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**DEVELOPMENT AND IMPLEMENTATION OF THE INTEGRATED PORT SAMPLING PROGRAM: UPDATE**

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**SUMMARY**

This document presents an update on the Integrated Port Sampling Program (IPSP), implemented in 2026 to replace and improve the Traditional Port-Sampling Program (TPS). The IPSP collects biological data from purse-seine tropical tuna catches to support stock assessments and fisheries management.

Major improvements in the sampling protocol for fleet-level species catch estimation include randomized sampling (trips, wells, fish) to reduce bias and improve statistical reliability. The protocol allows greater flexibility and more within-well coverage for catch from floating object sets. A second protocol gathers morphometric data to update length-weight relationships for tuna and bycatch species. The port-sampling data collected flows through a structured system (upload → validation → database), with potential use of AI transcription tools.

The IPSP supports key outputs like catch composition estimates, indices of abundance, the IATTC Fisheries Status Report, and Stock Assessments. It also contributes to trip-level bigeye tuna estimates in support of the Individual Vessel Threshold management measure and expands collaboration with stakeholders (e.g., training, workshops).

**1. BACKGROUND**

Since 2000, IATTC port-sampling data collection has played a central role in the methodology used to estimate the purse-seine fleet-level species and size composition of the total catch of tropical tunas (sum of catches of yellowfin (YFT), bigeye (BET) and skipjack (SKJ) tunas) by area, month of fishing, purse-seine set type and IATTC vessel size class category. In recent years, port-sampling data collection was expanded to cover other scientific research purposes, such as trip-level BET catch estimation in support of the

Individual Vessel Threshold (IVT) management measure and the update of the morphometric relationships (length-weight) of the three tropical tuna species and prioritized bycatch species.

Scientific analyses related to the development of the sampling protocol for trip-level estimates of BET, identified several potential areas of improvement to the sampling protocol for fleet-level species catch estimation ([SAC-16 INF-J](#)). The new fleet-level sampling protocol that resulted from these analyses includes key features such as random selection of trips, wells and fish within the well.

Starting in 2026, all purse-seine port- sampling data collection activities, including the updated sampling protocol for fleet-level catch composition estimation, are being implemented by the IATTC Integrated Port Sampling Program (IPSP), proposed by the staff in document [SAC-16-05](#) and approved by the Commission in [Resolution C-25-01](#). The IPSP serves as the IATTC operational platform that implements the collection of port-sampling data, maintaining rigorous data collection aligned with scientific research and management needs, while adapting to changes in data requirements over time (Figure 1).

This document provides an update on the implementation of the IPSP since its implementation in January 2026.

## **2. DATA COLLECTED BY THE IPSP**

Starting January 2026, the IPSP is being implemented in Manta and Playas, Ecuador, and Mazatlán and Manzanillo, Mexico. Thirteen sampling technicians, along with field office staff, collect biological data during the unloading of Class-6 purse-seine vessels through the implementation of two sampling protocols, one for data to estimate fleet-level catch composition and the other for data to update morphometric relationships of the three tropical tuna species.

### **2.1. Species and size composition sampling protocol**

Samples of fish for weight, or length, and species ID, obtained during the unloading of the purse-seine fleet catch, are the basic source of data used for estimating the species and age compositions of the catch of tropical tunas. These data are necessary to obtain age-structured estimates of the populations for various purposes, primarily the integrated modeling that the staff uses to assess the status of the stocks (see [Stock Assessment Reports](#)).

Based on simulation analysis made with data collected by the Enhanced Monitoring Program (EMP) (2023-2025) and by Project [C.1.b](#) (2024), that evaluated the sampling design for the best scientific estimate of tropical tuna catch composition, improvements were made to the sampling protocol for fleet-level species and size composition of the purse-seine tropical tuna catch, previously known as Traditional Port-Sampling (TPS).

The following is a description of the three major improvements made to the TPS protocol with a description of key aspects related to the implementation of those improvements by the IPSP.

1. Minimizes the potential for bias by eliminating opportunistic data collection practices through the random selection of trips, wells and fish within the well.
  - For the IPSP protocol, trips and wells are randomly selected based on information obtained from the observer at-sea reports, which are submitted by vessels on a weekly basis.
  - Additional collaboration was requested, with a positive response from the fleet, for a last at-sea report to be sent when the vessel has made its last set and is on route to port, providing the latest information for the random selection of wells, based on information on the sets placed in each well.

- The automated tool developed by the staff for the random selection of trips, wells and fish to be sampled, makes practical sampling selection updates twice per week.
2. Allows greater flexibility in stock assessment modelling by removing the temporal and spatial sampling restrictions of the TPS protocol.
    - For a well to be a candidate for sampling, the only requirement is that the catch within the well be from the EPO, a single set type and the same year.
  3. Reduces the estimated variance on species composition estimates for the floating-object (OBJ) fishery by sampling the entire well catch of OBJ-set wells.
    - OBJ-set wells are being sampled systematically from beginning to end of the unloading, without affecting the normal unloading process of the fleet.
    - As a result, any large-scale patterns in species composition during unloading of the well catch are captured in the sample data, producing a more representative sample for the well.

In addition, a modification to the protocol for selection of fish from wells with catch from sets on tunas associated with dolphins (DEL-set wells), and wells with catch from sets on unassociated school of tuna (NOA-set wells) unloaded by flotation, has been implemented. Initially, as described in document [SAC-16 INF-J](#), a sample of fish was to be obtained from a randomly selected quarter of the well. However, following the results of trial sampling in November-December 2025, the IPSP protocol was modified because: 1) it was not possible to accurately estimate the start and end of a quarter of the well in all ports of unloading, potentially resulting in bias in the estimation, and; 2) the [External Review](#) of the sampling protocol recommended that the entire well catch be sampled to generate data for future studies on IPSP protocol improvements, particularly as regards estimation of yellowfin tuna length composition in DEL-set wells. Therefore, the IPSP protocol was changed from sampling a quarter of the well to sampling between about 90% to 100% of the well, depending on the port of unloading. Results of analysis of the 2026 IPSP data will be used to address sampling challenges, further improving the IPSP protocol. These results and any revisions to the protocol will be presented by the staff at the 2027 Scientific Advisory Committee (SAC) meeting.

With the improvements described above, between January and March of 2026 the IPSP has covered 75 trips of 57 vessels, with 131 wells sampled. A summary of the sampling coverage for all of 2026 will be presented at the 2027 SAC meeting.

## **2.2. Morphometric protocol**

During 2025, the collection of morphometric measurements to refine length-weight, length-length, and weight-weight relationships for the three tropical tuna species, and for prioritized bycatch species, was implemented in Manta, Ecuador, and Mazatlán, Mexico. Analyses were carried out at the start of 2026 with the sampling protocol being updated to carry on with sampling efforts to further strengthen these relationships for both tropical tunas and prioritized bycatch species, and to provide robust insights into temporal and spatial variability.

## **3. DATABASE**

IPSP collected data follows a strict workflow before being finally incorporated into the IATTC database in order to be made available for scientific research. Once the forms and/or audio recordings are uploaded to the designated digital storage repository, IPSP office staff review the files with the samplers to resolve any uncertainties. The data is then keypunched using a dedicated application developed specifically for the IPSP. The use of AI tools to generate transcripts of audio recordings is also considered to ease and

streamline the capture of the IPSP data into the application. Once keypunched, data quality processes are run to identify inconsistencies, issues and gaps which are verified and corrected to ensure that the data is accurate and meets required quality standards. It is then transferred to the IATTC permanent database where it is securely made available for reports and analysis.

#### **4. SCIENTIFIC RESEARCH SUPPORTED BY THE IPSP**

Starting 2026, the IPSP will support research at different levels, improving and updating biological parameters and fisheries statistics such as:

- **Fleet-level catch composition.** The IPSP data will be used to determine the species and size composition of the tropical tuna catch and therefore play a very important role in the current Best Scientific Estimate (BSE) catch estimation methodology. The methodology uses the IPSP port-sampling data to estimate the species and size composition of the total catch of tropical tunas by stratum, where strata are defined by area and month of fishing, purse-seine set type and vessel size class category. These data are critical for the tropical tuna stock assessments.
- **Morphometric measurements.** Morphometric data collected through the IPSP will be used to further refine the length-weight, length-length, and weight-weight relationships for tropical tunas, within spatiotemporal strata, improving the long-outdated relationships used for fleet-level catch composition estimation (converting sampled lengths to weights) and stock assessments. While also considering variability in time and space, the collection of these data will also provide a mechanism for monitoring changes in these relationships over time, which may occur as oceans are impacted by climate change.

On a higher level, the IPSP data will be essential to IATTC scientific research on the purse-seine fishery and the population status of tropical tunas, which is presented in two major scientific reports:

- **Fisheries status report**

Every year, during the IATTC SAC meeting, the staff presents a report providing a summary of the catches and effort in the previous year of the fishery for tunas in the eastern Pacific Ocean, for whose management the IATTC is responsible. The Fisheries Status Report is based on data available to the IATTC staff. For this report the fleet-level catch composition by size and species is estimated using port-sampling data.

- **Stock assessments**

Fisheries stock assessment uses a variety of information including fleet specific catch data, catch-per-unit-of-effort based indices of relative abundance, length composition, and biological parameters (e.g., growth, length-weight relationships, natural mortality). Most of this information comes from catch sampling and biological sampling programs. It is important that this information is reasonably accurate and precise. The biological and fishing processes may change over time. Auxiliary analyses that use more detailed information (e.g., fine spatial and temporal scales and operational-level data) are conducted to identify and adjust for potential biases. Therefore, appropriate and continuing sampling programs are needed to ensure reliable stock assessments are available to provide management advice.

#### **5. ADDITIONAL SUPPORT TO THE COMMISSION PROVIDED BY THE IPSP**

For BET trip-level BSEs in support of the Individual Vessel Threshold (IVT) management measure, the IPSP:

- Provides a sampling presence in port, with trip coverage of prioritized vessels similar to that provided by the EMP in 2025. In 2025, the EMP sampled 43 trips of 19 prioritized vessels; during the first trimester of 2026 the IPSP has sampled 23 trips of 18 prioritized vessels.
- Generates data for a model that is being used, along with EMP data from 2023 to 2025, to estimate trip-level BET catch based on the well-level relationship between port-sampling and observer data ([SAC-16 INF-I](#)).

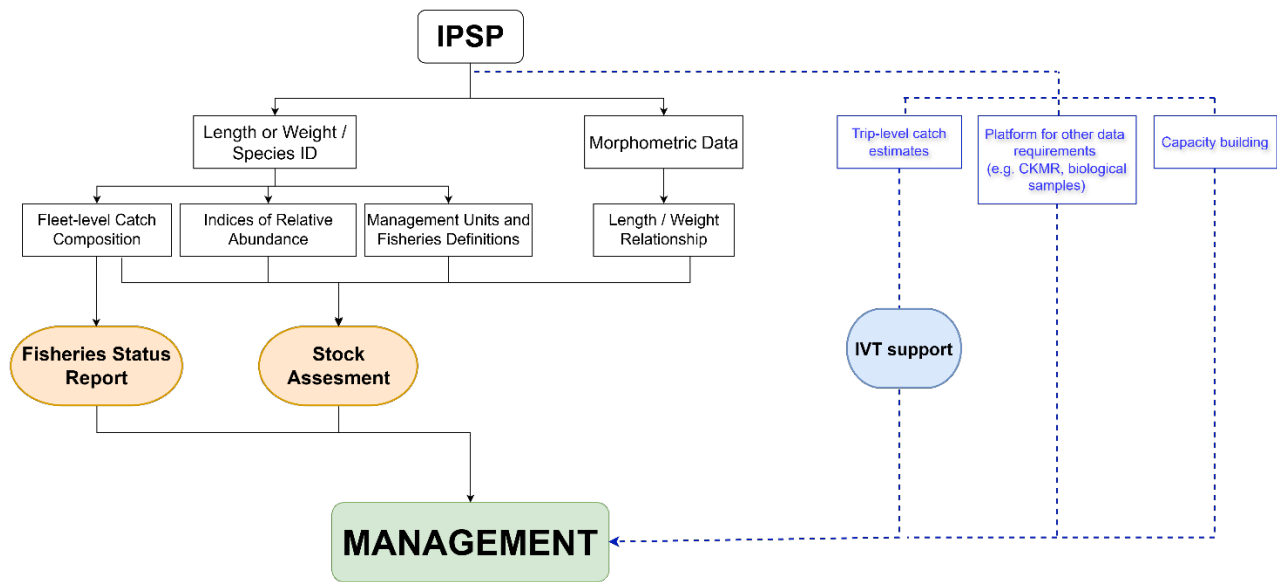
Several initiatives have been implemented to share the knowledge and expertise of the IATTC port-sampling staff with different stakeholders, such as:

- The participation of undergraduate students in port-sampling for biological data collection, through an MOU signed with the Universidad Laica Eloy Alfaro de Manabi (ULEAM) in Manta, Ecuador.
- Workshops on species ID of frozen tropical tuna species for the government and the industry.

Finally, the logistical infrastructure developed by the IPSP allows it to serve as the platform for the implementation of other scientific research initiatives, according to the Commission's requests for management, and is aligned to the IATTC's Strategic Science Plan. The IPSP will provide a platform for collecting biological samples from tropical tunas and other prioritized species as new projects are developed over the next several years. Staff will be trained on otolith extraction (for age estimation), stomach and tissue collection (genetics and trophic ecology), and other physical sample collection strategies.

## **6. ACKNOWLEDGEMENTS**

The IPSP is implemented thanks to the effort of the sampler technicians, Field Office staff, Data Collection and Database Unit staff, Stock Assessment scientific staff; with the collaboration of the IATTC and national observer programs; the fishing industry and national fisheries authorities.



**FIGURE 1.** Diagram detailing the IPSP data collection - length/weight/species ID and morphometric data - and its role in scientific research at several different levels, all ultimately informing management. Additionally, the IPSP acts as a platform in support of data requirements related to specific management measures and/or analysis requested by the Commission.

## Appendix A

### Model-based estimation of trip-level bigeye tuna catch

#### Overview

In support of the Individual Vessel Threshold (IVT) measure (Resolution C-21-04), in 2026 the IATTC scientific staff is providing model-based bigeye tuna (BET) trip-level Best Scientific Estimates (BSEs) to CPCs for trips of priority vessels<sup>1</sup> that were sampled by the Integrated Port-Sampling Program (IPSP). In previous years, trip-level BET BSEs (SAC-17 INF-G) were based on port-sampling data collected by the Enhanced Monitoring Program (EMP). Those trip-level BET BSEs did not require the use of models because the EMP sampling protocol was designed for trip-level estimation, with typically 6 to 8 wells sampled per trip, for trips of a relatively small group of vessels. The focus of the IPSP, which is different from that of the EMP, is collection of port-sampling data for estimation of fleet-level catch composition. As a result, more trips and more vessels, but fewer wells per trip, are sampled by the IPSP, and therefore estimation of the trip-level BET BSEs in 2026 relies on a model-based approach.

For each IPSP-sampled trip of the priority vessels, the estimate of trip-level BET catch is computed as the sum of estimates for IPSP-sampled wells (typically 2 wells per trip), which are based exclusively on the sample data (SAC-14-10; SAC-16 INF-I), and estimates for unsampled wells, which are computed using models (see SAC-16 INF-I for a general example). The model-based estimation for unsampled wells has three components: a) estimation of the proportion of BET in floating-object (OBJ)-set wells for which BET was present in the observer data; b) estimation of the proportion of BET in OBJ-set wells for which no BET was present in the observer data; and, c) estimation of the proportion of BET in unassociated (NOA)-set wells. The model-based estimation uses EMP data for 2023 – 2025 and IPSP data for 2026. For both unsampled and sampled wells, the estimated proportion of BET in the well is multiplied by the total well catch of tropical tuna (from observer data) to obtain the well-level estimate of BET. It is assumed that no BET catch will be present in dolphin (DEL)-set wells. Because unsampled wells can have catch from more than one set type, for mixed set-type wells the proportion of BET associated with the catch of each set type in the well is estimated separately and only applied to the corresponding tropical tuna catch. An estimate of variance on the trip-level BET estimates is also computed so that a coefficient of variation (CV) can be provided for the BET BSEs.

It is proposed that trip-level BET BSEs be provided quarterly, with final BSEs provided at year's end. Quarterly estimation will allow for more data to be available with which to estimate both annual and seasonal effects on the species composition of the catch in the models. The quarterly models will likely evolve over the course of the year. For example, in the first quarter of 2026, there will be less data with which to estimate any difference in the overall proportion of BET in the catch in 2026, as compared to 2023 – 2025, than at the end of the second and third quarters of the year. Under a quarterly estimation schedule, estimates for the first quarter would be made for all sampled 2026 trips of prioritized vessels

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<sup>1</sup> Priority vessels are those vessels that were the focus of the Enhanced Monitoring Program during 2023 to 2025. There are 36 priority vessels.

that had catch entirely from January 1 to March 31. Estimates for the second quarter would be made for all sampled 2026 trips of prioritized vessels that had catch entirely from January 1 to June 30<sup>th</sup>, and estimates for the third quarter would cover January 1 to September 30<sup>th</sup>. In this way, within-year estimates are updated as more data become available. The final estimates for the January 15, 2027, deadline (Resolution C-21-04) would cover all sampled trips of priority vessels for 2026.

Details of the estimation methodology for the three model components and the estimated variances are provided in this appendix in Sections 1 – 3. All data analysis presented in this appendix was done using the statistical freeware R (R Core Team 2025). In the Supplemental Material section, a simulation study, used to evaluate the reliability of the model estimates for the proportion of BET in unsampled OBJ-set wells with observer-reported BET (model component ‘a’ above), is described. The main findings of that simulation study were that the model estimates provided an improvement over using the unadjusted observer data. However, there may be some bias in the model estimates, with potential overestimation for wells that contain little catch of BET and potential underestimation for wells that contain a large amount of BET. Thus, further improvements to the model of Section 1.1.1, such as the use of additional well-level covariates, could be explored. Ultimately, developing a model-based approach that fits all the data within one model, rather than performing estimation separately for the three components, could be beneficial and would likely simplify variance estimation.

## 1. Estimation methodology

The estimation methodology for each of the three model components is described in this section. The estimation methods use both port-sampling data and observer data. The port-sampling data were collected by the EMP data during 2023 – 2025 and by the IPSP during 2026. Hereafter these data will be referred to as ‘sample’ data. The observer data were obtained from the Observer Set Summary database for those trips sampled by the EMP or by the IPSP.

### 1.1 Proportion of BET in unsampled OBJ-set wells

#### 1.1.1 Observer proportion of BET greater than zero

A Gaussian linear mixed-effects model (LME; Pinheiro and Bates 2004) was used to estimate the proportion of BET in unsampled OBJ-set wells of sampled priority-vessel trips with a positive OBS proportion of BET.

The LME model fitted to the paired data had the following form:

$$g(p_{sample_{ijk}}) = (\beta_0 + b_i + b_{ij}) + \text{pooled year} + \text{quarter} + \beta_1 g(p_{OBS_{ijk}}) + \epsilon_{ijk} \quad \text{eq.1}$$

where  $i$  indexes vessels,  $j$  indexes trips and  $k$  indexes wells;  $p$  is the proportion of BET in the well (‘sample’: EMP and IPSP; ‘OBS’: observer);  $g$  refers to a Box–Cox transformation (described below);  $\beta$ s denote fixed effects;  $b_i$  and  $b_{ij}$  denote random effects for vessels and trips within vessels, respectively, which modify  $\beta_0$ ; and,  $\epsilon_{ijk} \sim N(0, \sigma^2)$  is the within-group error, independent of the vessel and trip random effects. The ‘pooled year’ term is a fixed effect for the year of fishing that has two levels: 2023 and 2024 – 2026. These levels were selected based on results of analysis of EMP 2023 – 2025 data, which found that data for 2024

and 2025 were more similar to each other than to 2023 (see Table 2 of the Supplemental Material). Additionally, for the first quarter of 2026, there was only limited information with which to estimate a 2026 year effect. The ‘quarter’ term is a fixed effect for the quarter of the year in which fishing occurred. For the random effect vectors,  $\mathbf{b}_i \sim N(\mathbf{0}, \boldsymbol{\Psi}_1)$  and  $\mathbf{b}_{ij} \sim N(\mathbf{0}, \boldsymbol{\Psi}_2)$ , where the  $\mathbf{b}_i$  are independent for different vessels and the  $\mathbf{b}_{ij}$  are independent for different vessels and different trips of the same vessel. The covariance structure,  $\boldsymbol{\Psi}$ , is a general positive definite symmetric Log-Cholesky parametrization (Pinheiro and Bates 1996). The model of eq. 1 was fitted with the *lme* function of the *nlme* library (Pinheiro and Bates 2025). The estimates of the random effects were the Best Linear Unbiased Predictors (BLUPs). The models were fitted using the default method of restricted maximum likelihood. The terms in the model of eq. 1 were selected based on analysis of 2023 – 2025 EMP data (see Supplemental Material; and, SAC-16 INF-I). Some operational covariates (e.g. presence/absence of a hopper, presence/absence of double mesh on the brailer) could not be included in this first-quarter model because the information was missing for a few vessels sampled in the first quarter of 2026. However, that information is being collected and should be available for estimation in subsequent quarters.

Before fitting the mixed-effects model, a Box-Cox transformation was applied to the sample estimates of the proportion of BET to better conform to the assumed Gaussian distribution. The Box-Cox transformation, applied to a random variable  $Y$ , had the following form:

$$\hat{Y} = \frac{(Y+\delta)^\gamma - 1}{\gamma} \quad \text{eq. 2}$$

where the parameters  $\gamma$  and  $\delta$  were estimated from the data using the *geoR* library (Riberio et al. 2024). The parameters were estimated using the sample proportions, and then the same transformation (same estimated parameters) was applied to the OBS proportions to help preserve aspects of the untransformed relationship between the two data sources.

The fitted model of eq. 1 was used to estimate the proportion of BET in unsampled OBJ-set wells of the sampled priority-vessel trips. Estimates on the Box-Cox scale for each well were back-transformed using a bias correction (Hyndman and Athanasopoulos 2018) to the [0, 1] scale. The back-transformation equation, applied to a random variable  $\hat{Y}$  on the Box-Cox scale, had the following form:

$$\hat{Y}_{back\_transformed} = \left( (\gamma \hat{Y} + 1)^{\frac{1}{\gamma}} - \delta \right) \left( 1 + \frac{\sigma^2(1-\gamma)}{2(\gamma \hat{Y} + 1)^2} \right) \quad \text{eq. 3}$$

where  $\sigma^2$ , which is the variance on the transformed scale, was taken to be the LME within-group error in this application. Because the Box-Cox transformation does not guarantee that the back-transformed estimates will fall within the [0, 1] interval, any estimated proportions outside that interval were assigned the value of the closest endpoint (i.e., 0 or 1).

The estimated proportion of BET for unsampled well  $l$  of trip  $j$  and vessel  $i$ , on the [0, 1] scale, is given by the following equation:

$$\hat{p}_{ijl} = g^{-1} \left( (\widehat{\beta}_0 + \widehat{b}_i + \widehat{b}_{ij}) + \widehat{\text{pooled year}} + \widehat{\text{quarter}} + \widehat{\beta}_1 g(p_{OBS_{ijl}}) \right) \quad \text{eq. 4}$$

where  $g^{-1}(\dots)$  refers to the bias-corrected inverse of the Box-Cox transformation (i.e. eq. 3).

About 79% of the OBJ-set wells (1181 out of 1500) in the combined EMP and IPSP data set had a positive OBS proportion of BET (Table 1). These wells correspond to 197 trips of 36 vessels. The well-level relationship between the sample and OBS proportions of BET for these 1181 wells showed an increasing but noisy relationship (Figure 1). The estimated model parameters for the LME model are shown in Table 2 and model diagnostic plots in Figure 2.

### 1.1.2 Observer proportion of BET equal to zero

A hurdle model (Zuur et al. 2009) was used to estimate the proportion of BET in unsampled OBJ-set wells of sampled priority-vessel trips with an OBS proportion of BET equal to zero. Models for the two parts of the hurdle model, presence/absence of BET in the well and the positive proportion of BET in the well, were based on generalized additive mixed-effects models (GAMMs; Wood 2017). The same covariates were used for both parts, even if the term-specific p-value was not significant at the 0.05 level. The covariates used in these models were determined through preliminary analyses, however, models for subsequent quarters may include additional (or different) covariates. Because of the limited number of wells with an OBS proportion equal to zero (see below), only a vessel random effect on the overall constant was included in the each part of the hurdle model; however, this may be modified in the future.

The binomial GAMM for the presence/absence of any BET in the well had the following form:

$$\text{logit}(q_{prs/abs_{ijk}}) = \text{overall constant} + \text{pooled year} + \text{quarter} + s(\text{lon}, k = 3) + s(\text{OBS prop. YFT}_{ijk}, k = 3) + s(\text{vessel}, \text{bs} = 're')$$

eq. 5

where 'logit' refers to the logit link function,  $q_{prs/abs}$  is the probability of any BET in the well; 'pooled year' and 'quarter' are as defined for the LME model; 's(lon, k=3)' refers to a smooth term on longitude using thin plate regression splines and a basis dimension of 3; 's(OBS prop. YFT, k=3)' refers to a smooth term on the OBS proportion of yellowfin tuna (YFT) in the well using thin plate regression splines and a basis dimension of 3; and, 's(vessel, bs='re')' is to the vessel random effect on the overall constant (formulated as a smooth term with a random effects basis; see Wood 2017). The model of eq. 5 was fitted using the *gam* function of the *mgcv* library (Wood 2017). For the smooth terms for longitude and the OBS proportion of YFT, the basis dimension was set to a relatively small value to minimize overfitting. The default significance test provided by *mgcv* did not indicate oversmoothing for either term (p-values of the test  $\leq 0.62$ ). The model was fitted using restricted maximum likelihood so that the error on the estimated smoothing parameter could be incorporated into the variance on the estimated model coefficients (Wood 2017, page 343).

The Gaussian model for the positives had the following form:

$$g(p_{sample\_pos_{ijk}}) = \text{overall constant} + \text{pooled year} + \text{quarter} + s(\text{lon}, k = 3) + s(\text{OBS prop. YFT}_{ijk}, k = 3) + s(\text{vessel}, \text{bs} = 're') + \epsilon_{ijk}$$

eq. 6

where 'g(...)' refers to a Box-Cox transformation,  $p_{sample\_pos_{ijk}}$  refers the sample proportion of BET in the well; and, the other terms are the same as those of eq. 5. The default significance test provided by *mgcv* did not indicate oversmoothing for either smooth term (p-values  $\leq 0.15$ ). The Box-Cox transformation parameters, and back-transformation with bias correction, were obtained using the procedures described above for the LME model. As was done when fitting the model of eq. 5, restricted maximum likelihood was used so that the error on the estimated smoothing parameter could be incorporated into the variance on the estimated model coefficients.

The estimated proportion of BET for unsampled OBJ-set well  $l$  of trip  $j$  of vessel  $i$  is given by the following equation:

$$\hat{p}_{ijl} = \hat{q}_{prs/abs\_ijl} \hat{p}_{sample\_pos\_ijl} \quad \text{eq. 7}$$

which is the product of the estimated probability that there was any BET in the unsampled well (from the fitted model of eq. 5), multiplied by the estimated proportion of BET in the unsampled well (i.e. the back-transformed estimate for well  $l$  from the fitted model of eq. 6).

About 21% of OBJ-set wells (319 out of 1500) in the combined EMP and IPSP data set had an observer proportion of BET equal to zero (Table 1). These wells correspond to 105 trips of 32 vessels. Of the 319 wells, 202 wells had a positive sample proportion of BET (Table 1). The median of the positive sample proportions was 0.008, with an interquartile range of (0.003, 0.018) and a maximum of 0.237. The estimated model parameters for the two parts of the hurdle model are shown in Table 3 and the smooth terms in Figures 3 – 4.

### 1.2 Proportion of BET for unsampled NOA-set wells

Because of the limited sample data currently available for NOA-set wells, for the first-quarter estimation, no formal model was fitted to the data. Instead, the estimated proportion of BET in unsampled NOA-set wells was the 5% trimmed mean (e.g. Rice 1988) of the well-level proportion of BET in the combined EMP and IPSP sample data. As IPSP data for NOA-set wells of priority-vessel trips increases, it will be possible to formally model such data, e.g. using a hurdle model, to estimate the proportion of BET in unsampled NOA-set wells.

Data for 29 NOA-set wells were available in the combined EMP and IPSP data set (Table 1). These wells correspond to 8 trips of 6 vessels. There were 25 wells with a sample proportion of BET equal to zero, and one well with each of the following positive proportion values, 0.0009, 0.0021, 0.0067, and 0.0591. All 29 OBS proportions were zero. The 5% trimmed mean of the sample proportions was 0.0004.

## 2. Trip-level estimates

The estimate of BET per trip for IPSP-sampled trips of priority vessels was computed as follows:

$$\widehat{BET}_{ij} = \left( \sum_{n \in \text{wells of trip } j, \text{vessel } i} \hat{p}_{ijn} C_{ijn} \right) \quad \text{eq. 8}$$

where  $C_{ijn}$  is the total tropical tuna catch (from OBS data) in all, or part, of well  $n$  of trip  $j$  of vessel  $i$ , and  $\hat{p}_{ijn}$  is the estimated proportion of BET in well  $n$  of trip  $j$  of vessel  $i$ . The estimates,  $\hat{p}_{ijn}$ , are as follows:

- 1) OBJ-set well; OBS proportion BET > 0  
If the well was sampled,  $\hat{p}_{ijn}$  is the estimated proportion from the IPSP sample data.  
If the well was not sampled,  $\hat{p}_{ijn}$  is the estimated proportion from the LME model (eq. 4).
- 2) OBJ-set well; OBS proportion BET = 0  
If the well was sampled,  $\hat{p}_{ijn}$  is the estimated proportion from the IPSP sample data.

If the well was not sampled,  $\hat{p}_{ijn}$  is the estimated proportion from the hurdle model (eqs. 5 – 6).

3) NOA-set well

If the well was sampled,  $\hat{p}_{ijn}$  is the estimated proportion from the IPSP sample data.

If the well was not sampled,  $\hat{p}_{ijn}$  is the 5% trimmed mean (Section 1.2).

Trip-level estimates of BET for the 22 trips of the first quarter of 2026, plotted against the corresponding observer estimates, are shown in Figure 5.

### 3. Coefficient of variation on the trip-level BET estimates

An estimate of the coefficient of variation (CV) on the trip-level BET catch estimates was computed as the standard error (s.e.) on the trip estimate divided by the trip estimate (eq. 8). The s.e. was estimated as the square root of the sum of variance estimates for each of the three model components described in Section 1. (For a trip, it was assumed that the estimates for each of the three components were independent because they were each generated from different data sets and models.) When estimating the variance on each model component estimate, the data of sampled wells were treated as unsampled wells (but see comments below) and the total tropical tuna catch in each well was assumed to be known without error. The methodology for variance estimation for each of the model components is described below.

#### 3.1 OBJ-set wells

##### 3.1.1 Observer proportion of BET greater than zero

An estimate of the variance on this component was obtained using a simulation procedure. The simulation procedure estimates the variance by the sample variance of a large collection of synthetic estimates of trip-level BET catch, which are generated by resampling from the conditional distributions of the well-level estimates for unsampled wells.

The simulation had the following steps:

- 1) For each unsampled well of a trip, draw an observation from the corresponding Gaussian distribution of the well-level estimate.

Assuming that the fixed effects and random effects parameters of the LME model (Section 1.1.1) were estimated with small random errors, then conditional on the data, the distribution of the estimated proportion of BET in a well, on the Box-Cox scale, for an unsampled well  $l$  is given by (Minami 1993):

$$g(\hat{p}_{ijl}) \sim N \left( (\widehat{\beta}_0 + \widehat{b}_i + \widehat{b}_{ij}) + \widehat{\beta}_1 g(p_{OBS_{ijl}}) + \widehat{\text{pooled year}} + \widehat{\text{quarter}}, \right. \\ \left. \widehat{\sigma}^2 + \left[ \widehat{\sigma}_1^2 + \widehat{\sigma}_2^2 - (\widehat{b}_i^2 + \widehat{b}_{ij}^2 + 2\widehat{b}_i\widehat{b}_{ij}) \right] \right) \quad \text{eq. 9}$$

where  $N$  indicates a Gaussian distribution with mean and variance as specified within the parentheses,  $\widehat{\sigma}^2$  is the estimate of the variance of the within-group error distribution, and  $\widehat{\sigma}_1^2$  and  $\widehat{\sigma}_2^2$  are the estimated variances of the random effect distributions for vessels and trips, respectively. If the variance term in square brackets is negative, it is replaced with zero.

- 2) Back-transform the synthetic well-level estimates to the [0, 1] scale.

- 3) Multiply each synthetic estimated proportion by the total tropical tuna catch in the corresponding well to obtain a synthetic estimate of the BET catch in each well.
- 4) Sum the synthetic well-level estimates of BET across wells to get the synthetic trip-level estimate:
$$\widehat{BET}_a = \sum_l \tilde{p}_{ijl} C_{ijl\_tropical\_tuna}$$
- 5) Repeat steps (1) – (4) 1000 times, generating 1000 synthetic estimates of BET catch for the trip.
- 6) Estimate the variance of this component by the sample variance:  $\left(\frac{1}{999}\right) \sum_n \left(\widehat{BET}_{a\_n} - \overline{\widehat{BET}_{a\_}}\right)^2$

### 3.1.2 Observer proportion of BET equal to zero

An estimate of the variance on this component was obtained using the simulation procedure of Wood (2017, pages 342-343). This simulation had the following steps:

- 1) For each part of the hurdle model (eqs. 5 – 6), draw a vector of simulated coefficients estimates from the respective multivariate normal distribution, where the variance-covariance matrices were corrected for smoothing parameter uncertainty (Wood 2017). That is, resample from the posterior distribution of the respective estimated coefficient vectors of the hurdle model (eqs. 5 – 6).
- 2) Compute the synthetic well-level estimates of the proportion BET for each well of the trip, on the [0, 1] scale, by multiplying the model matrices corresponding to each of eqs. 5 – 6 by the respective simulated coefficient vector, back-transforming the synthetic estimate for the positives, and then evaluating eq. 7.
- 3) Multiply each synthetic estimated proportion by the total tropical tuna catch in the corresponding well to obtain a synthetic estimate of the BET catch in each well;
- 4) Sum the synthetic well-level estimates of BET across wells to get a synthetic trip-level estimate:
$$\widehat{BET}_b = \sum_l \tilde{p}_{ijl} C_{ijl\_tropical\_tuna} ;$$
- 5) Repeat steps (1) – (4) 1000 times, generating 1000 synthetic estimates of BET catch for the trip.
- 6) Estimate the variance of this component by the sample variance:  $\left(\frac{1}{999}\right) \sum_n \left(\widehat{BET}_{b\_n} - \overline{\widehat{BET}_{b\_}}\right)^2$

### 3.2 NOA-set wells

For the trip estimate of BET catch from NOA-set wells, an estimate of the variance on this component was computed as follows:

$$\widehat{Var} \left( \sum_n \hat{p}_{NOA} C_{n\_tropical\_tuna} \right) = \sum_n Var(\hat{p}_{NOA}) C_{n\_tropical\_tuna}^2 = Var(\hat{p}_{NOA}) \sum_n C_{n\_tropical\_tuna}^2$$

where  $Var(\hat{p}_{NOA})$ , which is the variance of the trimmed mean, was estimated based on variances and covariances of the order statistics, as outlined by Rice (1988, page 333).

Future work could be conducted to improve upon the methods for estimating variance. For example, incorporating the random error on the estimated fixed effects and random effects parameters of the LME model into the simulation of Section 3.1.1 would be useful because eq. 9 may underestimate variance. In addition, as more sample data become available for NOA-set wells, using a simulation approach for variance estimation might be possible. Finally, obtaining design-based variance estimates for sampled

wells, i.e. variance estimates based solely on the sample data and sampling protocol, may be desirable, but will not always be possible when the two sampled wells per trip fall into different estimation components.

The estimated CVs for 21 of the 22 trips ranged from approximately 0.1 to 1.8, with a median value of 0.26. For one of the 22 trips, the model-estimate of BET for the trip was zero, which resulted in a CV that was undefined (because of division by zero); the standard error on the BET estimate for that trip was 0.153. The estimated CVs increased as the estimated trip BET catch decreased, with CVs of 0.25 or greater associated with estimated trip-level BET catches of 100t or less (Figure 5).

## References

- Hyndman, R.J.; Athanasopoulos, G. Section 2.7—Box-Cox Transformations. In *Forecasting: Principles and Practice*, 2nd ed.; OTexts: Melbourne, Australia, 2018.
- Minami, M. 1993. Variance Estimation for Simultaneous Response Growth Curve Models. Ph.D. thesis, University of California, San Diego.
- Pineiro, J.C., Bates, D.M. 1996. Unconstrained parametrizations for variance-covariance matrices. *Statistics and Computing* 6: 289–296.
- Pineiro, J.C., Bates, D.M. 2004. *Mixed-Effects Models in S and S-PLUS*. Springer, New York. 528 pp. doi:10.1007/b98882. <https://doi.org/10.1007/b98882>
- Pineiro, J., Bates, D. 2025. *Linear and Nonlinear Mixed Effects Models*. doi:10.32614/CRAN.package.nlme. R package version 3.1-168. <https://CRAN.R-project.org/package=nlme>.
- R Core Team 2025. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/>
- Ribeiro, P.J., Jr.; Diggle, P.; Christensen, O.; Schlather, M.; Bivand, R.; Ripley, B. *geoR: Analysis of Geostatistical Data*. R Package Version 1.9-4. 2024. Available online: <https://CRAN.R-project.org/package=geoR>
- Rice, J.A. 1988. *Mathematical Statistics and Data Analysis*. Wadsworth & Brooks/Cole, Pacific Grove, California. 595pp.
- Wood, S. 2017. *Generalized Additive Models: An Introduction with R* (2nd edition). Chapman and Hall/CRC. 476 pp.
- Zuur, A. F., Ieno, E. N., Walker, N. J., Saveliev, A. A., & Smith, G. M. 2009. *Mixed effects models and extensions with R*. New York, NY: Springer. <https://doi.org/10.1007/978-0-387-87458-6>. 574 pp.

Table 1. Number of wells in the sample data according to set type and presence/absence of BET in the sampled data (EMP and IPSP data, combined), for 2023 through the 1<sup>st</sup> quarter of 2026, and 1<sup>st</sup> quarter of 2026 only.

2023 through 1 <sup>st</sup> quarter 2026			
<b>OBJ-set wells</b>	OBS > 0	OBS = 0	Total
Sample > 0	1144	202	1346
Sample = 0	37	117	154
Total	1181	319	1500
<b>NOA-set wells</b>			
Sample > 0	0	4	4
Sample = 0	0	25	25
Total	0	29	29
1 <sup>st</sup> quarter 2026			
<b>OBJ-set wells</b>			
Sample > 0	24	4	28
Sample = 0	0	11	11
Total	24	15	39
<b>NOA-set wells</b>			
Sample > 0	0	0	0
Sample = 0	0	5	5
Total	0	5	0

Table 2. Estimated fixed-effect coefficients and random effect standard errors (all on the Box-Cox scale) for the model for OBJ-set wells with an OBS proportion BET greater than zero (eq. 1). ‘s.e.’: standard error; ‘Quarter’: catch quarter; ‘CI’: confidence interval bound (approximate 95% confidence intervals).

Fixed effect	Coefficient	s.e.	p-value
Intercept	-0.073	0.0575	0.203
Pooled year	-0.157	0.0389	< 0.001
Quarter 2	-0.104	0.0411	0.012
Quarter 3	-0.237	0.0456	< 0.001
Quarter 4	-0.229	0.0559	< 0.001
OBS slope	0.886	0.0236	< 0.001
<b>Random effect s.e.</b>			
	Lower CI	Estimate	Upper CI
Vessel	0.0650	0.1074	0.1773
Trip	0.1804	0.2116	0.2483
<b>Within-group s.e.</b>			
	0.2910	0.3042	0.3181

Table 3. Estimated coefficients for the logistic and positive components of the hurdle model for OBJ-set wells with an OBS proportion of BET equal to zero (eqs. 5 - 6). 's.e.': standard error; 'Quarter': catch quarter; 'lon': longitude; 'obs.propyft': OBS proportion of YFT in the well; 'edf': estimated degrees of freedom.

<b>Logistic model</b>	Coefficient	s.e.	p-value
Intercept	1.301	0.4065	0.001
Pooled year	-0.277	0.3454	0.423
Quarter 2	-0.118	0.4598	0.797
Quarter 3	-0.752	0.3755	0.045
Quarter 4	-0.832	0.4278	0.052
Smooth terms	edf	p-value	
s(lon)	1.9	< 0.001	
s(obs.propyft)	1.6	0.172	
s(vessel)	5.7	0.130	
<b>Positives model</b>	Coefficient	s.e.	p-value
Intercept	-4.160	0.3504	< 0.001
Pooled year	-0.744	0.2878	0.010
Quarter 2	0.121	0.3617	0.739
Quarter 3	-1.090	0.2916	< 0.001
Quarter 4	-1.129	0.3266	0.001
Smooth terms	edf	p-value	
s(lon)	1.0	< 0.001	
s(obs.propyft)	1.8	0.097	
s(vessel)	11.0	0.015	

Figure 1. Plot of the OBS estimate of the proportion BET per well (x-axis) versus the sample estimate (EMP and IPSP) of the proportion of BET per well (y-axis), for OBJ-set wells for which the OBS proportion of BET was greater than zero. Each open circles is an individual well; red open circles are the IPSP data through March 2026, and black open circles are the EMP data.

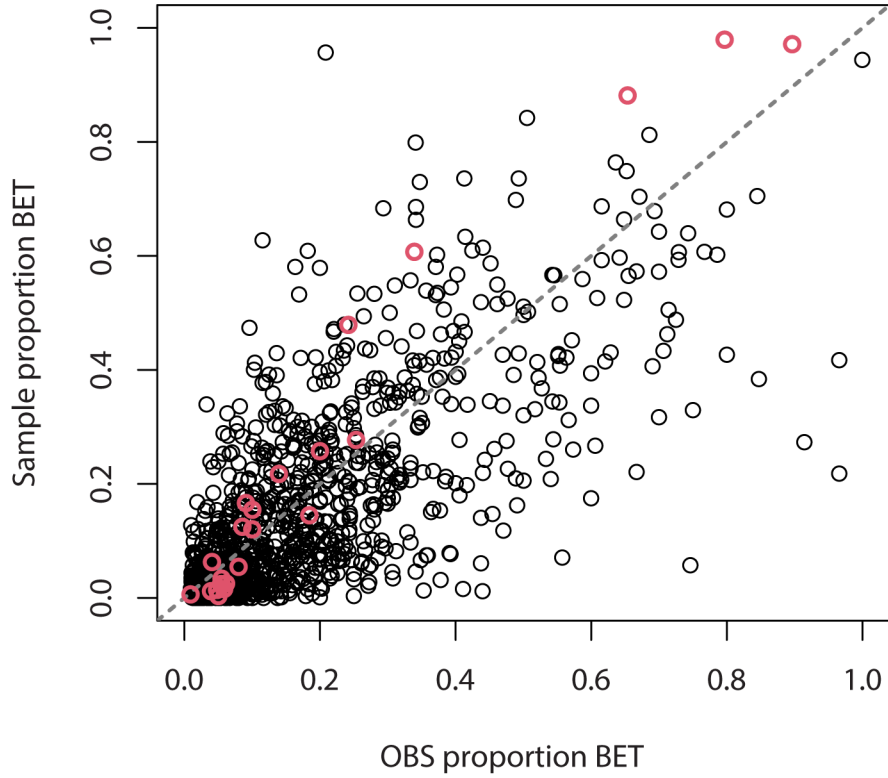


Figure 2. Model diagnostics graphs for the LME model for OBJ-set wells for which the OBS proportion of BET in the well was greater than zero. Upper left panel: fitted values versus Pearson standardized residuals, where the blue dashed line shows a LOESS smooth of the residual pattern (span = 0.75, degree = 1); upper right panel: quantile-quantile plot ('Q-Q Plot') of the residuals, where the red line shows the line that passes through the 1<sup>st</sup> and 3<sup>rd</sup> quartiles; lower left panel: quantile-quantile plot of the vessel random effects; lower right panel: quantile-quantile plot of the trip random effects.

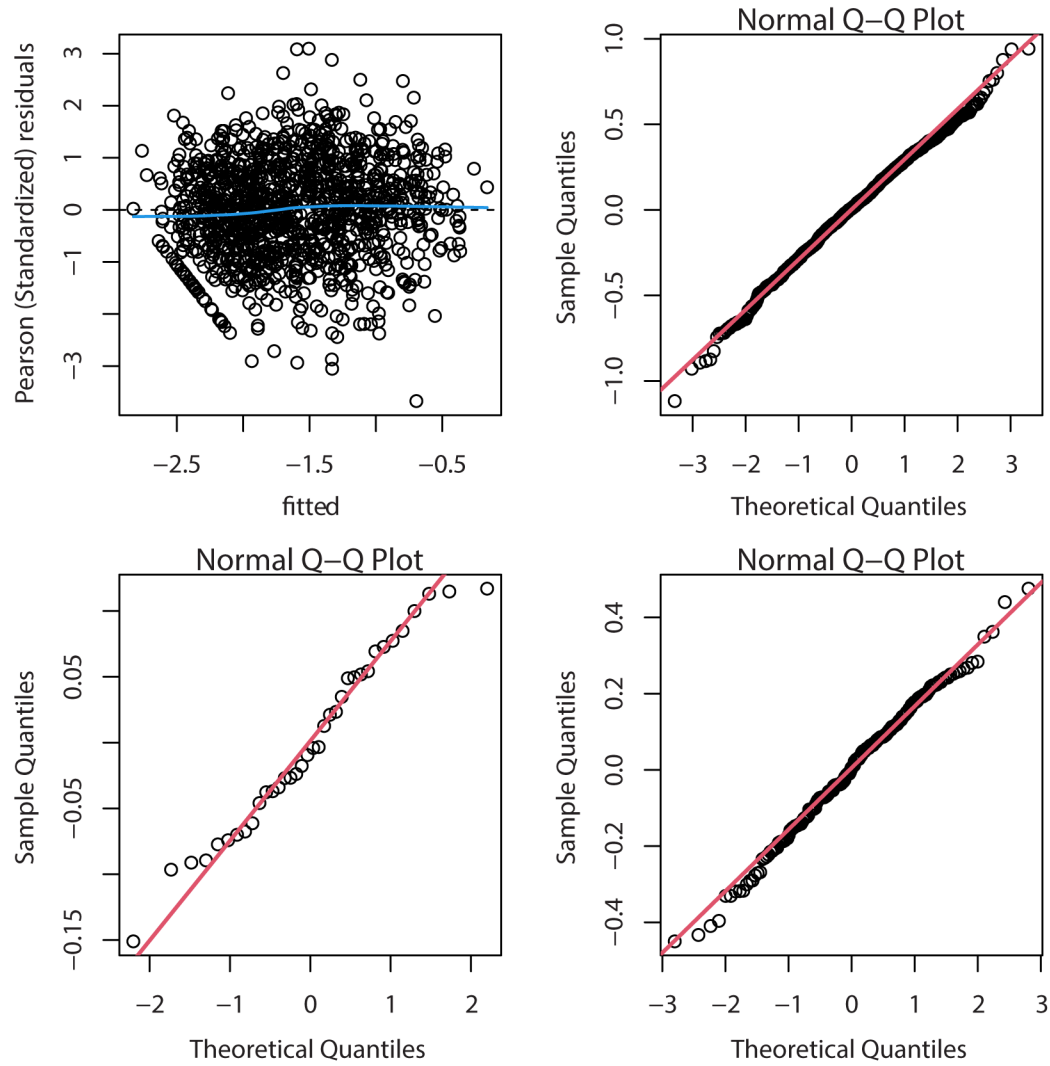


Figure 3. Smooth terms from the logistic part of the hurdle model (upper row of panels) and quantile-quantile plot of the vessel random effects (lower-left panel). 'lon': longitude; "obs.propyft": OBS proportion of YFT in the well.

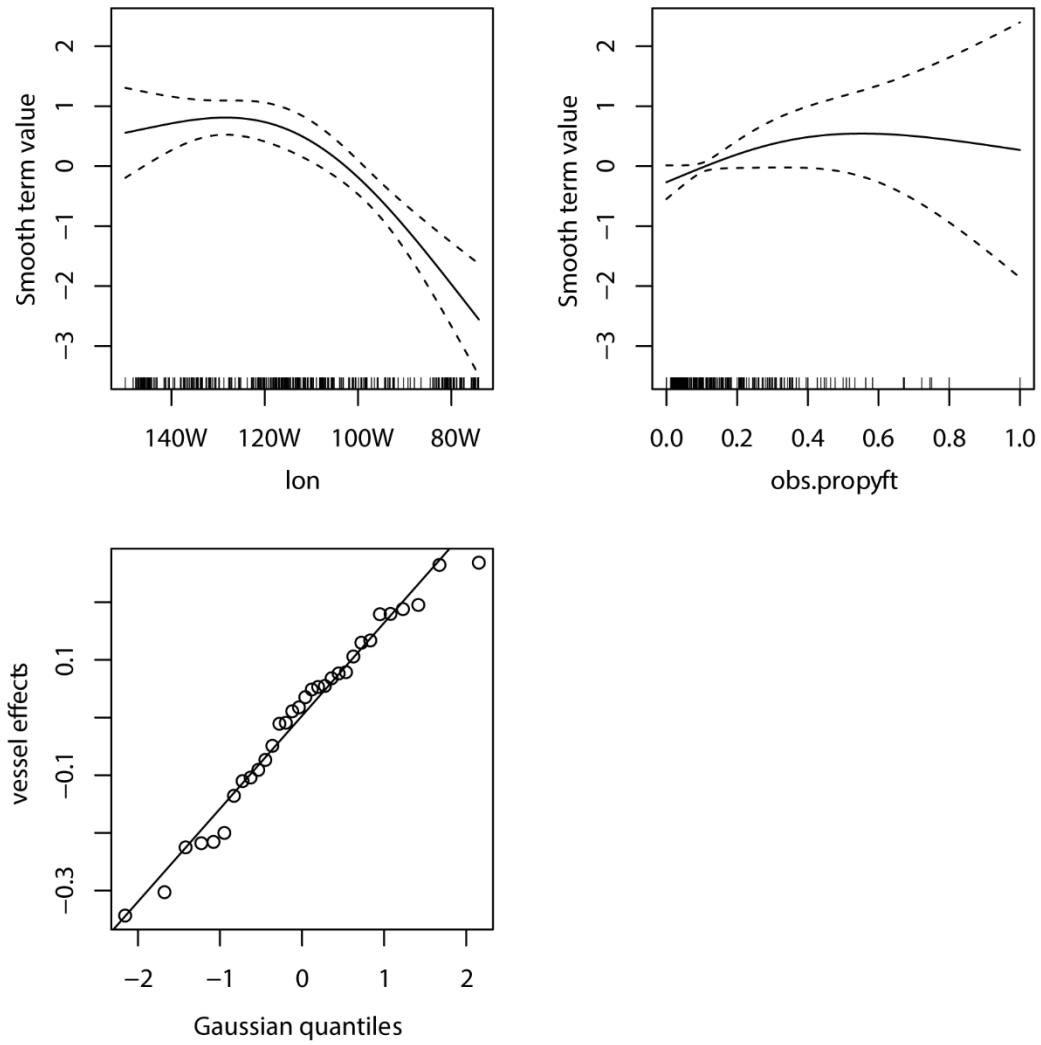


Figure 4. Smooth terms from the positives part of the hurdle model (upper row of panels) and quantile-quantile plot of the vessel random effects (lower-left panel). 'lon': longitude; "obs.propyft": OBS proportion of YFT in the well.

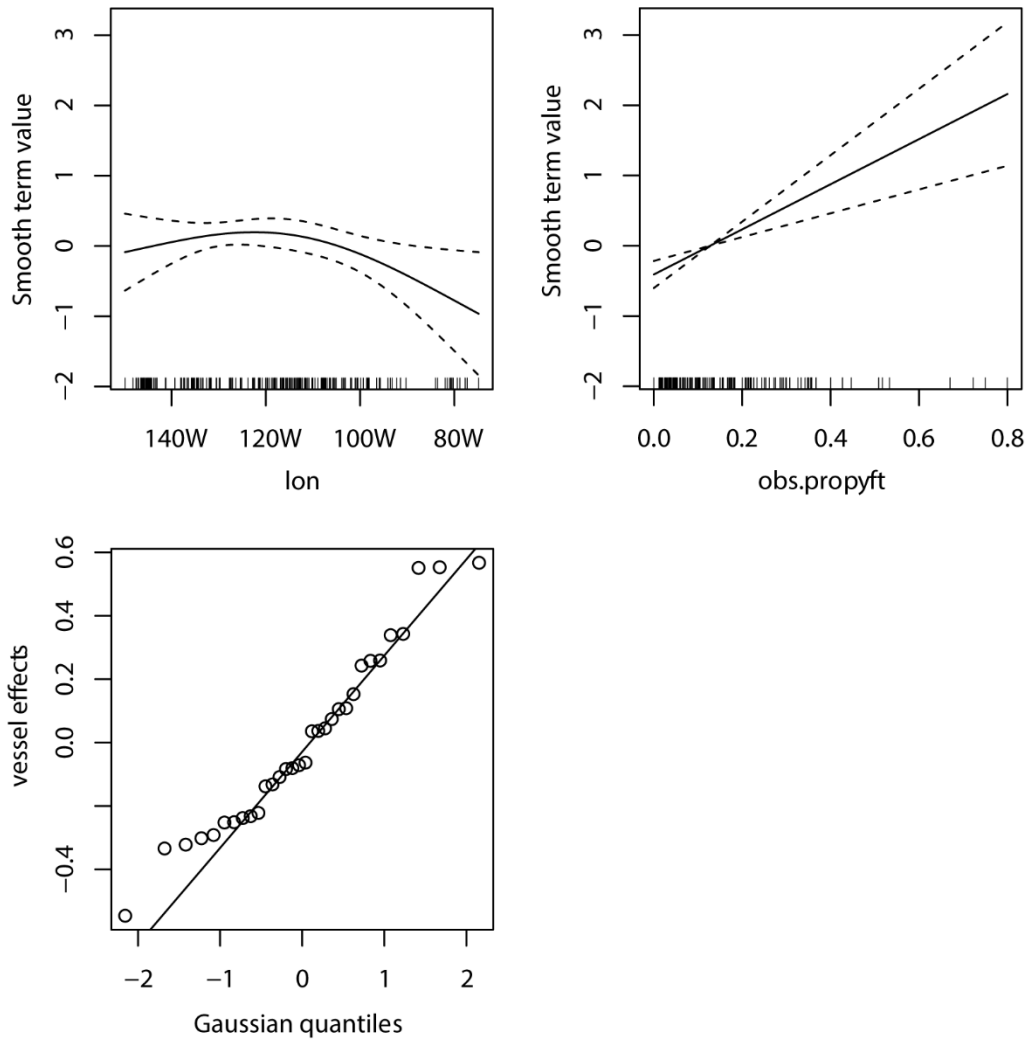
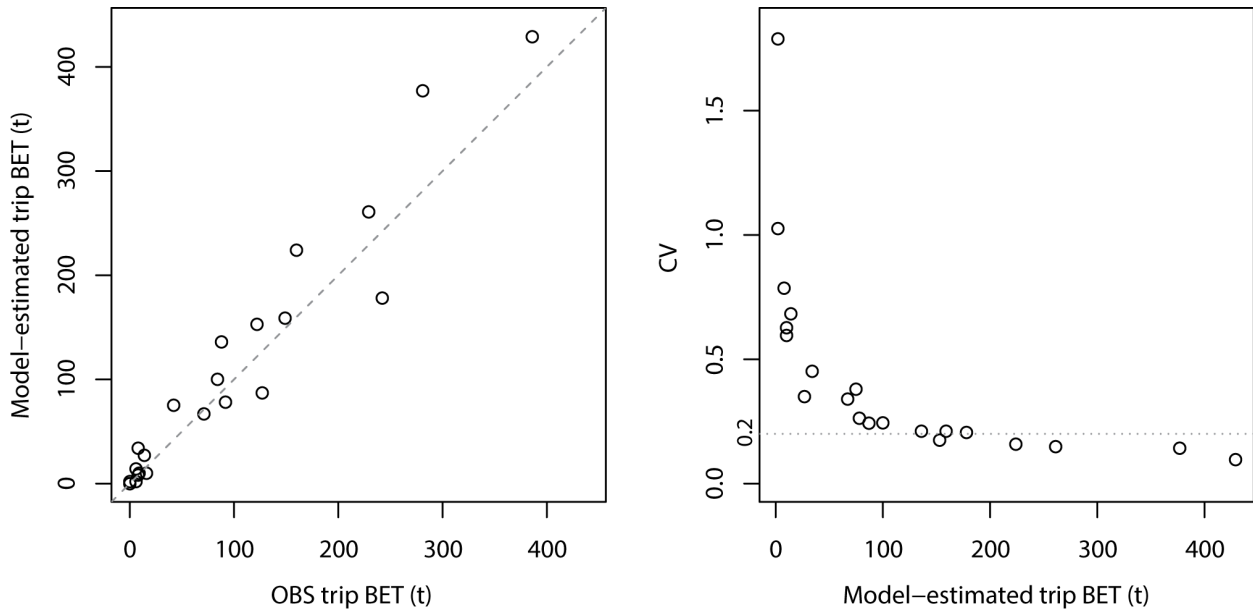


Figure 5. Model-estimated BET per trip versus observer estimates for the same trips (left-hand figure), and estimated coefficient of variation (CV) versus model-estimated BET per trip (right-hand figure), for IPSP-sampled trips with fishing activity that took place exclusively in the 1<sup>st</sup> quarter of 2026. The gray dashed line shown in the left-hand figure is the 1-to-1 line. The gray dashed line shown in the right-hand figure indicates a CV value of 0.2. Each open circle (both figures) represents an individual trip. Not shown in the right-hand figure is the one trip with an undefined CV (and an estimated BET catch for the trip of 0).



## SUPPLEMENTAL MATERIAL

The Supplemental Material section contains information on a simulation study that was conducted to evaluate model performance for trip-level BET estimation, focusing on estimation for OBJ-set wells with a positive observer proportion for BET.

### *Data*

The data used in the simulation were the EMP sample data and the observer (OBS) data (Set Summary data), for 2023 - 2025. The observer data were limited to only those trips that were sampled by the EMP.

### *Data processing*

EMP data for some wells were excluded:

- 1) Not completely sampled
- 2) Not data quality 1
- 3) Mixed set type
- 4) Wells with 'pulpos' not in the data
- 5) Wells unloaded using cargo nets
- 6) Wells for which operational covariate information was missing
- 7) From trips with only 1 sampled well (IPSP is currently targeting to sample 2 wells per trip)

Well-level estimates of the proportion of BET in the well, for each data source, were based on the methods of SAC-16 INF-I.

### *Covariates used*

- Vessel-level operational covariates: brailer capacity, double/single mesh on brailer, presence/absence of a hopper.
- Vessel company. Two different company variables were created: one based solely on the IATTC vessel register information; and, one based on both the vessel register, plus other information, which allowed a slightly higher degree of aggregation of vessels into groups.
- Well-level latitude, longitude, catch quarter, catch year (from observer data).  
If there was catch from multiple sets in the well, the covariate is taken to be the catch-weighted average; i.e. for covariate  $x$  the estimated value for well  $k$  is given by:

$$\tilde{x}_k = \frac{\sum_{sets\ in\ well\ k} x_{set} C_{tropical\ tuna\_set}}{\sum_{sets\ in\ well\ k} C_{tropical\ tuna\_set}}$$

where  $C_{tropical\ tuna\_set}$  is the catch amount of tropical tunas in well  $k$  from a specific set.

- Well-level OBS proportion of yellowfin tuna (YFT) in the well.

### *Brief description of the data*

There was an overall positive, albeit noisy, relationship between the EMP and OBS proportions of BET per well (Figure 1). A large fraction of the EMP data are for wells with a proportion of BET less than or equal to 0.2 (Figure 2). The overall EMP – OBS relationship, after applying a Box-Cox transformation to both the EMP and OBS proportions of BET in the well is shown in Figure 3.

### *Some modeling assumptions and considerations*

- The sample proportions (EMP, IPSP) are assumed to be more reliable than the OBS proportions because of the way in which the two estimates are made (from a sample of individual fish versus estimating composition by eye from brailers). In addition, results of a simulation study conducted with EMP pilot study data (SAC-14-10) concluded that EMP sample data would be more reliable for estimating the proportion of BET in a well than the OBS data because:
  - The error (OBS estimate – EMP pilot study estimate) could be larger than the largest error between the EMP pilot study estimate and the simulated EMP protocol estimate.
  - When grouped by trip, there are multiple trips with large errors.
- There may be differences in the observer-sampling relationship between years (SAC-16 INF-I), which may require a different parameterization of temporal effects (e.g. year, quarter) in the mid-year models, as compared to the final model fitted at year’s end. Therefore, several temporal formulations were tested in the simulations (year and quarter, both considered categorical variables): year, quarter; pooled years (see below), quarter; and, year-quarter.
- The non-Gaussian nature of the EMP proportions, which were taken as the response variable in the modeling (see below), and the presence of zero-valued EMP proportions, complicate the analysis. First, all transformations encountered so far that will address non-Gaussian nature of the sample proportion BET are not defined at 0 (or 1). This suggests that either a constant needs to be added to the zero-valued response proportions or a hurdle model has to be fitted to the data. For  $OBS > 0$ , only 3.2% of wells had a zero-valued sample proportion, which means there is not likely much information with which to fit a hurdle model. Second, it seems simpler R packages (those using non-Bayesian estimation methods) that are intended to model proportions not derived from counts (using a beta distribution), either won’t handle zero-valued proportions or won’t accommodate nested random effects. Therefore, given the small percentage of zero-valued EMP proportions when the OBS proportions were positive, the current approach is to apply a Box-Cox transformation (with small constant added to EMP zeros) and using the *nlme* package for estimation (because of its random effects modeling capabilities).

#### *Results of fitting models to all EMP data*

To explore the relative importance of available covariates using 2023-2025 EMP data, various Gaussian linear mixed-effects models were fitted to the data of OBJ-set wells.

Most of the linear mixed-effects models fitted had the following general form, but a few other variations were also explored (see Table 1).

$$g(p_{EMP_{ijk}}) = (\beta_0 + b_i + b_{ij}) + \beta_1 g(p_{OBS_{ijk}}) + \beta_2 X_{2_{ijk}} \dots + \beta_u X_{u_{ijk}} + \epsilon_{ijk}$$

Model specifics are the same as those of eq. 1 above in Section 1.1.1 of the Appendix. Polynomial terms for latitude and longitude were also included in some models.

Results from the model fitting can be summarized as follows.

- 1) Among the fixed-effects covariates considered, the OBS proportion of BET in the well seemed to be the most important covariate (per reduction in AIC, Table 1).
- 2) Available covariates, beyond the OBS proportion of BET in the well, year and quarter, and perhaps the OBS proportion of YFT in the well, did not lead to substantially lower AIC models, as compared to the minimal model that contains only the OBS proportion BET and nested random effects for trips within vessels (Table 1).
- 3) The estimated year effects for 2024 and 2025 are significantly different from the overall intercept, which includes 2023, but are not likely significantly different from each other given the approximate standard errors (Table 2). Thus, for within-year estimation of BET trip-level catch for the first quarter of 2026, formulating the year covariate in the within-year model as having two levels (2023 *versus* 2024 and onwards) may be reasonable.
- 4) Having a vessel effect on the OBS slope, in addition to a vessel effect on the overall intercept, does not seem that beneficial, as measured by reduction in AIC (Table 1), despite the fact that the relationship between sample and observer proportions differ among some vessels. This suggests that, when considering all vessels, there is a high degree of variability in the among-trip patterns for an individual vessel.

#### *Evaluation of performance of mid-year models for estimating the proportion of BET*

A simulation was run to compare the estimated well-level proportion of BET for the first, second and third quarters of the year for 2025, using 2023-2024 data and 2025 data up to and including the quarter of interest. The year 2025 was selected for creating test data sets because of the apparent change in the year effect, 2024-2025, relative to 2023 (Table 2). Thus, for estimating the proportion of BET for test data of trips unloading in quarter  $q$  of 2025, the training data included all wells sampled in 2023-2024 and a subset of wells sampled for trips unloading in quarters less than or equal to  $q$  of 2025; the latter is to simulate the amount of 2026 data that will actually be available. The simulation procedure is described in detail below.

The steps in the simulation were as follows:

- 1) Create 5000 synthetic data sets:
  - a. Each training data sets contained all of the EMP data for 2023-2024 and 2 wells of every 2025 EMP trip that unloaded in quarters less than or equal to the quarter of interest (“estimation quarter”).
  - b. Each test data set contained the remaining sampled wells of each 2025 trip unloading in the estimation quarter (typically 4-6 wells per trip). The assignment of wells to training and test subsets for each trip unloading in 2025 was done at random. However, the assignment did not take into consideration combinations of wells already assigned in other synthetic data sets, so the 5000 synthetic data sets will contain some duplication.
  - c. The set-up of the synthetic data sets for the estimation quarter was intended to mimic what is expected to occur in 2026, where the IPSP is targeting to sample two wells of each trip in the randomly selected clusters of trips.
- 2) For each of the 5000 synthetic data sets:
  - a. A linear mixed-effects model was fitted to the training subset of the data, and that fitted model was used to estimate the proportion of BET per well for the test data. That model fitted corresponds to the model of Table 4 with an AIC of 840, but with catch year replaced by the pooled catch year (2023 *versus* 2024+); i.e. the model had the following form:  $g(\text{EMP proportion BET}) = g(\text{OBS proportion BET}) + \text{pooled year effect} + \text{catch quarter effect}$ , with nested random effects on the intercept for trips within vessels.

- b. The fitted model was used to make estimations on the Box-Cox scale, which were then back-transformed to the [0, 1] interval using a bias correction for the Box-Cox back-transformation.
- 3) Performance of the model was summarized in several ways:
- a. The difference between the EMP proportion of BET and the linear mixed-effects model (LME) estimated proportion of BET was computed for all test wells, over all synthetic data sets that contained each well) and presented in the form of boxplots of the differences, by well with wells ordered according the EMP proportion.
  - b. Mean squared error between the EMP estimate of BET catch for test wells and LME estimate, or the OBS estimate, of BET catch for the test wells, averaged over trips in the test data. That is:

$$\overline{\delta^2} = \left(\frac{1}{n \text{ trips}}\right) \sum_{\text{test trips}} \left(\frac{1}{n \text{ wells}}\right) \sum_{\text{test wells of trip}} (\text{EMP BET catch} - \text{other estimate})^2$$

where  $n \text{ trips}$  and  $n \text{ wells}$  are the number of trips in the test data and the number of wells of a test data trips, respectively, and *other estimate* is either the LME estimate or the OBS estimate of BET catch. For all three estimates sources (EMP, LME, OBS), the well-level catch estimate is equal to the source estimated proportion of BET in the well multiplied by the total tropical tuna catch in the well (from the OBS data). Histograms were used to summarize the values of  $\overline{\delta^2}$  over the 5000 synthetic data sets.

For comparison, the simulation procedure was also run using nearly all covariates in a random forest algorithm to estimate the proportion of BET for test data wells. A random forest algorithm was used because, in some respects, it allows for more flexible modeling. In particular, interactions and some types of nonlinear relationships are obtained automatically, and it does not require a data transformation. A limitation of the random forest approach is that a trip effect could not be included due to the large number of levels that would have been required; over 140 trips were included in the training data (the number depending on the estimation quarter), however, the randomForest package (Liaw and Wiener 2002) in R used to build the algorithm cannot handle categorical variables with more than 53 levels. Beyond that, a nested structure (trips within vessels) cannot be specified in the random forest algorithm.

Results of the simulation can be summarized as follows:

- 1) Using the linear mixed-effects model, the LME-estimated catch of BET in test wells was a closer fit to the EMP estimates, per the metric  $\overline{\delta^2}$ , than the OBS catch estimates were to the EMP estimates (Figure 4). This result was obtained for all three quarters (results not shown for quarters 2 and 3).
- 2) Although the LME estimates are more similar to the EMP estimates on the test data than the OBS estimates, the LME estimates appear to be biased (Figure 5). In particular, the LME estimates appear to overestimate the proportion of BET in the well at small sample proportions and underestimate at the highest sampled proportions. This result was consistent across all three quarters (results not shown for quarters 2 and 3).
- 3) From Figure 5, it follows that the effect of this bias on the trip-level BET catch estimate will depend on the well size and the true proportion of BET for the well, across all wells of the trip, because the wells of many trips spanned a range of proportion of BET values. For those wells with a small true proportion BET, any overestimation may have limited effect on estimated trip catch relative to the IVT, given that a large percentage of wells sampled in 2023-2025 that had a proportion BET

of less than 0.20 (Figure 2). However, potentially large underestimation could occur for wells with true catch that is nearly all BET.

- 4) The tendency for bias in the LME estimates was present regardless of the various other LME models tested for quarter 1 (sensitivities not run for quarters 2, 3):
  - a. Models that included other covariates, such as presence/absence of a hopper, the tonnage and mesh on the brailer, latitude, longitude, and the OBS proportion of YFT in the well, as well as some interaction terms.
  - b. Quadratic and cubic terms added for the OBS proportion of BET.
  - c. The EMP zeros were dropped from the data sets (both training and test).
  - d. A vessel effect on the OBS proportion BET slope (in addition to the vessel effect on the intercept).
  - e. Adding a trip effect on the OBS proportion BET slope (while maintaining nested random effects for vessel and trip on the intercept).
  - f. Fitting a linear model without vessel or trip random effects.
- 5) Using random forests to estimate the proportion of BET per well for the test data did not perform as well as using an LME in terms of the metric  $\overline{\delta^2}$ . This may be due to the fact that a trip effect could not be included in the random forest algorithm.
- 6) The random forest estimated proportions of BET per well showed similar bias to the LME estimates, suggesting that, for the available covariates, the bias is not due to a lack of interactions in the model or a lack of nonlinear terms.

In summary, as regards bias in the LME estimated proportions, neither available fixed-effect covariates/nonlinear terms, nor the current formulation of vessel and trip random effects, appears to fully capture the relationship between sampling estimates and observer estimates. The LME bias may be due to a lack of covariates at the well level to explain variability within a trip and the limited number of wells available with which to estimate a trip effect (2 wells, consistent with expectation for IPSP data) for the test year. Patterns among trips of the same vessel ranged from EMP and OBS estimates clustered closed to the origin, to roughly linear relationships with slopes either greater than 1 or less than 1 (e.g. Figure 6). Such variability was seen for a number of vessels sampled by the EMP.

## References

Liaw, A., Wiener, M. 2002. Classification and Regression by randomForest. R News 2(3): 18-22.  
<https://CRAN.R-project.org/doc/Rnews/>

Table 1. AIC for fitted models, 2023-2025, OBJ-set wells only. "OBS p": OBS proportion BET in the well. "ctch.yr": catch year of the fish in the well. "ctch.qrtr": catch quarter of the fish in the well. "ctch.yr.qrtr": the year-quarter of the fish in the well.

Models	AIC
~1, random=~1   vesno, tripno	1738
Box-Cox(OBS p), random=~1   vesno, tripno	846
Box-Cox(OBS p), random=~1   company, tripno	849
Box-Cox(OBS p), random=~1   parent company, tripno	845
Box-Cox(OBS p), random=~ OBS p   vesno, ~1   tripno	844
Box-Cox(OBS p), random=~1   ctch.yr, vesno, tripno	845
Box-Cox(OBS p)+ctch.yr, random=~1   vesno, tripno	847
Box-Cox(OBS p)*ctch.yr, random=~1   vesno, tripno	859
Box-Cox(OBS p)+ctch.qrtr, random=~1   vesno, tripno	846
Box-Cox(OBS p)+ctch.yr+ctch.qrtr, random=~1   vesno, tripno	840
Box-Cox(OBS p)+ctch.yr*ctch.qrtr, random=~1   vesno, tripno	857
Box-Cox(OBS p)+ctch.yr.qrtr, random=~1   vesno, tripno	857
Box-Cox(OBS p)+ctch.yr+ctch.qrtr, random=~ OBS   vesno, ~1   tripno	838
Box-Cox(OBS p)+ctch.yr.qrtr, random=~ OBS   vesno, ~1   tripno	855
Box-Cox(OBS p)+ctch.yr+ctch.qrtr, random=~1   vesno, ~ OBS   tripno	841
Box-Cox(OBS p)+hopper, random=~1   vesno, tripno	850
Box-Cox(OBS p)*hopper+ctch.yr+ctch.qrtr, random=~1   vesno, tripno	844
Box-Cox(OBS p)+brailer tonnage, random=~1   vesno, tripno	852
Box-Cox(OBS p)*brailer tonnage+ctch.yr+ctch.qrtr, random=~1   vesno, tripno	845
Box-Cox(OBS p)+double mesh, random=~1   vesno, tripno	850
Box-Cox(OBS p)*double mesh+ctch.yr+ctch.qrtr, random=~1   vesno, tripno	850
Box-Cox(OBS p)+OBS prop_YFT, random=~1   vesno, tripno	843
Box-Cox(OBS p)+Box-Cox(OBS_prop_YFT)+ctch.yr+ctch.qrtr, random=~1   vesno, tripno	839
Box-Cox(OBS p)+Box-Cox(OBS_prop_YFT)+ctch.yr+ctch.qrtr, random=~ OBS   vesno, ~1   tripno	838
Box-Cox(OBS p)+Box-Cox(OBS_prop_YFT)+ctch.yr+ctch.qrtr, random=~OBS   tripno	853
Box-Cox(OBS p) + lat, random=~1   vesno, tripno	854
Box-Cox(OBS p) + lat+lat^2, random=~1   vesno, tripno	867
Box-Cox(OBS p) + lon, random=~1   vesno, tripno	858
Box-Cox(OBS p) + lon+lon^2, random=~1   vesno, tripno	877
Box-Cox(OBS p) + lon+lon^2+lon^3, random=~1   vesno, tripno	896
Box-Cox(OBS p) + lat + lon, random=~1   vesno, tripno	867
ctch.yr + ctch.qrtr + lat + lon, random=~1   vesno, tripno	1716
ctch.yr + ctch.month + lat + lon, random=~1   vesno, tripno	1746
ctch.yr + ctch.qrtr + lat + lat ^2 + lon + lon^2 + lon^3, random=~1   vesno, tripno	1749
ctch.yr + ctch.qrtr + lon + lon^2 + lon^3, random=~1   vesno, tripno	1726
ctch.yr*ctch.qrtr + lon + lon^2 + lon^3, random=~1   vesno, tripno	1733

ctch.yr + ctch.qrtr + hopper+ double mesh + brailer tonnage + lon + lon^2 + lon^3, random=~1   vesno, tripno	1730
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Table 2. Estimated fixed-effect coefficients, on Box-Cox scale, and conditional test for the two models of Table 1 with the lowest AIC values (838 and 840). "OBS\_p\_BET: Box-Cox transformed OBS proportion of BET in the well.

Model	2023-2025	
	Coeff. (s.e.)	p-value
~ random = ~ OBS_p_BET vesno, ~1 tripno		
Intercept	-0.098 (0.0727)	0.18
OBS_p_BET slope	0.871 (0.0308)	< 0.01
Year effect: 2024	-0.167 (0.0430)	< 0.01
Year effect: 2025	-0.187 (0.0508)	< 0.01
Quarter effect: 2nd	-0.070 (0.0422)	0.10
Quarter effect: 3rd	-0.227 (0.0468)	< 0.01
Quarter effect: 4th	-0.240 (0.0566)	< 0.01
~ random = ~1 vesno, ~1 tripno		
Intercept	-0.083 (0.0602)	0.17
OBS_p_BET slope	0.876 (0.0244)	< 0.01
Year effect: 2024	-0.166 (0.0432)	< 0.01
Year effect: 2025	-0.193 (0.0510)	< 0.01
Quarter effect: 2nd	-0.081 (0.0423)	0.06
Quarter effect: 3rd	-0.231 (0.04713)	< 0.01
Quarter effect: 4th	-0.238 (0.0569)	< 0.01

Figure 1. Well-level relationship between sample (EMP) estimates of the proportion of BET and observer (OBS) estimates of the proportion of BET (all sampled wells), 2023-2025. Each open circle is an individual well. The red dashed line is the 1-to-1 line.

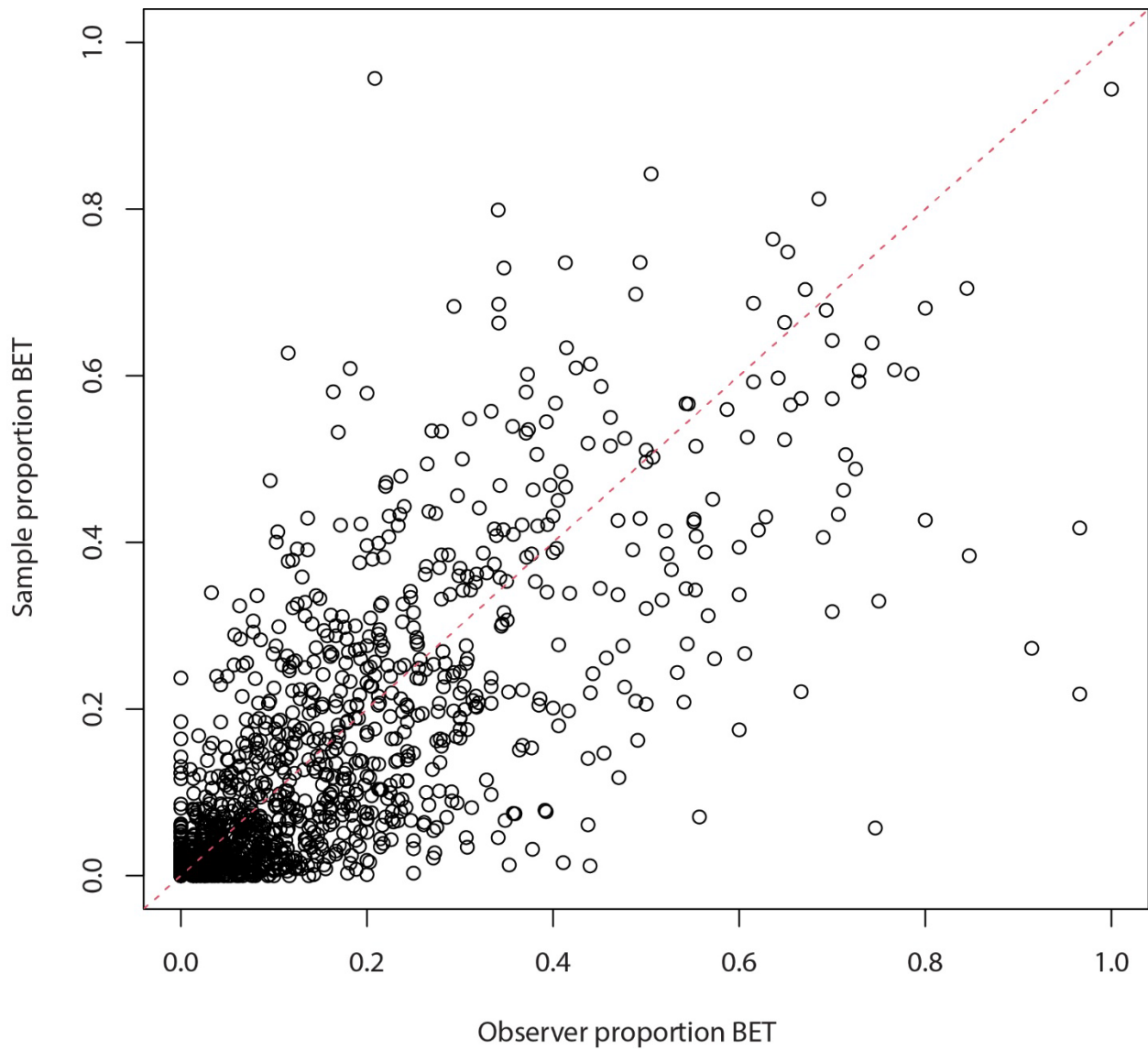


Figure 2. Frequency distribution of the sample (EMP) proportion of BET per well (all sampled wells), 2023-2025.

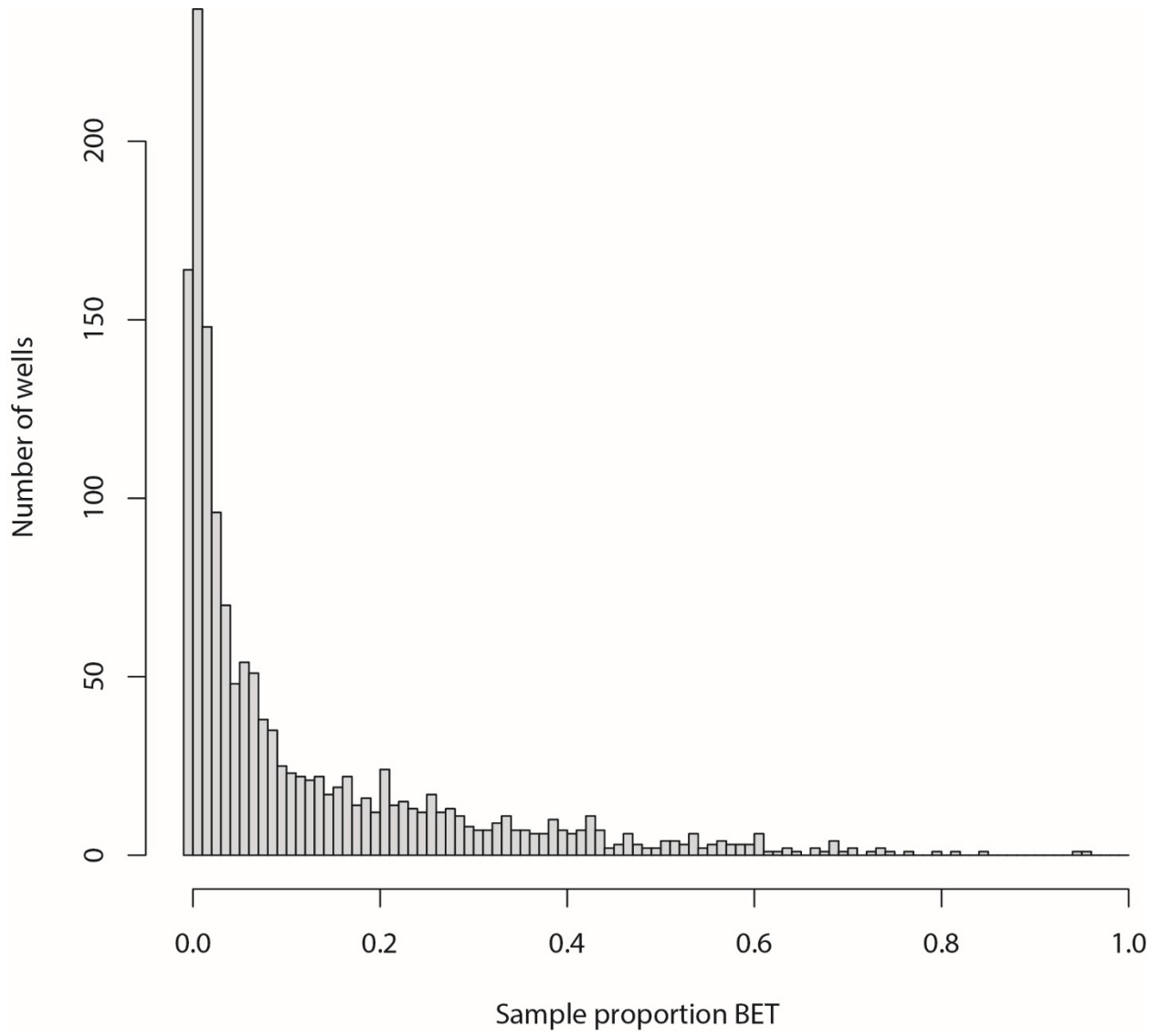


Figure 3. Plot of well-level Box-Cox transformed observer (OBS) proportion of BET versus Box-Cox transformed sample (EMP) proportion BET, OBJ-set wells only, 2023-2025. Each open circle is an individual well. The red dashed line is the 1-to-1 line. The row of open circles that parallel the x-axis at the bottom of the figure correspond to those wells for which the sample estimate of the proportion of BET was zero (35 wells; two fewer than shown in Table 1 due to data trimming).

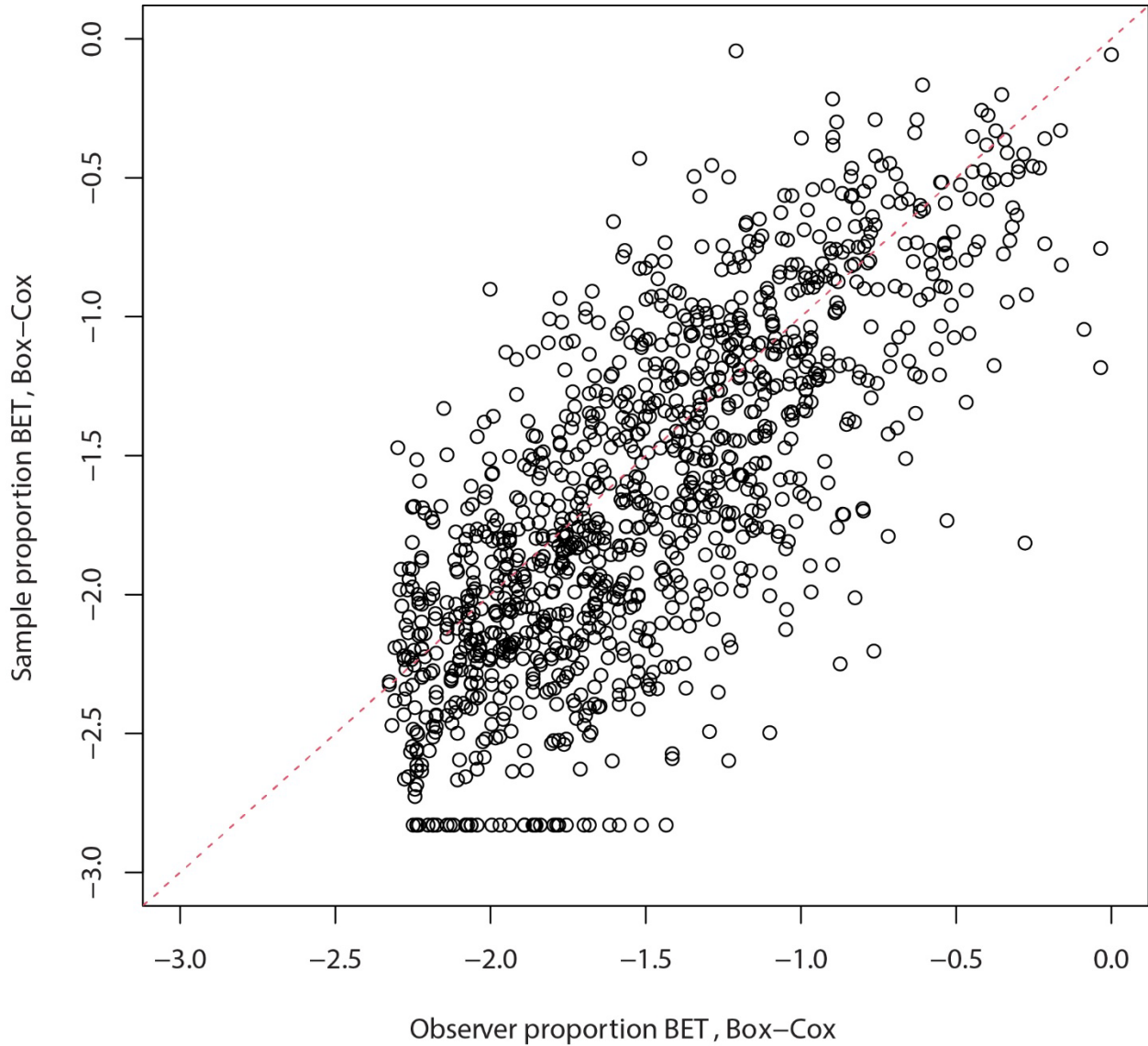


Figure 4. Histograms of  $\bar{\delta}^2$  (x-axis) for sample (EMP) versus OBS (top panel), sample versus LME estimated (middle panel), and difference between these two (bottom panel); test data, first quarter.

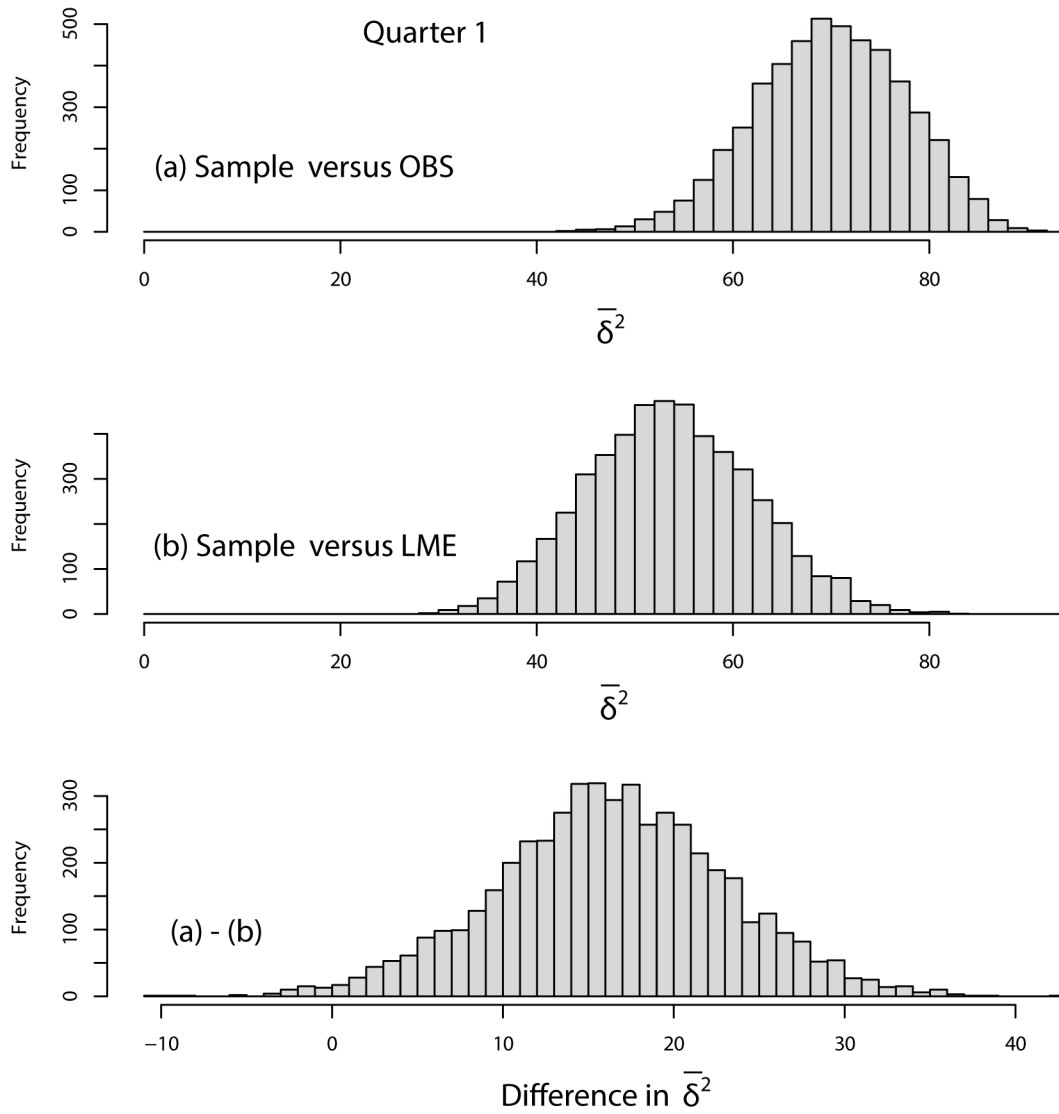


Figure 5. Box-and-whisker plots of the difference between the EMP proportion of BET and the linear mixed-effects model estimated proportion of BET, for the same well (y-axis), for test data set wells of the first quarter of 2025, ordered by the actual EMP proportion BET, from left to right. Each box-and-whisker plot represents the variability across synthetic data sets of the difference for a single well. The colors indicate the trip to which the wells belong.

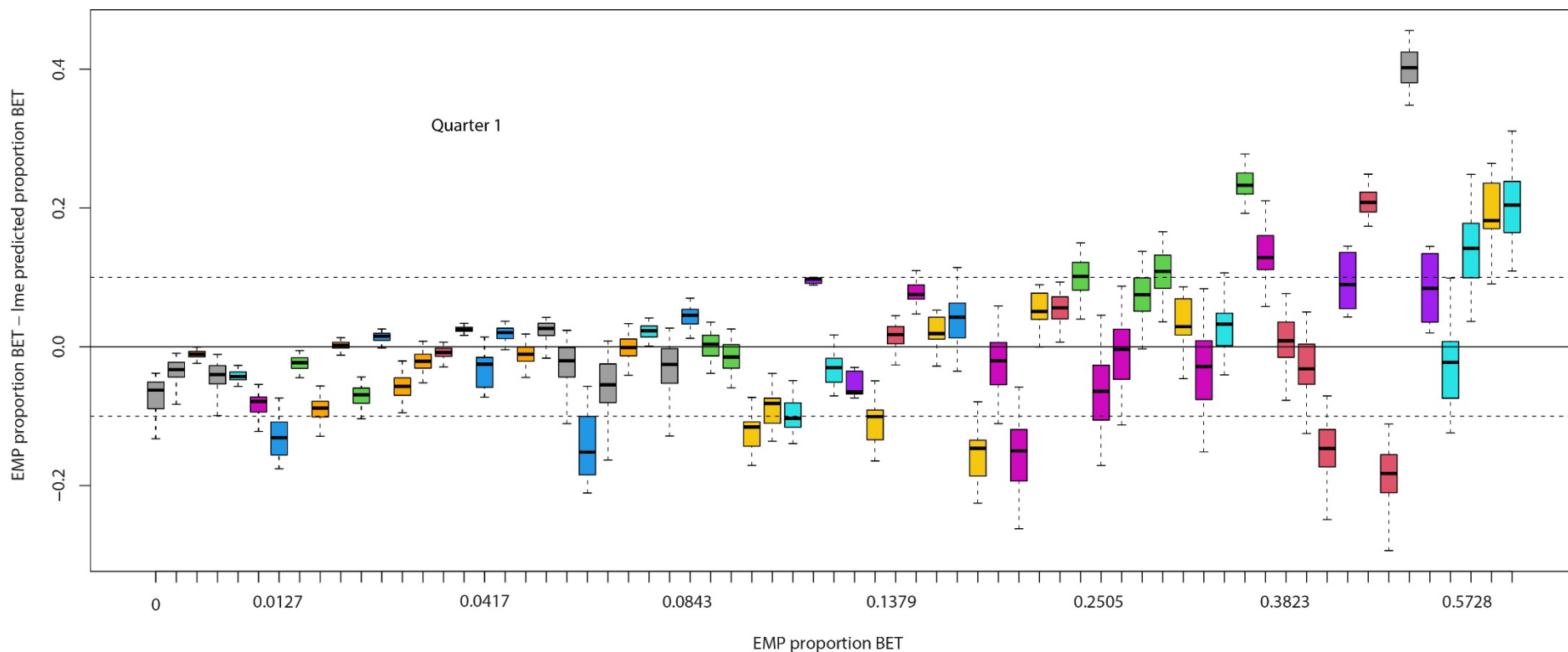


Figure 6. Plots of the relationship between observer (OBS) and sample (EMP) estimates of the proportion of BET per well (open circles), by trip, for one vessel, 2023-2025. Each panel shows the data for sampled wells of one trip. The red dashed line is the 1-to-1 line. Panels are ordered by increasing trip number, from upper left to lower right, which is very roughly a chronological ordering. [change order to year instead of trip number]

