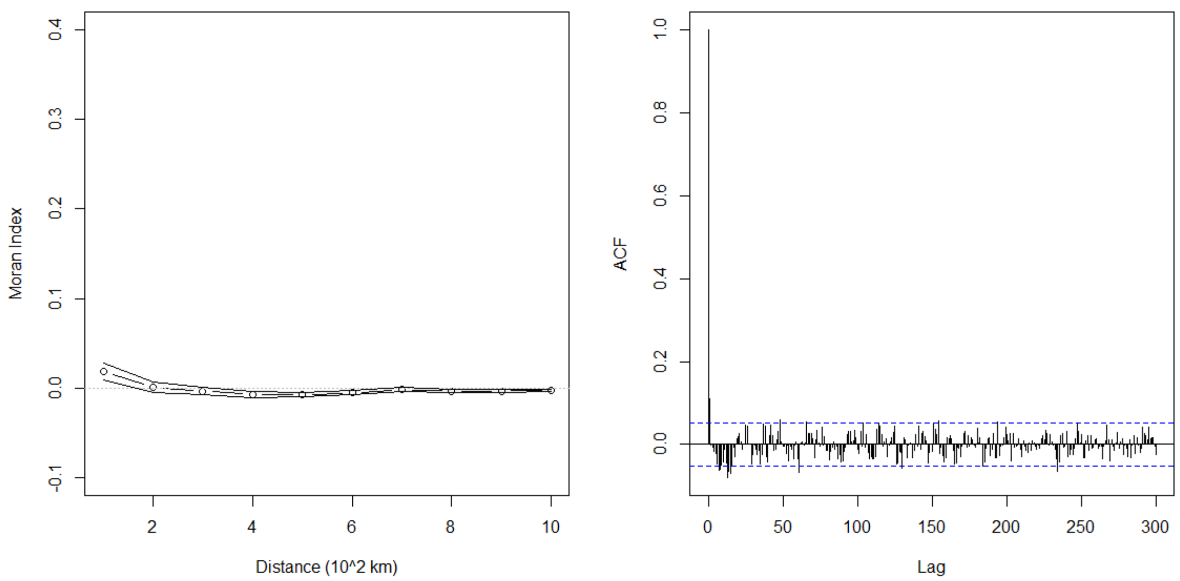


Figure A2-4: Spatial and temporal autocorrelation of residuals of GAM on free school calculated separately. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

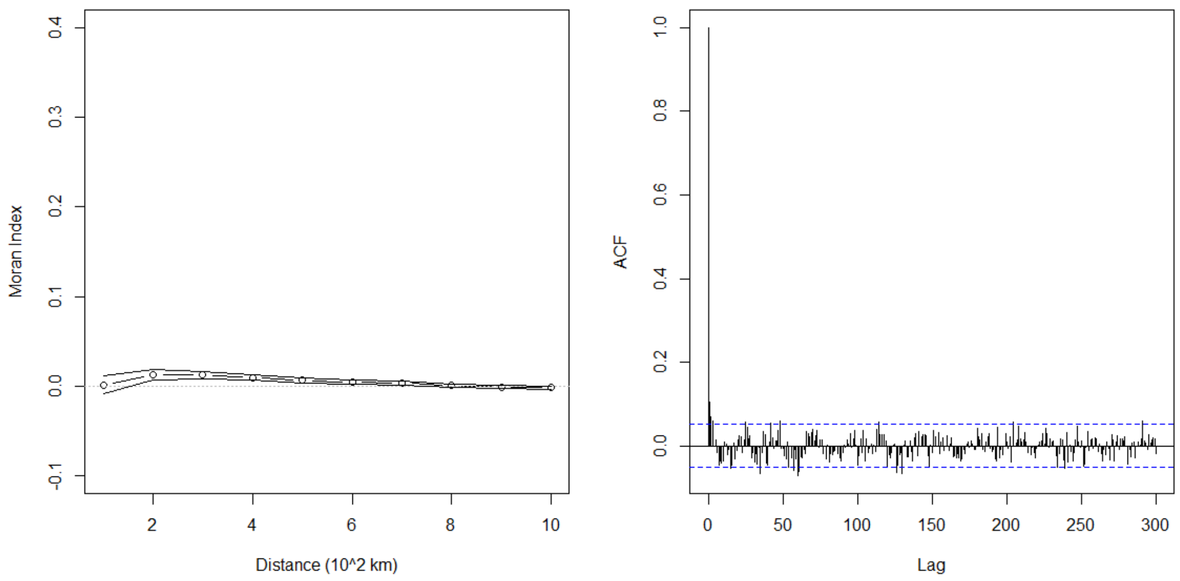


Figure A2-5: Spatial and temporal autocorrelation of residuals from best random forest model on free school. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

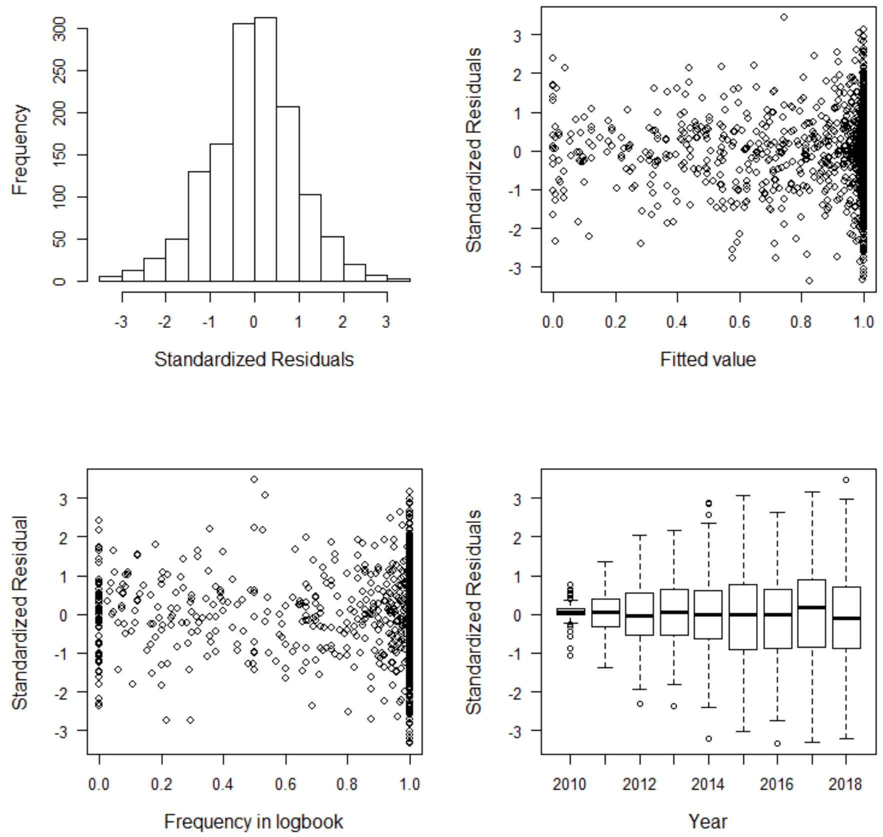


Figure A2-6: Model diagnostic of MSTK on YFT in FSC

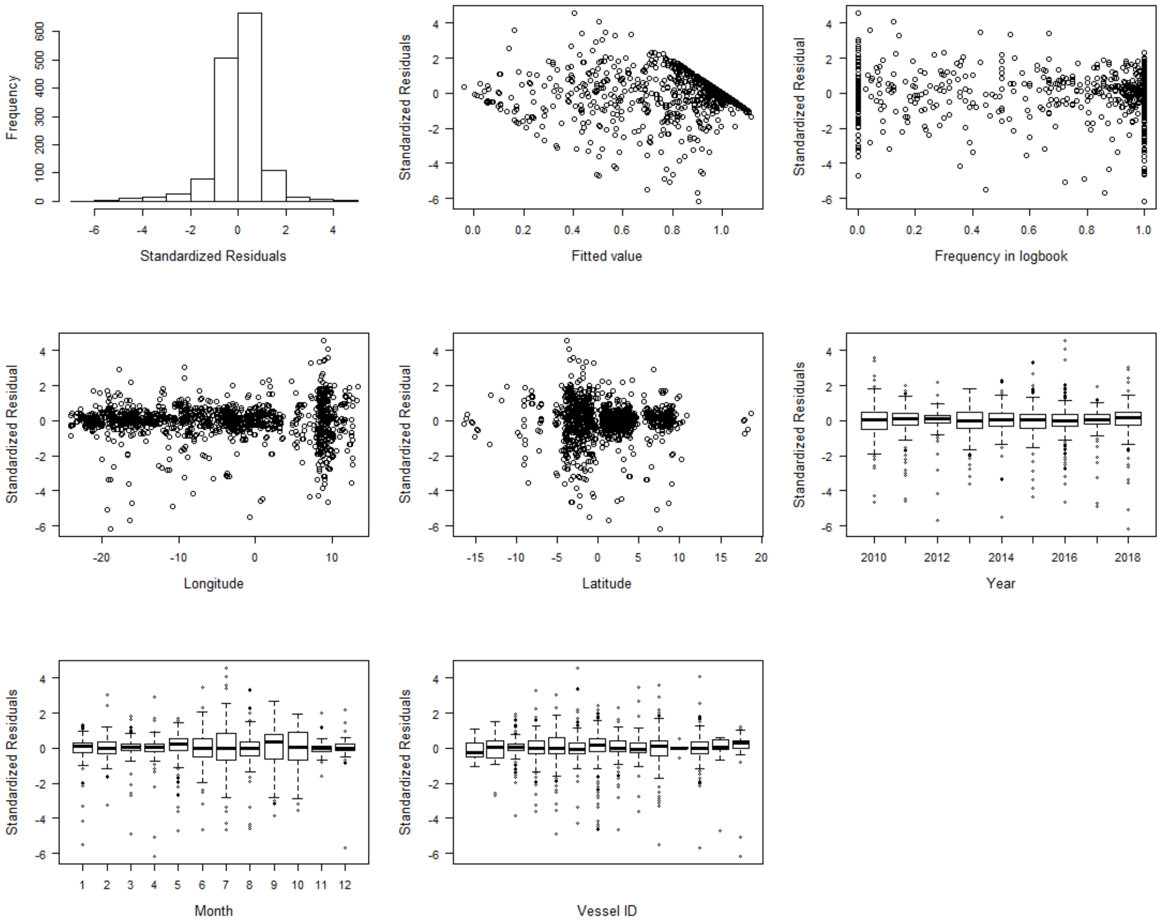


Figure A2-7: Model diagnostic of GAM on YFT in FSC.

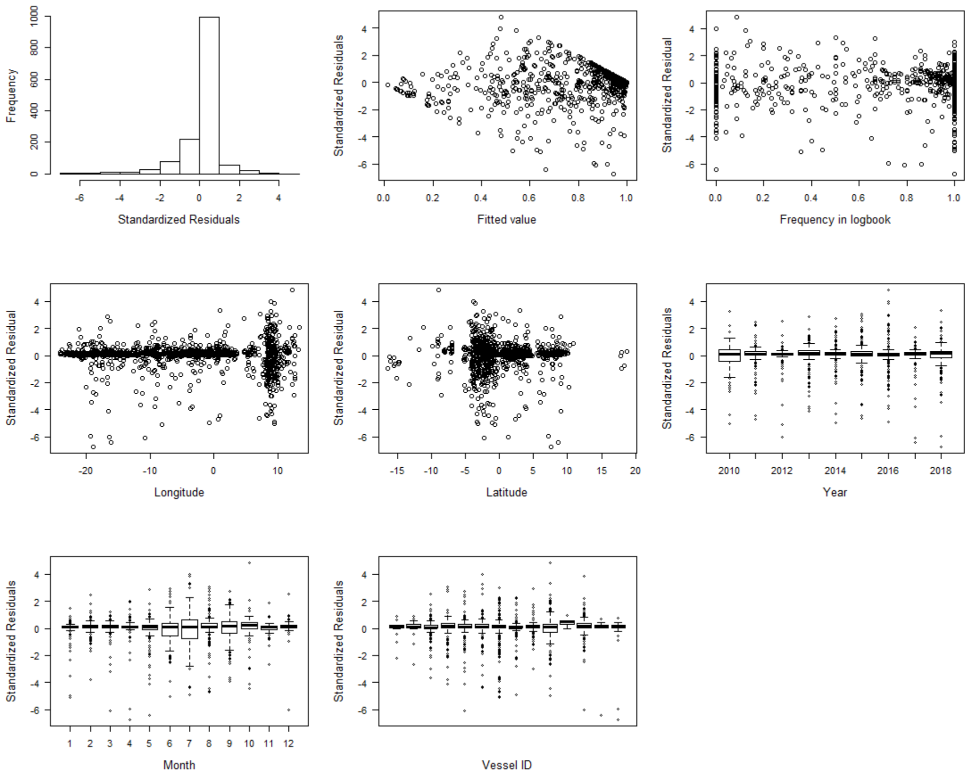


Figure A2-8: Model diagnostic of RF on YFT in FSC.

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

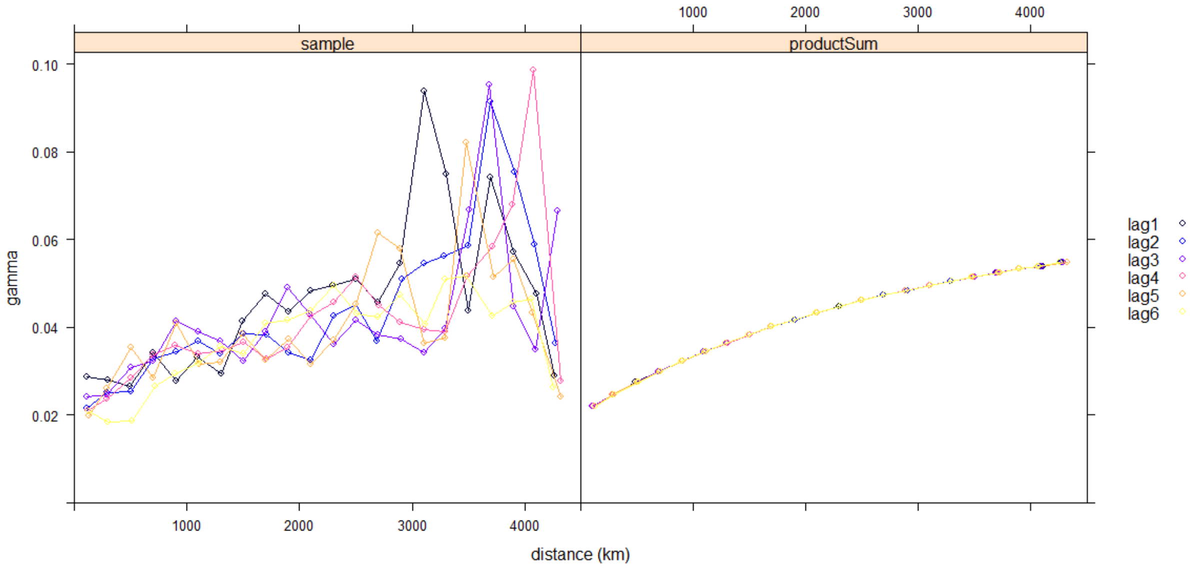


Figure A3-1: Left panel: Spatio-temporal variogram on SKJ frequency in sample on associated school. Lag 1 to 6 represents 1 to 6 months' time laps. Right panel: Fit of the best Spatio-temporal variogram model. (product sum metric type, MSE =1.39e-04).

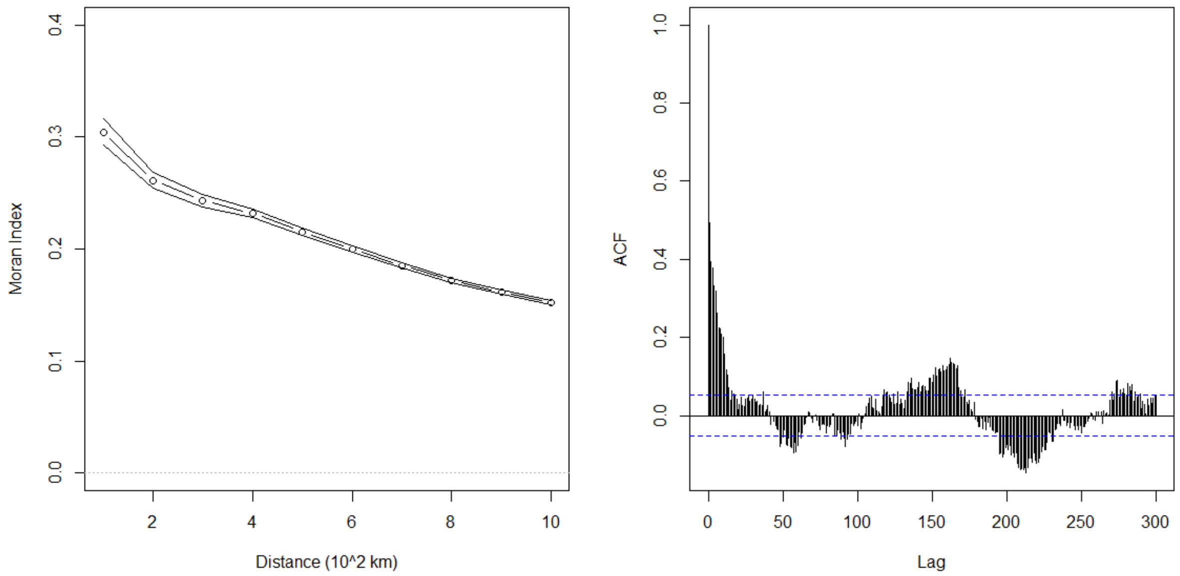


Figure A3-2: Spatial and temporal autocorrelation of SKJ frequency (square root transformed) in sample on associated school calculated separately. Left panel: Mean and SD of Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation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

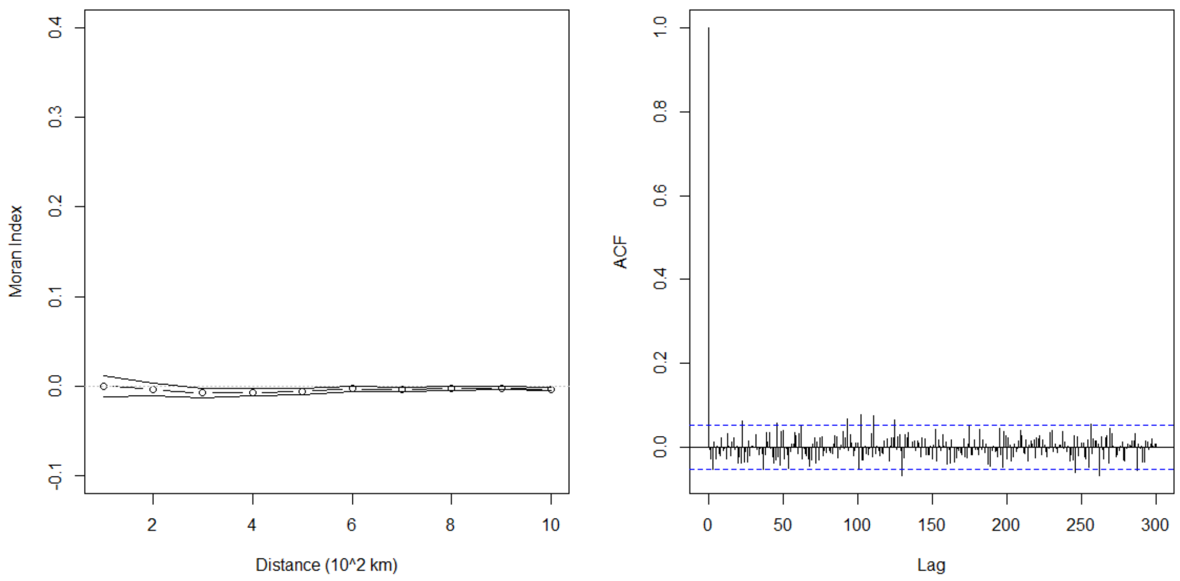


Figure A3-3: Spatial and temporal autocorrelation of residuals of the MSTK on SKJ in associated school calculated separately. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

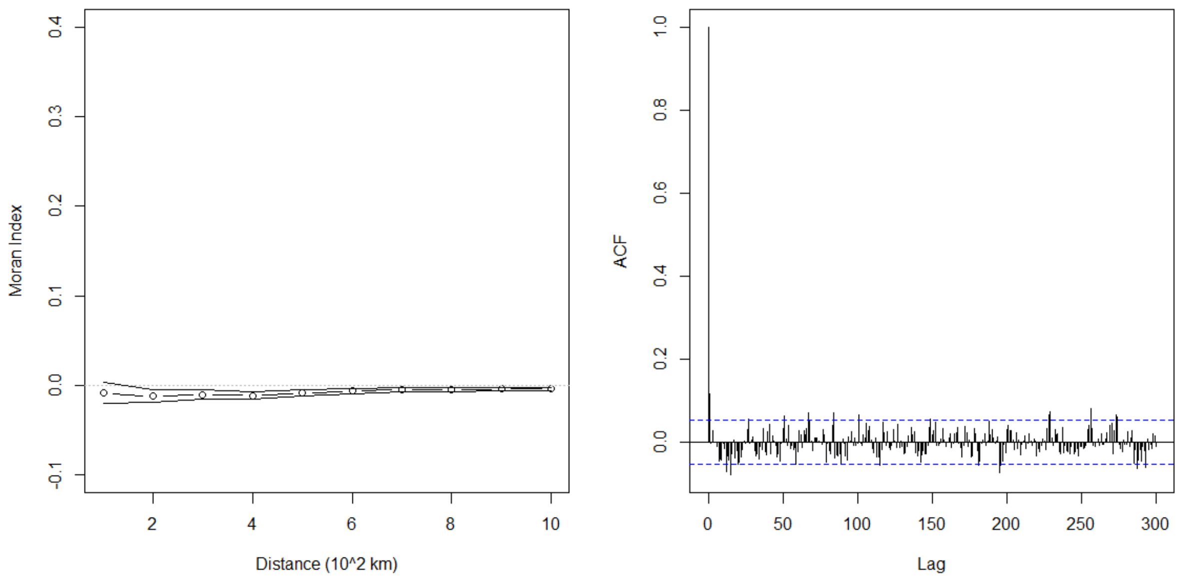


Figure A3-4: Spatial and temporal autocorrelation of residuals of GAM on associated school calculated separately. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

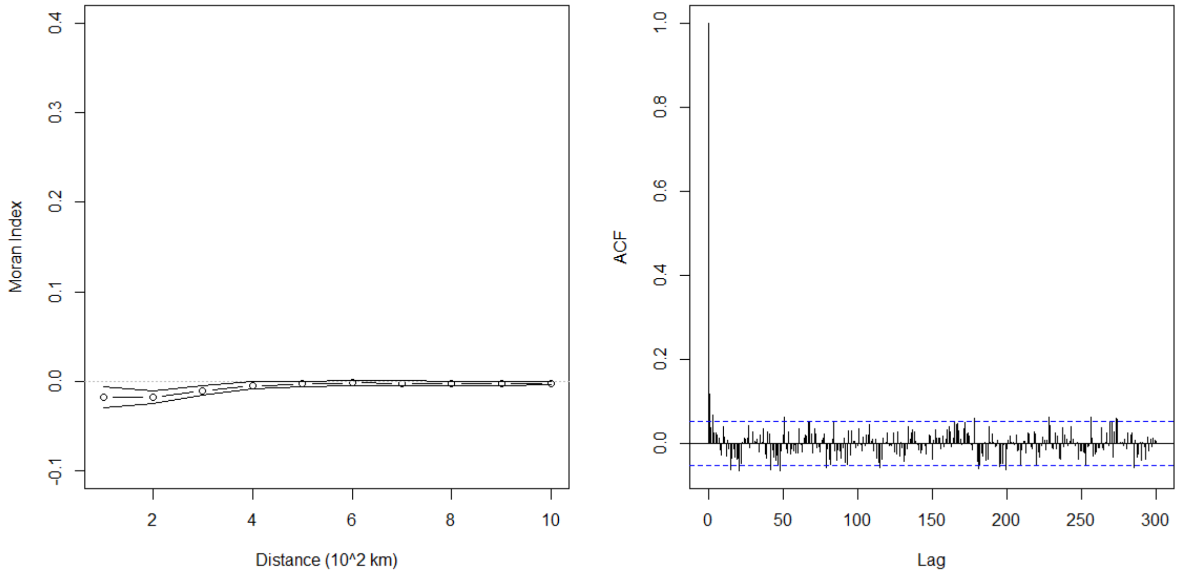


Figure A3-5: Spatial and temporal autocorrelation of residuals from best random forest model on associated school. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

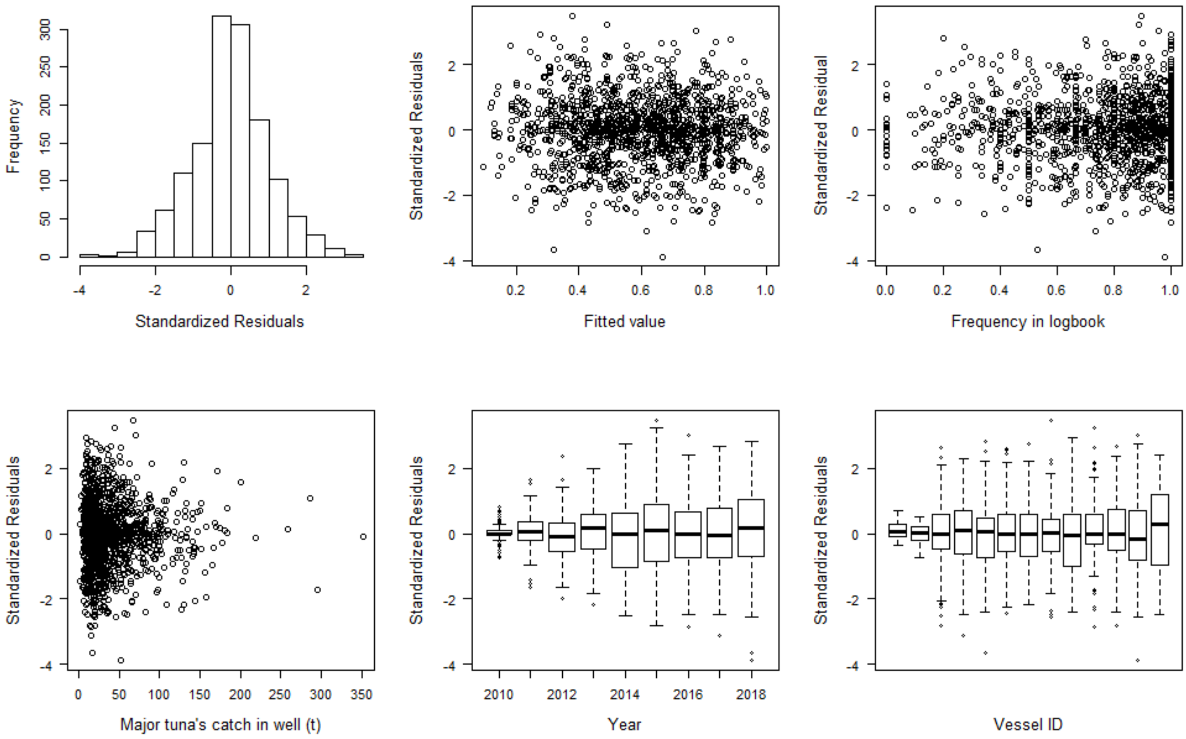


Figure A3-6: Model diagnostic of MSTK on SKJ in FOB

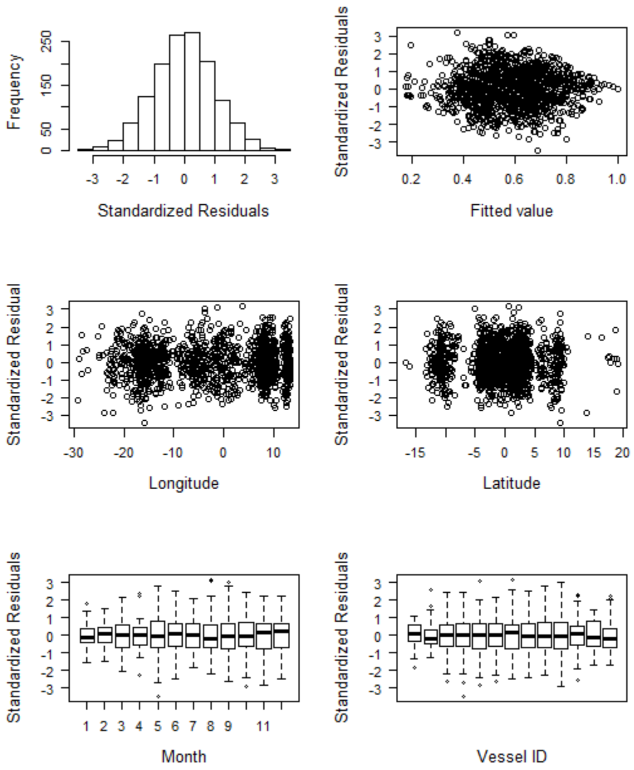


Figure A3-7: Model diagnostic of GAM on SKJ in FOB.

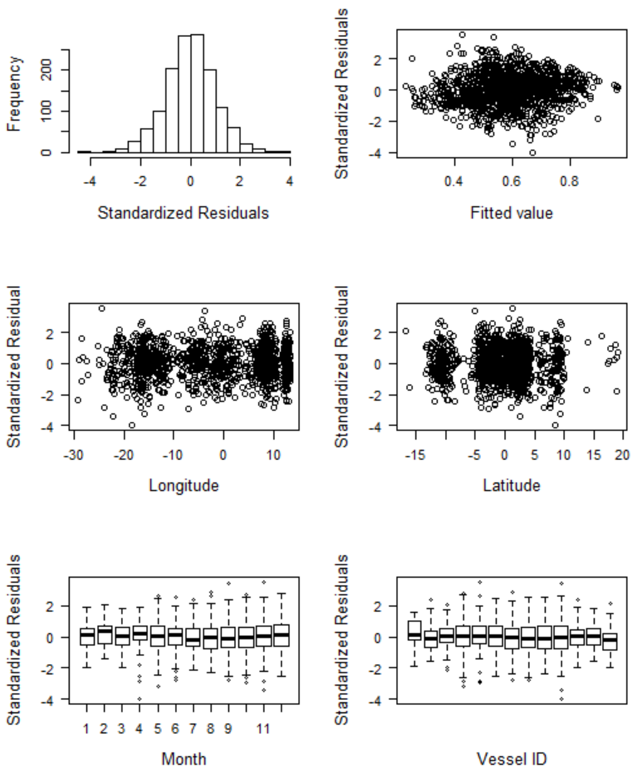


Figure A3-8: Model diagnostic of RF on SKJ in FOB.

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

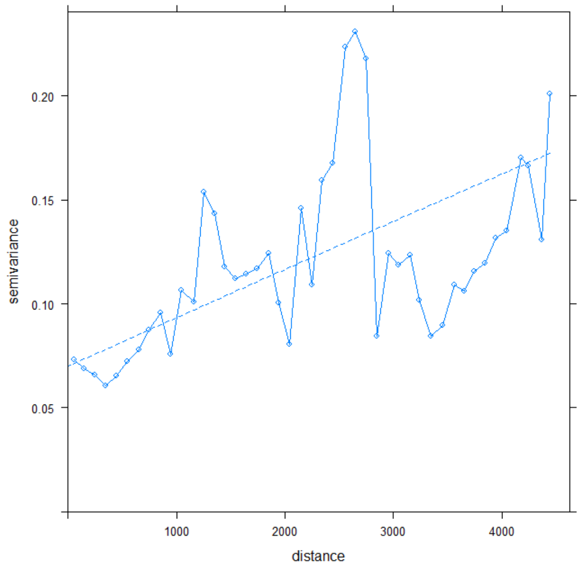


Figure A4-1: Variogram and the fitted model of SKJ frequency in sample on free school.

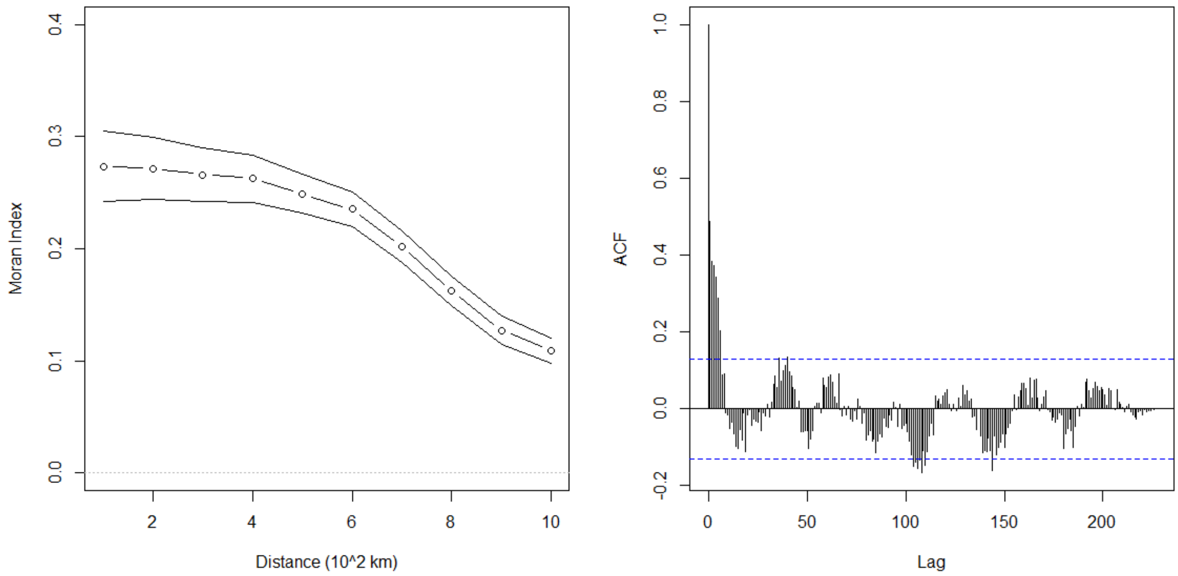


Figure A4-2: Spatial and temporal autocorrelation of SKJ frequency in sample on free school calculated separately. Left panel: Mean and SD of Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation ($p$-value $< 0.05$).

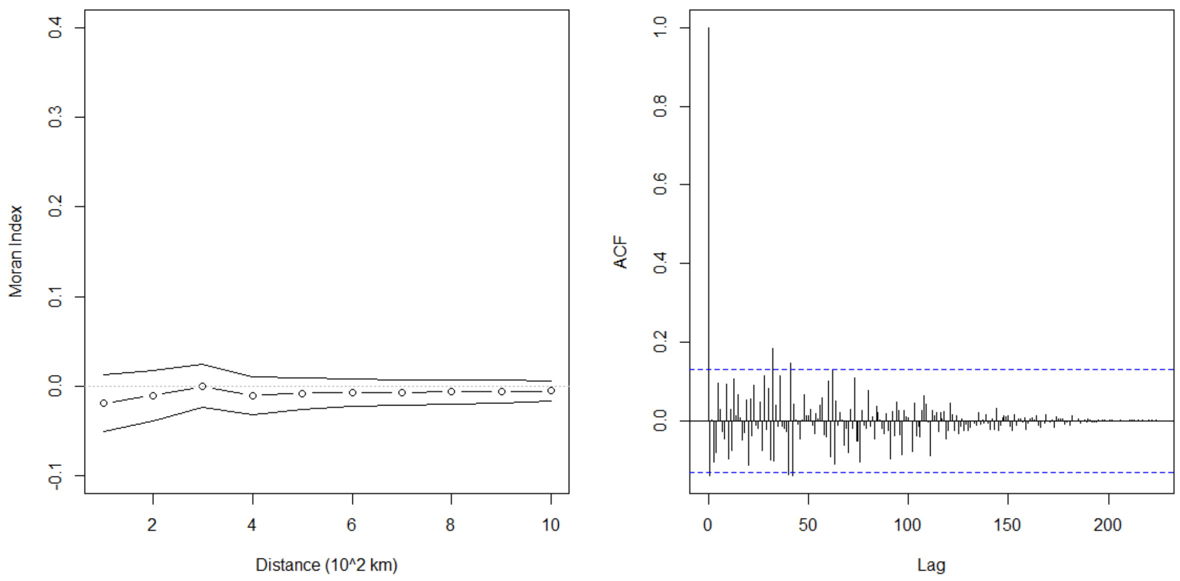


Figure A4-3: Spatial and temporal autocorrelation of residuals of the MSTK on SKJ in free school calculated sets. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

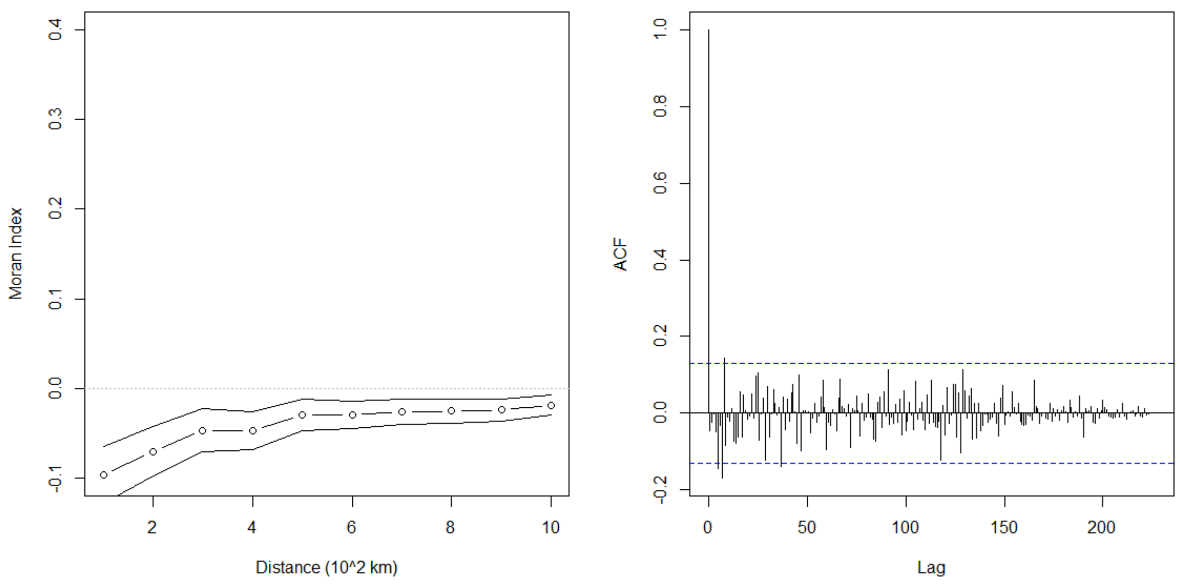


Figure A4-4: Spatial and temporal autocorrelation of residuals of GAM on associated school calculated separately. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

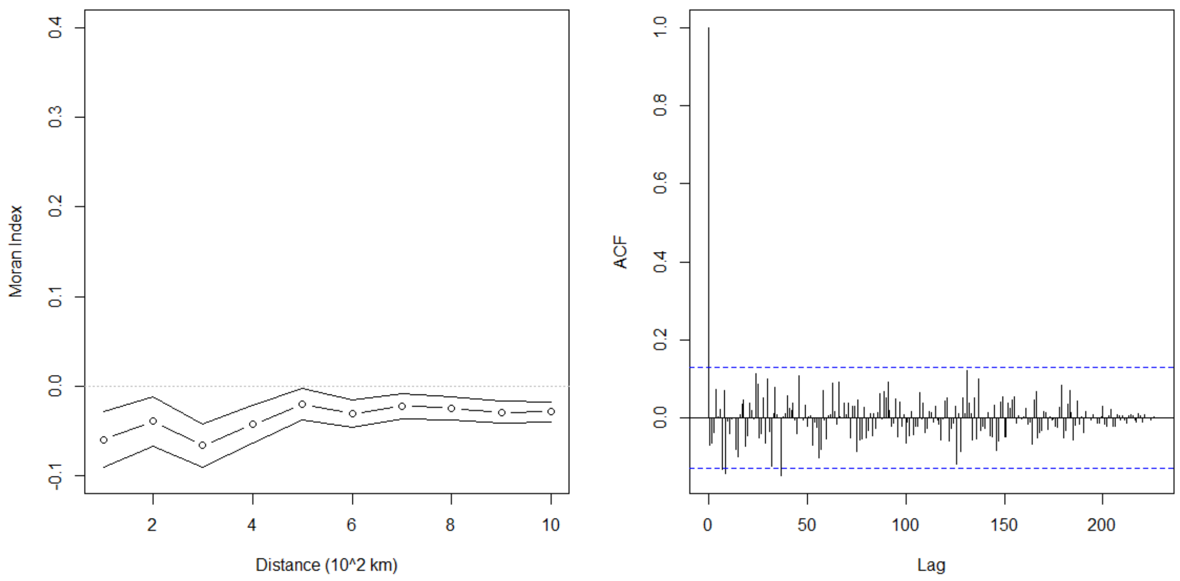


Figure A4-5: Spatial and temporal autocorrelation of residuals from best random forest model on associated school. Left panel: Moran Index. Right panel: Autocorrelation Function (with day lag). Dashed lines represent significant threshold for autocorrelation (p-value < 0.05).

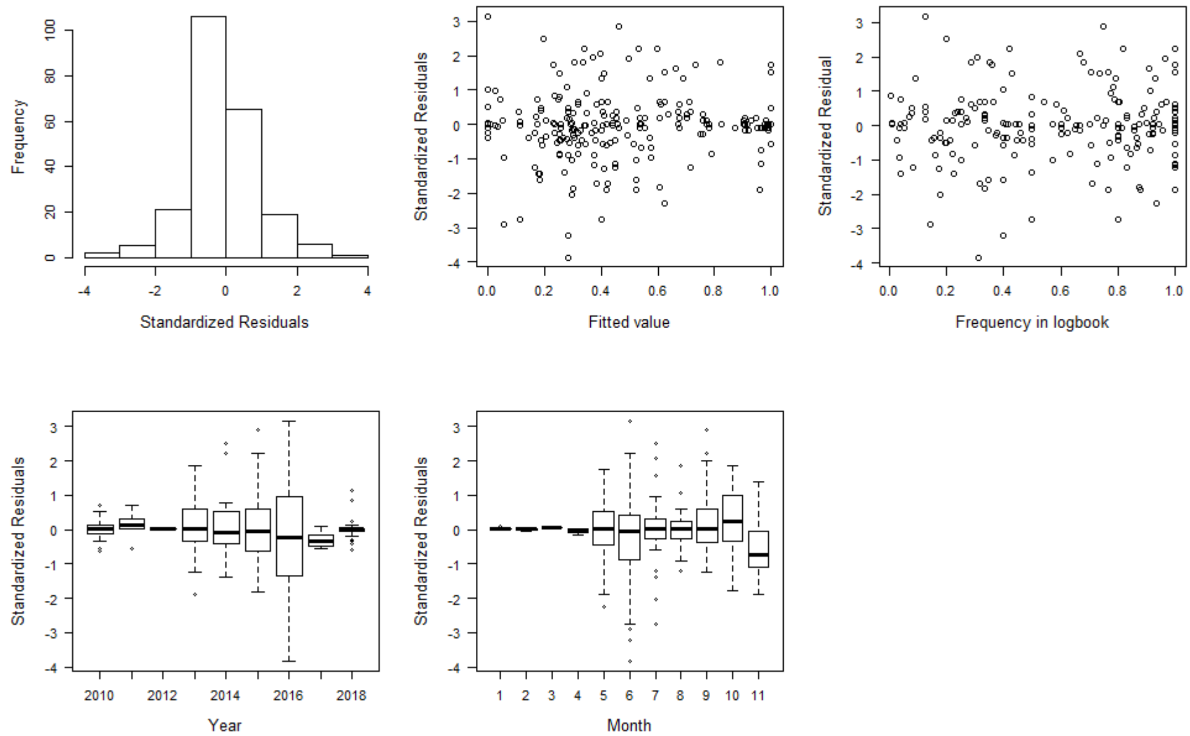


Figure A4-6: Model diagnostic of MSTK on SKJ in FSC

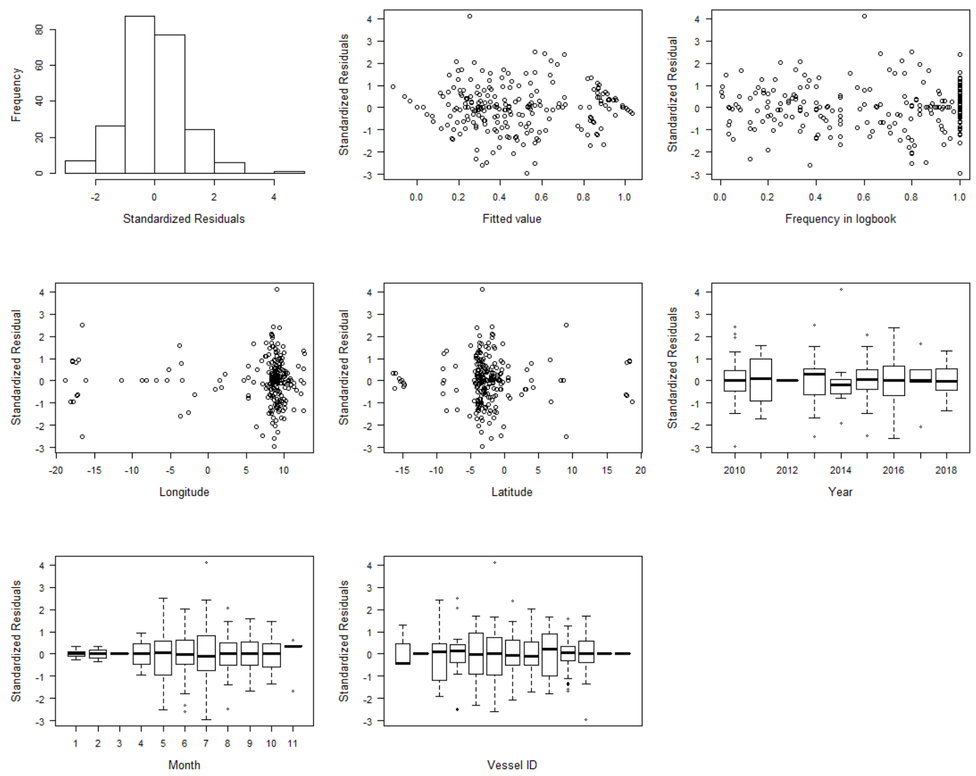


Figure A4-7: Model diagnostic of GAM on SKJ in FSC

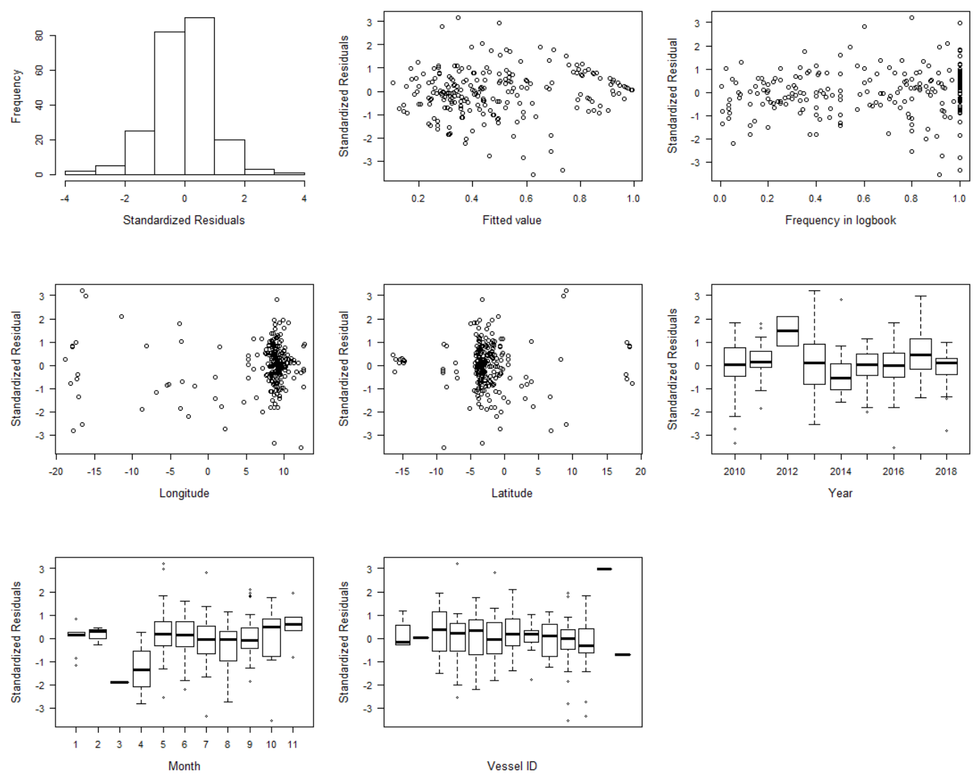


Figure A4-8: Model diagnostic of RF on SKJ in FSC