Agreement on the Conservation of Albatrosses and Petrels

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Comparing results of black petrel capture interactions with bottom longlines using different data collection methods

Meyer, S.; Hickcox R.

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SUMMARY

Black petrels (*Procellaria parkinsoni*) are assessed as being the petrel species at greatest risk from incidental captures in New Zealand domestic fisheries. These seabirds breed in north-eastern New Zealand and are caught primarily by bottom longline vessels fishing in that area. To gather additional data on capture rates, a trial camera monitoring programme was undertaken between 2016 and 2022 to these bottom longline vessels. This programme was developed in collaboration with commercial fishers, who volunteered their time and the use of their vessels.

The effect of additional observations from the trial camera programme for estimating captures of black petrels was evaluated. In addition to this, the influence of observer and/or camera presence on the reporting of protected species captures was assessed.

The results showed that estimated black petrel captures were lower when using observer data and electronic monitoring data combined compared with model fits against observer data alone. Simulating data with different proportions of assessed video footage revealed strong biases of estimated black petrel captures for scenarios that were comparable with the proportion of assessed video footage in the actual data that are used to estimate captures. Hence, current bycatch models seem to overpredict black petrel captures in bottom longline vessels fishing off the north-east coast of New Zealand.

When comparing fisher-reported black petrel captures with model estimates there was reasonable alignment between both, even when cameras were present and video footage was not assessed. For fishing events that had neither an observer on-board nor cameras present, the fisher-reported captures were below capture estimates, but as aforementioned these also seem to be overpredicted. Therefore, the results highlight two main benefits from electronic monitoring, which are the ability to increase the proportion of monitored fishing events, thus reducing bias, and more accurate reporting of captured birds when cameras are present.

RECOMMENDATIONS

We recommend that SBWG;

1. note that observer data can be combined with electronic monitoring data to increase the precision of seabird bycatch estimates.
2. note that seabird bycatch estimates may be biased when made using only observer data (e.g. if fishers undertake shorter trips or stay closer to shore when an observer is present on-board).
3. note that when assessing reporting rates for fisher-reported protected species captures there is a need account for potential bias in the data used to fit models to estimate total captures.
4. review ACAP guidance on seabird bycatch data collection and assessment to reflect the conclusions from this study.

Comparación de los resultados de las interacciones de captura del *Procellaria parkinsoni* con palangres de fondo utilizando diferentes métodos de recopilación de datos

RESUMEN

La especie *Procellaria parkinsoni* se considera la especie de petreles con mayor riesgo de captura secundaria en las pesquerías nacionales de Nueva Zelanda. Estas aves marinas se reproducen en el noreste de Nueva Zelanda y son capturadas principalmente por buques palangreros de fondo que pescan en esa zona. Para recopilar datos adicionales sobre las tasas de captura, entre 2016 y 2022 se llevó a cabo un programa de prueba de vigilancia con cámaras en estos buques palangreros de fondo. Este programa se desarrolló en colaboración con pescadores comerciales, que ofrecieron voluntariamente su tiempo y el uso de sus embarcaciones.

Se evaluó el efecto de observaciones adicionales del programa de prueba de vigilancia con cámaras para estimar las capturas de *Procellaria parkinsoni*. Además, se evaluó la influencia de la presencia de observadores o cámaras en el informe de capturas de especies protegidas.

Los resultados mostraron que las capturas estimadas de *Procellaria parkinsoni* fueron menores cuando se utilizaron los datos de los observadores y los datos de seguimiento electrónico combinados en comparación con los ajustes del modelo con los datos de los observadores solos. La simulación de datos con diferentes proporciones de secuencias de video evaluadas reveló fuertes sesgos de la captura estimada de *Procellaria parkinsoni* para escenarios que eran comparables con la proporción de imágenes de video evaluadas en los datos reales que se utilizan para estimar las capturas. Por lo tanto, los modelos actuales de captura secundaria parecen sobrepredecir las capturas de *Procellaria parkinsoni* en los buques palangreros de fondo que pescan frente a la costa nordeste de Nueva Zelanda.

Al comparar las capturas de *Procellaria parkinsoni* informadas por los pescadores con las estimaciones del modelo, hubo una alineación razonable entre ambas, incluso cuando las cámaras estaban presentes y no se evaluaron las imágenes de video. En el caso de los eventos de pesca en los que no había un observador a bordo ni cámaras presentes, las capturas informadas por los pescadores estuvieron por debajo de las estimaciones de captura, pero como se mencionó anteriormente, estas también parecen estar sobrepredichas. Por lo tanto, los resultados destacan dos beneficios principales del seguimiento electrónico, a saber: la capacidad de aumentar la proporción de eventos de pesca monitoreados, reduciendo así el sesgo, y un informe más preciso de las aves capturadas cuando hay cámaras presentes.

RECOMENDACIONES

Recomendamos que GdTCS tome las siguientes medidas:

1. Tomar nota de que los datos de los observadores pueden combinarse con los datos de seguimiento electrónico para aumentar la precisión de las estimaciones de la captura secundaría de aves marinas.
2. Tomar nota de que las estimaciones de captura secundaría de aves marinas pueden estar sesgadas cuando se realizan utilizando solo datos de observadores (p. ej., si los pescadores realizan viajes más cortos o permanecen más cerca de la costa cuando hay un observador presente a bordo).
3. Tomar nota de que, al evaluar las tasas de notificación de las capturas de especies protegidas notificadas por los pescadores, es necesario tener en cuenta el posible sesgo en los datos utilizados para ajustar los modelos a fin de estimar las capturas totales.
4. Revisar las orientaciones del ACAP sobre la recopilación y evaluación de datos sobre captura secundaría de aves marinas para reflejar las conclusiones de este estudio.

Comparaison des résultats des interactions de capture de puffins *Procellaria parkinsoni* avec les palangres de fond à l'aide de différentes méthodes de collecte de données

RÉSUMÉ

Procellaria parkinsoni est considérée comme l'espèce de puffins la plus menacée par les captures accidentelles dans les pêcheries domestiques néo-zélandaises. Ces oiseaux de mer se reproduisent dans le nord-est de la Nouvelle-Zélande, et sont principalement capturés par les palangriers de fond qui pêchent dans cette zone. Pour recueillir des données supplémentaires sur les taux de capture, un programme d'essai de suivi par caméra a été mis en œuvre entre 2016 et 2022 sur ces palangriers de fond. Ce programme a été développé en collaboration avec des opérateurs de pêche commerciaux, qui ont donné de leur temps et permis l'utilisation de leurs navires.

L'effet des observations supplémentaires entraînées par le programme a lui aussi été évalué. A également été évaluée l'influence de la présence d'observateurs et/ou de caméras sur le signalement des captures d'espèces protégées.

Les résultats ont montré que les captures estimées de *Procellaria parkinsoni* étaient plus faibles lorsque les données des observateurs et les données de suivi électronique étaient combinées avec les ajustements du modèle, par rapport aux seules données des observateurs. La simulation de données basée sur différentes proportions de séquences vidéo évaluées a révélé de forts biais dans les captures estimées de *Procellaria parkinsoni,* pour des scénarios comparables à la proportion de séquences vidéo évaluées dans les données réelles utilisées pour estimer les captures. Par conséquent, les modèles actuels de captures accessoires semblent surestimer les captures de *Procellaria parkinsoni* dans les palangriers de fond pêchant au large de la côte nord-est de la Nouvelle-Zélande.

La comparaison entre les captures de *Procellaria parkinsoni* signalées par les pêcheurs avec les estimations du modèle révélait une concordance raisonnable entre les deux séries de données, même lorsque des caméras étaient présentes et que les séquences vidéo n'étaient pas évaluées. Concernant les événements de pêche qui n'avaient ni observateur à bord ni caméras, les captures déclarées par les pêcheurs étaient inférieures aux estimations mais, comme mentionné ci-dessus, elles semblent également être surestimées. Les résultats mettent donc en évidence deux avantages principaux du suivi électronique, à savoir la possibilité d'augmenter la proportion d'événements de pêche surveillés, réduisant ainsi les biais, et des rapports plus précis sur les oiseaux capturés lorsque des caméras sont présentes.

RECOMMANDATIONS

Nous recommandons que le GTCA :

1. Note que les données des observateurs peuvent être combinées aux données de suivi électronique pour accroître la précision des estimations des captures accessoires d'oiseaux de mer.
2. Note que les estimations de captures accessoires d'oiseaux de mer peuvent être biaisées lorsqu'elles sont effectuées uniquement en utilisant les données des observateurs (par ex. si les pêcheurs entreprennent des voyages plus courts ou restent plus près de la côte lorsqu'un observateur est présent à bord).
3. Note que lors de l'évaluation des taux de déclaration des captures d'espèces protégées fournies par les pêcheurs, il est nécessaire de tenir compte du biais potentiel dans les données utilisées pour ajuster les modèles afin d'estimer les captures totales.
4. Examine les directives de l'ACAP sur la collecte et l'évaluation des données sur les captures accessoires d'oiseaux de mer afin de refléter les conclusions de cette étude.

Fisheries New Zealand

Tini a Tangaroa

Comparing results of black petrel capture interactions with bottom longlines using different data collection methods

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EXECUTIVE SUMMARY

Meyer, S.[1]; Hickcox R. (2023). Comparing results of black petrel capture interactions with bottom longlines using different data collection methods.

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The effect of additional observations of non-target captures of black petrels (*Procellaria parkinsoni*) by electronic monitoring (EM) and observers was evaluated for commercial small-vessel bottom longline (BLL) fisheries. Moreover, the influence of observer and/or camera presence on fisher's compliance to report protected species captures (specifically black petrels) was assessed. The results showed that estimated black petrel captures were lower when fitting models to observer data and EM data combined (i.e., increasing the proportion of monitored fishing events in the data) compared with model fits against observer data alone. Simulating data with different proportions of assessed video footage revealed strong biases of estimated black petrel captures (against the 'true' number of simulated captures) for scenarios that are comparable with the proportion of assessed video footage in the actual data that are used to estimate captures. Hence, current bycatch models seem to overpredict black petrel captures in small-vessel BLL fisheries in FMA 1. However, comparing fisher-reported black petrel captures (i.e., those being independently reported from observers or camera footage if present) with model estimates suggested reasonable alignment between both, even when only cameras were present and video footage was not assessed. For fishing events that had neither an observer on-board nor cameras present, the fisher-reported captures were below capture estimates, but as aforementioned these also seem to be overpredicted. Therefore, the results highlight two main benefits from EM, which are the ability to increase the proportion of monitored fishing events (ideally close to 100%), thus reducing the need for estimating captures or at least reduce bias, and the need for more accurate reporting of captured birds when cameras are present.

[1] Both authors: Proteus, New Zealand.

1. INTRODUCTION

Bycatch, the unintentional catch of non-target species, in New Zealand's commercial fisheries is monitored via the fisheries observer services[2]. Observers are tasked to collect data to assess, for example, catch levels of targeted fish, safety compliance, fishing positions, and bycatch of marine mammals and seabirds. Sending fisheries observers on commercial vessels is an expensive and logistically challenging task, and therefore only a fraction of all commercial fishing trips can be observed each year. Further, placing observers on fishing vessels is driven by logistic factors (e.g., better communication with specific vessel operators, vessels with planned longer trips resulting in less down time, more comfortable vessels offering a better working environment), and as a result the observed fishing events might not necessarily represent a random sample of all operating fishing activity. However, adequate levels of observer coverage are needed to enable robust estimation of bycatch of non-target species in New Zealand's commercial fisheries.

To improve observer coverage, electronic monitoring (EM) technologies have been introduced into New Zealand's commercial fisheries. Between 2015 and 2019, EM was carried out by seafood industry research provider Trident Systems in inshore trawl and longline fisheries that predominantly targeted snapper in Fisheries Management Area (FMA) 1, off the north-east of New Zealand (Middleton & Guard 2021). Camera systems were installed on fishing vessels to obtain video observations and generate EM data to either supplement or substitute data collected by human observers. EM data are compiled via post-hoc assessment of collected video material.

The black petrel (*Procellaria parkinsoni*) is classified as Vulnerable by the International Union for Conservation of Nature and Natural Resources (BirdLife International 2018) and as Nationally Vulnerable by the New Zealand Threat Classification System (Robertson et al. 2021). Black petrels are range restricted and only breed from October to May in New Zealand on Great Barrier Island/Aotea and Little Barrier Island/Hauturu-o-Toi in the Hauraki Gulf. They forage within FMA 1 off the north coast of the North Island and in deeper oceanic waters (Freeman et al. 2010). Outside the breeding season, black petrels are known to feed off the west coast of the North Island and around Central and South America (Quinones et al. 2020). The most recent estimates of the number of black petrel breeding pairs are 3130 breeding pairs on Great Barrier Island/Aotea (Bell et al. 2021) and 620 breeding pairs on Little Barrier Island/Hauturu-o-Toi (Bell et al. 2016). Black petrels are at risk of being unintentionally caught in commercial fisheries because their at-sea distribution during the breeding season overlaps with the distribution of bottom longline (BLL) and trawl fisheries operating within FMA 1 (Abraham et al. 2015).

FMA 1 has a long history of longline fishing (and other fishing methods such as trawling) predominantly targeting snapper (*Chrysophrys auratus*) (Johnson & Haworth 2004, Paul 2014). BLL fishing within FMA 1 occurs throughout the entire year and therefore overlaps temporally with the breeding season of black petrels. Since the 1998–99 fishing year, all BLL vessels fishing in FMA 1 have been classified as small vessels (< 34 metres) operating under the New Zealand flag. Between the fishing years 1998–99 and 2019–20 (fishing year spans the dates October 1 to September 30 in the next year), annual fishing effort by small BLL vessels in FMA 1 ranged from 11 486 475 to 18 170 415 hooks. Official estimates of black petrel capture in all New Zealand's small-vessel BLL fisheries (i.e., in all areas of the exclusive economic zone (EEZ)) ranged from 151 to 487 birds between the 2002–03 and 2017–18 fishing years and predominantly occurred within FMA 1 or along the west and east coasts of the North Island (Abraham & Richard 2020). During that time between 0 and 43 black petrel captures were reported by observers placed on small BLL vessels. However, observer coverage in those years was relatively low, ranging from 0 to 4.5% of all small-vessel BLL fishing events between the 2002–03 and 2017–18 fishing years (Abraham & Richard 2020).

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[2] Ministry for Primary Industry Fisheries observers. https://www.mpi.govt.nz/about-mpi/careers/working-mpi/roles-at-mpi/fisheries-observers/. Last reviewed: 6 July 2023.

The National Plan of Action (2013) to reduce the incidental catch of seabirds in New Zealand fisheries acknowledges that reliably estimating seabird bycatch in all fisheries is difficult due to low observer coverage in some areas (Ministry for Primary Industries 2013). In response to that, EM trials were implemented in the BLL fisheries targeting snapper within FMA 1 (McKenzie 2021, Middleton & Guard 2021). By using seabird proxies (seabird models that were made from dyed and handwoven New Zealand flax (*Phormium tenax*) leaves) deployed on longlines, the trial showed that 89% of proxy captures can be detected by post-hoc video footage assessment, which increased to 94% after multiple video views (Middleton & Guard 2021). This initiated the black petrel EM project where 9–12 of the most active bottom longline vessels in FMA 1 were monitored each year and is ongoing (Middleton & Guard 2021).

A preliminary assessment of data from the black petrel EM project, collected between the 2016–17 and 2018–19 fishing years, showed that estimated black petrel captures in New Zealand's small-vessel BLL fisheries would be lower than suggested by a statistical model fitted to data that only include fishing events monitored by human observers (unpublished). Here, an extension of this analysis was carried out by including the 2019–20 fishing year and assessing how increased observer coverage due to additional data from EM affects estimated captures of black petrels. The specific objectives of this project are given below.

Objective One: *To conduct a review of outputs from the standardised seabird captures model (PSB2019-01) for the FMA 1 bottom longline fishery targeting snapper, comparing estimates derived from observer data and when combined with electronic monitoring data.*

The seabird captures model was refitted, as described by Abraham & Richard (2020), to data of black petrel captures collected by human observers plus black petrel captures that were detected via EM. The focus was on small-vessel BLL fisheries and how including the additional EM data would potentially change estimated captures of black petrels on all BLL fishing activity in FMA 1 between the 1998–99 and 2019–20 fishing years in comparison to previous estimates obtained from human observer data only. All target fisheries were considered and estimates of back petrel captures for each fishery in small-vessel BLL fisheries in FMA 1 were further assessed.

Objective Two: *Resampling of coverage (both observer and camera-monitored) in FMA 1 to assess representativeness and propose targets to improve precision.*

EM technologies can potentially be installed on every fishing vessel. However, only a fraction of the collected video footage is reviewed because it must still be assessed by humans. Therefore, in this objective the needed proportion of video material to be reviewed for robust estimation of black petrel captures was determined. Fishing events with a known number of black petrel captures (based on events with human observers and analysed video footage) were resampled to create a new fishing year of effort, fishing locations, and black petrel captures. From this resampled dataset with known total captures, datasets with different observer/camera coverage were generated and reanalysed using the modelling framework described by Abraham & Richard (2020).

Objective Three: *To compare these estimates with fisher-reported data.*

Since 2008, it has been mandatory for fishers to report protected species captures[3], and the dataset of fisher-reported captures, managed by Fisheries New Zealand, provides an additional opportunity to evaluate estimated captures based on the currently applied modelling framework described by Abraham & Richard (2020). Therefore, observer-reported black petrel captures, black petrel captures based on EM, and estimated black petrel captures were compared with black petrel captures that were reported from small-vessel BLL fisheries in FMA 1 fisheries between the 2016–17 and 2019–20 fishing years.

[3] See Fisheries (Reporting) Regulations 2001 (SR 2001/188). https://www.legislation.govt.nz/regulation/public/2001/0188/latest/whole.html

2. METHODS

2.1 Study area

This study focused on small-vessel BLL fishing in FMA 1 (Figure 1). Fishing activity in FMA 1 is a significant contributor to New Zealand's economy, with one of the largest catch values within New Zealand's EEZ (Williams et al. 2017). The top-5 species caught by all fishing methods in FMA 1 between the 2016–17 and 2019–20 fishing years (i.e., the period overlapping with the EM study) were snapper (*Chrysophrys auratus*), trevally (*Pseudocaranx georgianus*), tarakihi (*Nemadactylus macropterus* & *N. rex*), kahawai (*Arripis trutta* & *A. xylabion*), and grey mullet (*Mugil cephalus*) (Table A-1). The top-5 fishing methods (based on the number of fishing events) in FMA 1 between the 2016–17 and 2019–20 fishing years were set net (70 029 fishing events), trawling (19 888 fishing events), bottom longlining (18 002 fishing events), crab potting (9198 fishing events), and Danish seining (6930 fishing events) (Table A-2). Bottom longline vessels operating within FMA 1 between the 2016–17 and 2019–20 fishing years were all classified as small vessels (< 34 metres) and predominantly targeted snapper (14 323 fishing events targeted snapper compared with 1548 fishing events targeting all other species combined) (Table A-3).

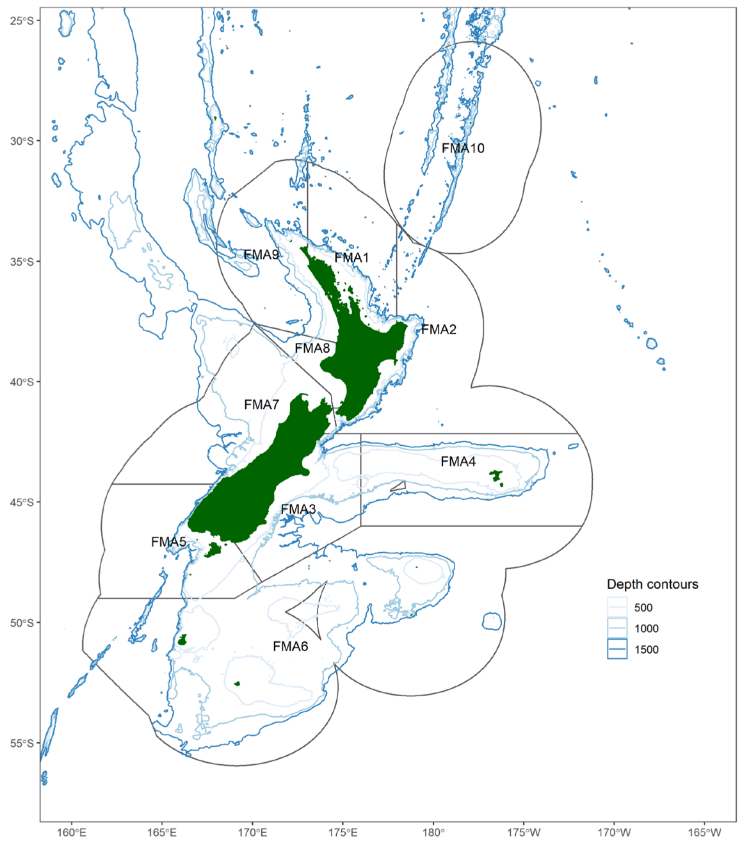

Figure 1: New Zealand Fishery Management Areas (FMAs), with FMA 1 located off the north coast of the North Island; also shown are 500, 1000, and 1500 m depth contours.

2.2 Data

Protected Species Captures Database

Data collected via the fisheries observer services are stored in the Centralised Observer Database (Sanders & Fisher 2020), and data reported by fishers are stored in the Ministry for Primary Industries (MPI) Enterprise Data Warehouse (EDW). Seabird bycatch is retained for subsequent examination and identification via necropsy. For seabirds that could not be retained (e.g., when interacting with the fishing gear leading to death, but bird was not hauled on-board), photos were taken for subsequent identification. Seabird identifications are carried out by Wildlife Management International (WMIL). Data collected by observers, reported by fishers, and post-mortem identifications are groomed and merged into the Protected Species Captures (PSC) Database (Abraham & Berkenbusch 2019), which is then made available to researchers to analyse non-target bycatch in New Zealand's commercial fisheries[4]. In this analysis, we used data from the PSC database version 6, which includes data up to the 2019–20 fishing year.

The PSC database comprises three main tables:

- catch_effort_t: containing all commercial fishing events within New Zealand's EEZ including information on start fishing location, start fishing date and time, target species, etc.
- observer_effort_t: containing all human-observed commercial fishing events within New Zealand's EEZ including information on start fishing location, start fishing date and time, target species, etc.
- all_captures_t: containing reported protected species captures on human-observed fishing events within New Zealand's EEZ.

Fishing events in these three tables are linked via an event_key column.

EM data

EM data were provided by Fisheries New Zealand on 09/04/2021. The provided dataset was compiled under project PSB2019-06/07 (review footage collected from the 18/19 Black Petrel Electronic Monitoring Programme and continued for the 19/20 summer; Middleton & Abraham 2023), which was submitted to MPI and NIWA on 03/02/2021.

Two files were provided:

1. em_reviewed_events.csv: statutory fishing events (i.e., events present in the MPI EDW) that have been reviewed for seabird captures using video observation. This includes reviewed bottom longline fishing events in FMA 1 with reported target species BNS, GUR, HPB, KAH, KIN, LIN, RBY, RIB, RRC, RSN, SCH, SKI, SNA, SWO, TAR, TRE (SNA targeting predominates).
2. em_seabird_captures.csv: seabird captures identified by the video observation process.

Project PSB2019-06 focused on the November-May period from the 2018–19 to 2019–20 fishing years. Data for the fishing years 2016–17 and 2017–18 were provided by Trident Systems Limited Partnership. As per data description[5], BLL events in FMA 1 with a target species of SWA (silver warehou *Seriolella punctata*) were recoded to SNA (snapper *Chrysophrys auratus*). The EM data cover the dates 24/11/2016 to 06/07/2020. The em_reviewed_events dataset contained 2310 records (i.e., 2310 fishing events observed via EM), and em_seabird_captures contained 161 records, of which one had two recorded (flesh-footed shearwater (*Puffinus carneipes*)) assigned captures (i.e., 162 captures were recorded via EM).

Data linking

Adding additional observations from EM data to the PSC database required linking each fishing event with assessed video footage to commercial fishing events stored in the PSC database. First, fishing events in the commercial fishing events table (catch_effort_t) of the PSC database were matched against fishing events in em_reviewed_events to identify those additionally camera-monitored events from the EM data that needed to be added to the observed fishing events table (observer_effort_t) of the PSC database. This was done by matching vessel identifiers, start fishing date, and start fishing time between

[4] https://protectedspeciescaptures.nz/PSCv6/released/about.html
[5] https://marlin.niwa.co.nz/dataset/overview/6942

records of the two data sources (i.e., catch_effort_t and em_reviewed_events). Next, fishing events in table catch_effort_t that were matched against em_reviewed_events were added to the table observer_effort_t, unless they were already human observed (i.e., already in table observer_effort_t). This was done to avoid duplication and due to the similarities in EM and human-observed data when collected from the same fishing events (Middleton & Guard 2021). Additional observed events from em_reviewed_events were flagged in table observer_effort_t. For those additional EM fishing events that were added to the table observer_effort_t, black petrel captures recorded in em_seabird_captures were added to the observed captures table (all_captures_t) of the PSC database.

Some manual data grooming was required to improve the data linking process. In consultation with David Middleton (Pisces Research Limited), 17 fishing events in em_reviewed_events were identified that had a wrong vessel key assigned (these were identified by carefully assessing fishing start date and times in em_reviewed_events that could initially not be linked to the fishing events stored in the PSC database). Here, the vessel key was changed from 337 to 4077. In the table catch_effort_t table, 722 events had missing values for the column start_datetime and were filled with values from the alternative columns start_date and start_time. Time zones in EM data and the PSC database were aligned to Pacific/Auckland time zone. EM data were filtered to dates prior to 01/10/2020 (i.e., to only include data up to the 2019–20 fishing year). Initial data assessment showed that one vessel key (3777) in em_reviewed_events was missing in the PSC database. Reviewing the original data for commercial catch and effort (from the MPI EDW) revealed that this vessel in em_reviewed_events was linked to a single fishing event (vessel key: 3777, start date: 06/12/2018, start time 05:30:00) that was not included in the PSC database (i.e., it did not pass the data grooming process from EDW to the PSC database). Hence, this single fishing event was not included in this analysis here. In total, there existed 2310 fishing events in the filtered em_reviewed_events that were available for analysis. Of those, 220 were already observed by humans and thus already contained within the PSC database table observer_effort_t. That means 2090 fishing events from the EM data were added to the observer_effort_t table. The date range for these additional observed fishing events based on EM was from 28/11/2016 to 31/05/2020.

Data from em_seabird_captures were filtered for black petrels (species code: XBP) and added to the table all_captures_t (the table containing observed protected species captures) of the PSC database following the same procedure for adding em_reviewed_events to the observer_effort_t table. The total number of black petrel captures recorded in the EM data was 43, of which 41 captures were added to the table all_captures_t, because two captures occurred on fishing events that had already been monitored by human observers.

The PSC database was stored in PostgresSQL version 4.28[6] and data processing was done in R (R Core Team 2021).

2.3 Model fitting (Objective 1)

To assess how additional records from the black petrel EM project affect the estimation of black petrel captures, the original model for seabird captures described by Abraham & Richard (2020) was refitted to black petrel captures based on observer and EM data combined (further referred to as the expanded dataset; as opposed to data of black petrel captures based on observer data alone which from here on, referred to as the original dataset).

As per Abraham & Richard (2020), the mean catch rate (μ_i) for a single fishing event in the group *i* of events (event-based data were grouped by each model variable; see below for details) was modelled as:

$$\mu_i = \alpha M_{m,v,i} F_i A_i R_i S_i Y_{m,v,y,i} \qquad (1)$$

[6] https://www.postgresql.org/

where

- α is the intercept
- $M_{m,v,i}$ is a combination of fishing method (m) and vessel class (v) for a single fishing event in the group i (Table B-1)
- F_i denotes the target fishery for a single fishing event in the group i (Table B-2)
- A_i is the area for a single fishing event in the group i (Table B-3)
- R_i is the region ("north" or "south") for a single fishing event in the group i (Table B-3)
- S_i denotes the season for a single fishing event in the group i (Table B-4)
- $Y_{m,v,y,i}$ is fishing year y nested within method m for a single fishing event in group i.

The subscript v for vessel class implies that the year effect was only applied to large vessels. Here fishing years ranged from 1998–99 to 2019–20. As per Abraham & Richard (2020), fixed effects were modelled using a base case taken as the combination of method, vessel class, region, and season having the highest number of observed captures. All prior distributions and model constraints (Table B-5) were applied as described by Abraham & Richard (2020). Three Markov chain Monte Carlo (MCMC) chains with 40 000 iterations were fitted, using a thinning interval of 30. The first 2000 iterations were discarded as burn-in. The Stan code (Appendix C: Stan code) was implemented using the R package "RStan" (Stan Development Team 2022). The estimation of bycatch rates was done by fitting the model against observed fishing events, and then using the model estimates to predict total captures on unobserved events. To account for zero-inflated capture data, a negative binomial distribution with mean μ and an overdispersion parameter φ was fitted to observed captures following the most recent implementation by Abraham & Richard (2020), including an overdispersion scaling parameter ν to avoid that estimated numbers of observed captures can exceed the actual number of observed captures (as per Abraham & Richard 2020). Model convergence was assumed if the potential scale reduction factor for each parameter was less than 1.1 (Gelman & Rubin 1992). Following Abraham & Richard (2020), sample size adjusted for autocorrelation was calculated, and the percentage of samples lost due to autocorrelation was assessed.

Following Abraham & Richard (2020), event-level data were grouped by summing the number of fishing events and the number of observed captures by each model variable. To assess predicted black petrel captures specifically in small-vessel BLL fisheries in FMA 1, captures were predicted on event-level data (for both model fits with and without EM data) to allow more fine-scaled aggregation of black petrel captures (Appendix D: R code for individual fishing event capture predictions). Predictions were only made for unobserved fishing events and combined with observed black petrel captures to obtain a total capture estimate for all fishing events combined.

2.4 Assessing required proportion of video material to be reviewed for robust estimation of black petrel captures (Objective 2)

The required proportion of video material to be reviewed for robust estimation of black petrel captures was determined. Fishing events with a known number of black petrel captures (based on events with human observers and analysed video footage) were used to create a new fishing year of effort, fishing locations, and black petrel captures for small-vessel BLL fishing in FMA 1. This dataset would reflect a fishing year with all fishing events using EM and 100% of video footage being assessed. Note, that only monitored fishing events with known captures could be used to create this dataset (i.e., originally unmonitored events could not be used). From this dataset with known total captures, datasets with different proportions of reviewed video footage were generated and reanalysed using the modelling framework described by Abraham & Richard (2020). Note that historical data (i.e., 1998–99 to 2019–20 fishing years) were still included in the model fitting as done in previous seabird captures modelling (e.g., Abraham & Richard 2020).

The dataset with known total captures was generated using a combination of data cloning (Lele et al. 2007, 2010) and bootstrapping (Efron & Tibshirani 1985) techniques to create a dataset with known effort, fishing locations, and captures. From this dataset, the expected properties of the Bayesian modelling analysis were evaluated with different proportions of assessed video footage. Data cloning involved aggregating 1000 replicated datasets into a single dataset, where each replicated dataset represents a single realisation of potential real-world data. Each of the potential real-world datasets was created via bootstrapping observed and/or EM fishing events from the expanded dataset (i.e., including EM data) between the 2016–17 and 2019–20 fishing years. The total number of fishing events for bootstrapping was based on the average total number of fishing events (i.e., observed/EM and unobserved) in each fishery and statistical area (a more fine-scaled geographic subdivision compared to FMAs). The sampling was stratified by fishery and statistical area to account for differences in fishing activity across space within FMA 1. From the dataset with known total captures, datasets with different proportions of reviewed video footage (1%, 5%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90%) were generated by randomly sampling fishing events without replacement. Each of these datasets were then analysed using the Bayesian model. The resulting posterior distributions for the quantities of interest provide an indication of the expected results that could be obtained from a single set of real-world data; however, the posterior distribution will be overly precise for a single dataset, so summary statistics can be adjusted using basic sampling theory. The adjusted results represent the expected values for the posterior mean and standard deviation for an analysis of a single dataset.

The analysis steps were as follows:

1. **Dataset for additional fishing year with known fishing effort and black petrel captures:** Bootstrapping fishing events from observed and EM data between the 2016–17 and 2019–20 fishing years (total number of fishing events were based on the average total number of fishing events in each fishery and statistical area). This dataset represents EM across all fishing events and 100% of video footage being assessed.
2. **Dataset for additional fishing year with different proportion of assessed video footage:** Subsample (without replacement) the dataset from step 1 based on proportions of 1%, 5%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90% (yielding 11 datasets).
3. **Multiple replicated datasets to allow for stochasticity:** Repeat steps 1–2 1000 times.
4. **Single dataset (data cloning step) for each proportion of assessed video footage:** For each of the 11 datasets, aggregate replicated datasets from step 3 into a single dataset (i.e., there are 11 single datasets containing 1000 realisations of steps 1–2).
5. **Original dataset (2016–17 and 2019–20 fishing years) for all fisheries and areas plus additional fishing year for small-vessel BLL fishing in FMA 1:** To each of the 11 datasets created in step 4, attach expanded dataset for the 2016–17 and 2019–20 fishing years.
6. **Data grouping:** Group event-level data by summing the number of fishing events and the number of observed captures by each model variable (see Section 2.3).
7. **Model fitting:** Fit the model described in Section 2.3 separately to original dataset with additional year attached (from steps 5–6).
8. **Model prediction:** Predicting black petrel captures for additional fishing year for small-vessel BLL fishing in FMA 1, separately for each of the 11 model fits (i.e., with different proportion of assessed video footage).

Predicted black petrel captures were divided by 1000 (the number of bootstrap samples) to obtain an expected average estimate of black petrel captures as if they were obtained from fitting the model to 1000 separate datasets and then combining the resulting posterior distributions. The expected standard deviation (SD) was calculated as SD(combined resamples)*sqrt(number of resamples) = SD(combined samples)*1000. To measure the error of the model in predicting the actual or known simulated black petrel captures, the Root Mean Square Error (RMSE) was calculated for each model fitted to bootstrapped data with different monitoring effort. RMSE was calculated as sqrt(SD^2+bias^2), where bias = (predicted captures – known bootstrapped number of captures).

2.5 Assessing fisher-reported black petrel captures (Objective 3)

It is mandatory for fishers in New Zealand to report any protected species captures during fishing. A file with fisher-reported black petrel captures (14510_EstCatch_BlackPetrel.txt) and all seabird captures (14510_EstCatch_AllBirds.txt) was provided by MPI on 04/08/2022. Fisher-reported black petrel and all seabird captures were filtered to include fishing years from 2016–17 to 2019–20. Start date and time was converted to Pacific/Auckland time zone to align with the PSC database. 14510_EstCatch_BlackPetrel.txt only contained captures reported within FMA 1, whereas 14510_EstCatch_AllBirds.txt contained reported captures within the EEZ and was therefore filtered to FMA 1. For both datasets, fishing events were matched against the expanded observer_effort_t table (i.e., including EM data) of the PSC database by matching vessel key, start date, and start time between both datasets. Fishing events in the fisher-reported data were flagged as observed or EM when they were also monitored by human observers and/or EM, respectively. Moreover, fishing events were flagged as having cameras deployed but with video footage was not assessed. This was done by matching vessel keys in the em_reviewed_events data (see Section 2.2) against a separate dataset (provided by David Middleton from Pisces Research Limited on 12/10/2022) providing the first and last date for available camera footage (separately for each vessel) which was used as a proxy for the date range of vessel-specific camera presence. Fishing events from those vessels that had no observer on-board and for which no reviewed camera footage was available were flagged as camera-observed but with unreviewed video footage if these events occurred within the date range of vessel-specific camera presence. All remaining fishing events (i.e., with either no observer or camera deployed) were flagged as unobserved.

There were 20 rows in the table observer_effort_t without start times, and thus these could not be linked to the fisher-reported data (i.e., there were some events in the fisher-reported data that are treated as unobserved because they could not be linked to the observer table in the PSC database). The total number of fisher-reported black petrel captures and all bird captures, including captures categorised as alive and injured, alive and uninjured, and dead, were then summarised per year and separately for events that were either fully unobserved (no human observer and no camera present), human-observed (some of these could have cameras deployed as well), camera-monitored (no observer present) with assessed video footage, or camera-monitored (no observer present) but unassessed video footage.

3. RESULTS

3.1 Fishing effort, observer coverage, and assessed EM data in small-vessel BLL fisheries in FMA 1

Since the 1998–99 fishing year, the number of fishing events and total number of hooks for small-vessel BLL fishing in FMA 1 has steadily declined from 16 217 to 6329 fishing events and 16 255 812 to 12 274 565 hooks, respectively (Table 1 and Table 2). Based on human observers only, the observer coverage ranged from 0 to 5.96% of total fishing events and 0 to 6.54% of total hooks set between the 1998–99 and 2019–20 fishing years. Between the 2016–17 and 2019–20 fishing years (the period overlapping with the EM study), there were 23 313 fishing events. Of those 920 events were observed by human observers and 2089 by cameras. For the same period, observer coverage ranged from 2.61 to 5.96% of total fishing events and 2.53 to 6.54% of total hooks set. The coverage of assessed video observations ranged from 7.73 to 10.10% of total fishing events and 10.10 to 13.89% of total hooks set between the 2016–17 and 2019–20 fishing years. When both human and video observations were combined, the coverage ranged from 11.73 to 16.05% of total fishing events and 14.55 to 20.43% of total hooks set (Tables 1 and 2, respectively).

Table 1: Summary of number of the fishing events (total, observed, EM, and observed and EM combined), observer coverage, electronic monitoring coverage, and both combined in small-vessel (< 34 metres) bottom longline fisheries in FMA 1 between the 1998–99 and 2019–20 fishing years. Note that electronically monitored refers to monitored events based on assessed video footage (i.e., more events might have been monitored via cameras, but footage was not assessed) of fishing events that were not already human-observed.

	Fishing events						
Fishing year	Total	Obs.	% obs.	EM	% EM	Obs. or EM	% obs. or EM
1998–99	16 217	0	0.00				
1999–00	16 780	0	0.00				
2000–01	16 648	35	0.21				
2001–02	14 995	0	0.00				
2002–03	11 603	0	0.00				
2003–04	10 943	151	1.38				
2004–05	10 237	192	1.88				
2005–06	8 303	67	0.81				
2006–07	8 266	135	1.63				
2007–08	7 592	39	0.51				
2008–09	7 418	252	3.40				
2009–10	8 017	419	5.23				
2010–11	8 430	27	0.32				
2011–12	7 396	0	0.00				
2012–13	6 780	114	1.68				
2013–14	6 724	344	5.12				
2014–15	6 304	16	0.25				
2015–16	5 752	175	3.04				
2016–17	5 703	228	4.00	441	7.73	669	11.73
2017–18	5 311	159	2.99	437	8.23	596	11.22
2018–19	5 970	156	2.61	572	9.58	728	12.19
2019–20	6 329	377	5.96	639	10.10	1 016	16.05

Table 2: Summary of fishing effort (total, observed, EM, and observed and EM combined), observer coverage, electronic monitoring coverage, and both combined in small-vessel (< 34 metres) bottom longline fisheries in FMA 1 between the 1998–99 and 2019–20 fishing years. Note that electronically monitored refers to monitored effort based on assessed video footage (i.e., more effort might have been monitored via cameras, but footage was not assessed) of fishing effort that was not already human-observed.

	Fishing effort (Number of hooks)						
Fishing year	Total	Obs.	% obs.	EM	% EM	Obs. & EM	% obs. and EM
1998–99	16 255 812	0	0.00				
1999–00	17 331 787	0	0.00				
2000–01	18 170 415	32 763	0.18				
2001–02	16 392 058	0	0.00				
2002–03	13 828 477	0	0.00				
2003–04	14 120 711	181 393	1.29				
2004–05	14 139 824	260 510	1.84				
2005–06	13 406 269	154 980	1.16				
2006–07	12 229 718	157 840	1.29				
2007–08	12 149 755	126 800	1.04				
2008–09	11 486 475	343 224	2.99				
2009–10	13 622 037	701 768	5.15				
2010–11	14 197 734	33 400	0.24				
2011–12	13 072 761	0	0.00				
2012–13	12 356 821	381 520	3.09				
2013–14	13 285 801	791 550	5.96				
2014–15	13 537 627	26 890	0.20				
2015–16	12 558 753	347 465	2.77				
2016–17	12 783 063	568 046	4.44	1 291 654	10.10	1 859 700	14.55
2017–18	11 890 436	329 516	2.77	1 380 926	11.61	1 710 442	14.39
2018–19	12 459 301	315 235	2.53	1 629 770	13.08	1 945 005	15.61
2019–20	12 274 565	802 843	6.54	1 705 310	13.89	2 508 153	20.43

Figure 2 shows the spatial distribution of fishing events and effort as well as the proportion of observed events and events with EM in small-vessel BLL fisheries in FMA 1 between the 2016–17 and 2019–20 fishing years. The same data are further summarised in 25-km distance (from mainland) bands in Table 3. Figure 2A & E and Table 3 suggest that BLL fishing activity in FMA 1 between the 2016–17 and 2019–20 fishing years was predominantly inshore fishing events within 0 to 25 km (19 025 fishing events vs. 1794 fishing events for all other distance bands combined) from the mainland coastline, although the number of fishing events decreased especially for coastal areas within the inner Hauraki Gulf. The spatial distribution of observed fishing events was, however, somewhat inverted to the distribution of total fishing activity. For example, there were 4.03% of observed fishing events within 0–25 km of the coastline compared to 10.93% of observed fishing events within the >100–150 km distance band (Figure 2B & F, Table 3). In contrast, fishing events with EM were more equally distributed across the entire BLL fishing activity within FMA 1 (e.g., 9.07% and 14.65% of fishing events within the 0–25 km and the >100–150 km distance bands, respectively; Figure 2C & D, Table 3). Similarly, a better representation of total BLL fishing activity within FMA 1 was achieved when combining data collected by observers and via EM (Figure 2D & H, Table 3).

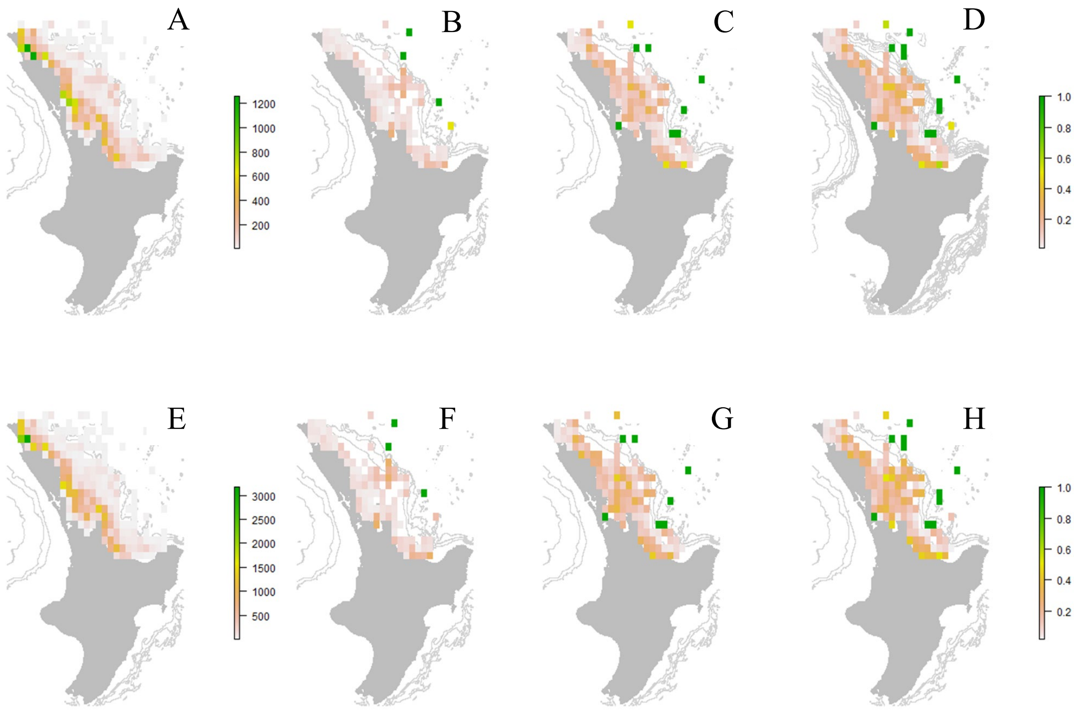

Figure 2: Spatial distribution of small-vessel BLL fishing and proportion of observed and electronically monitored (EM) fishing events and effort in FMA 1 between the 2016–17 and 2019–20 fishing years; shown are the number of total fishing events (A), proportion of observed fishing events (B), proportion of electronically monitored (EM) fishing events (C), proportion of either observed or EM fishing events (D), total number of hooks (thousands of hooks) (E), proportion of observed hooks (F), proportion of EM hooks (G), and proportion of either observed or EM hooks (H). The resolution is 0.2° grid cells, with 500 m, 1000 m, and 1500 m depth contours shown in grey.

Table 3: Summary of fishing events (all events, observed events, electronically monitored (EM) events, either observed or EM monitored events) at 25-km distance bands from mainland coastline in small-vessel BLL fisheries in FMA 1 between the 2016–17 and 2019–20 fishing years.

Distance	Number of events				Percentage of total events		
(km)	Total	Observed	EM	Observed/EM	Observed	EM	Observed/EM
0–25	19 025	767	1 725	2 492	4.03	9.07	13.10
>25–50	2 490	42	176	218	1.69	7.07	8.76
>50–75	747	33	82	115	4.42	10.98	15.40
>75–100	600	30	42	72	5.00	7.00	12.00
>100–150	430	47	63	110	10.93	14.65	25.58
>150	17	1	1	2	5.88	5.88	11.77

3.2 Predicted black petrel captures based on data including EM (Objective 1)

All parameters for the model fitted against the expanded dataset passed the convergence criteria (Table F-1) and were similar to the estimates based on original dataset (Figure 3). A reduction in effective length of chains caused by autocorrelation was less than 15% of the initial length (Table F-1) which met the same criteria applied to a model fitted to the original dataset (Abraham & Richard 2020).

There was also a slight decrease in the estimated intercept when compared with the model fitted to the original dataset, but the 95% credible intervals between both models overlapped (Figure 3).

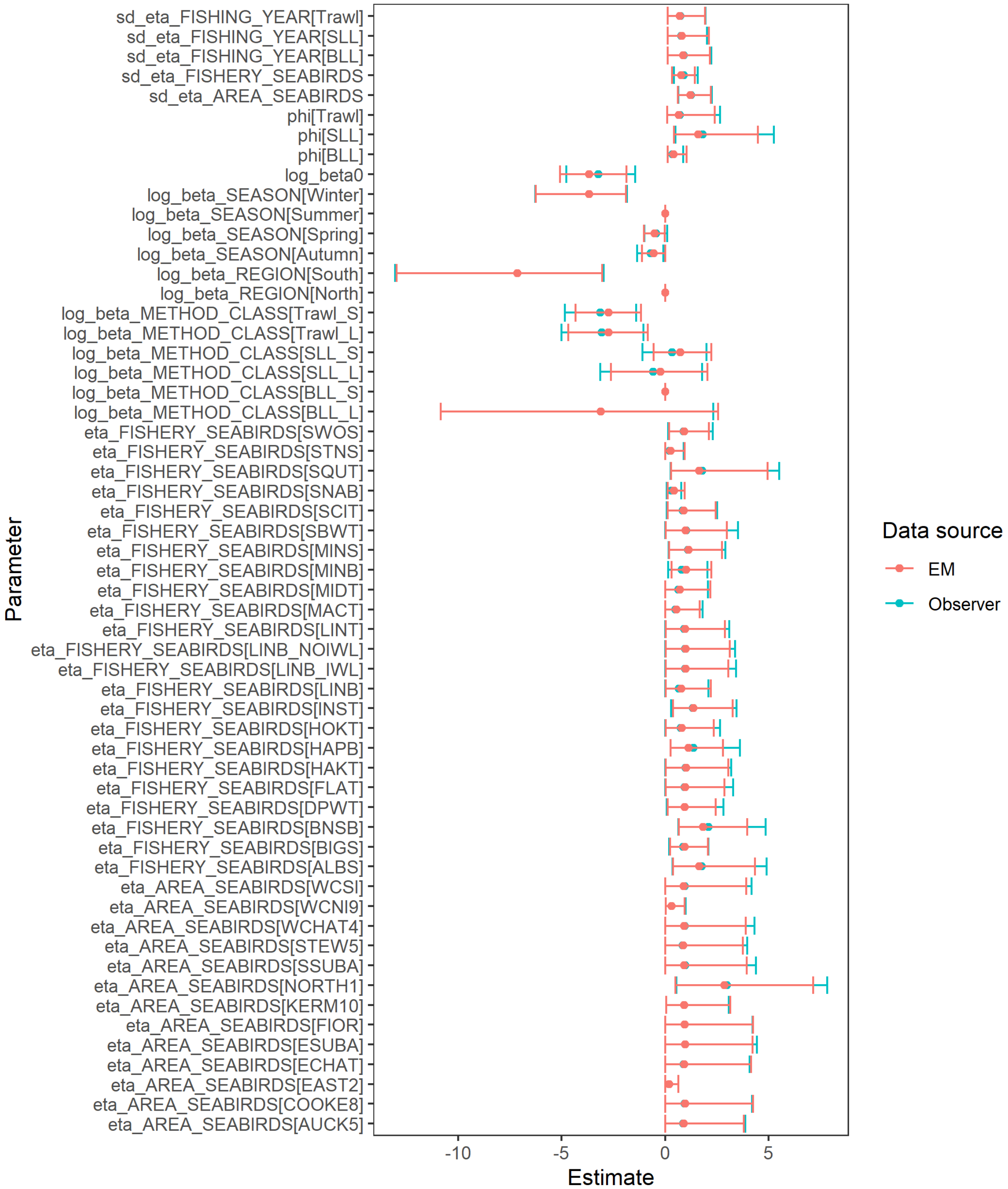

Figure 3: Estimated model parameters for models fitted against black petrel captures with and without EM data (i.e., based on observer data only). Estimated parameters from observer only models were estimated during project PSB2019-01. See Table B-1 and Table B-4 for a description of each model factor.

Figure 4 shows estimated model parameters for the total black petrel captures for all fishing events in small-vessel BLL fisheries in FMA 1 between the 1998–99 and 2019–20 fishing years, which were derived from predicted black petrel captures over unobserved fishing events plus the observed captures from the expanded dataset ('EM' in Figure 4). For comparison, the same time series is shown for the model fitted with the original dataset ('Observer' in Figure 4). Model predictions based on expanded data produced smaller average predictions of total black petrel captures compared with model predictions based on original data. Furthermore, the 95% credible intervals were generally narrower for models fitted to expanded dataset, because black petrel captures had to be predicted over a smaller number of unobserved fishing events. The improved precision in predicted black petrel captures is also reflected in Figure 5–Figure 8, which show the posterior distributions of black petrel captures specifically for each fishery between the 2016–17 and 2019–20 fishing years. These results also suggest that predicted black petrel captures are especially smaller in fisheries targeting bluenose (*Hyperoglyphe antarctica*) when EM data are included in the model.

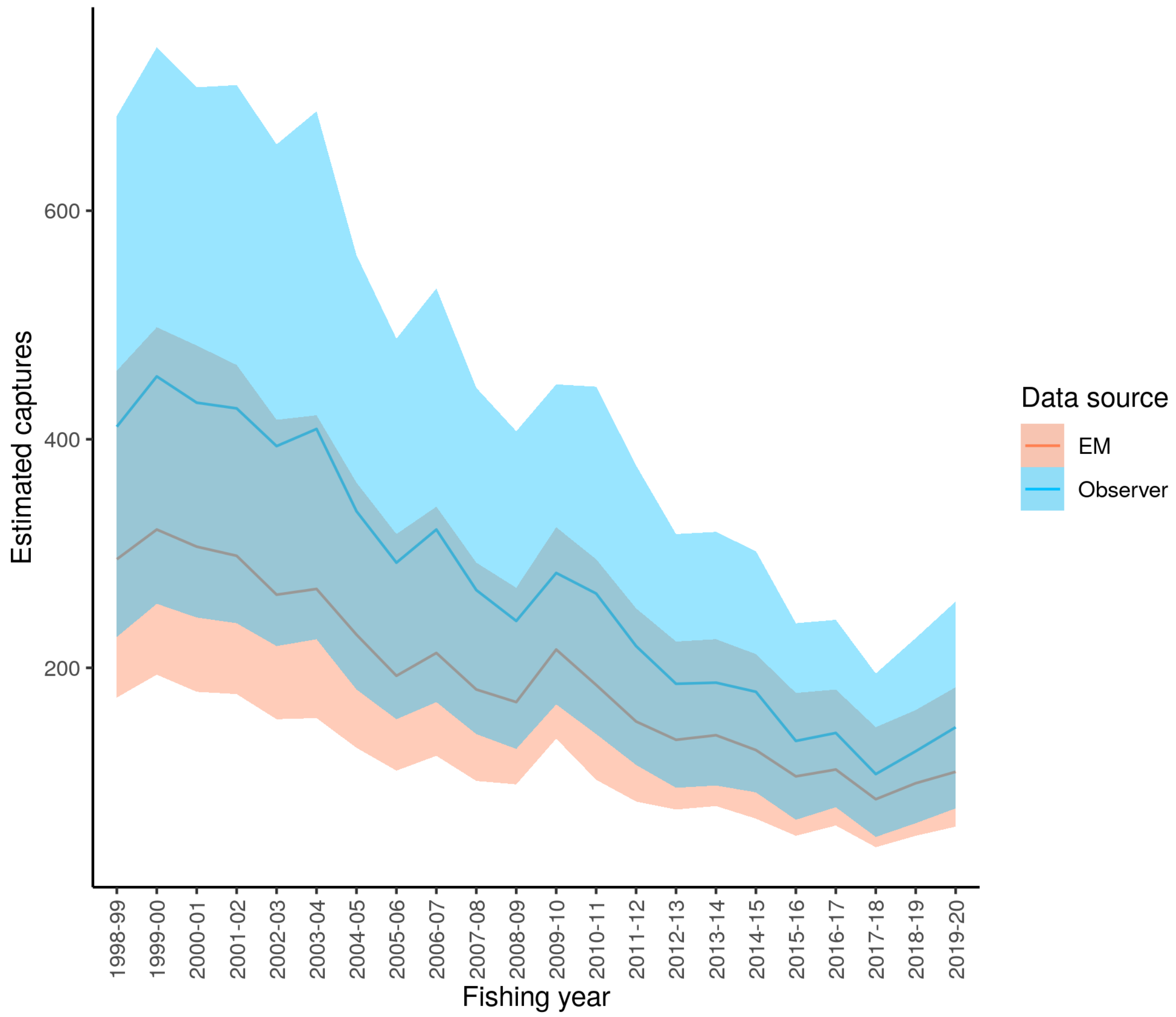

Figure 4: Time series of black petrel captures (small-vessel bottom longline fishing in FMA 1) based on the original PSC database (blue) and the expanded PSC database with additional electronic monitoring data (EM). Lines depict mean estimates and coloured areas are the 95% credible intervals.

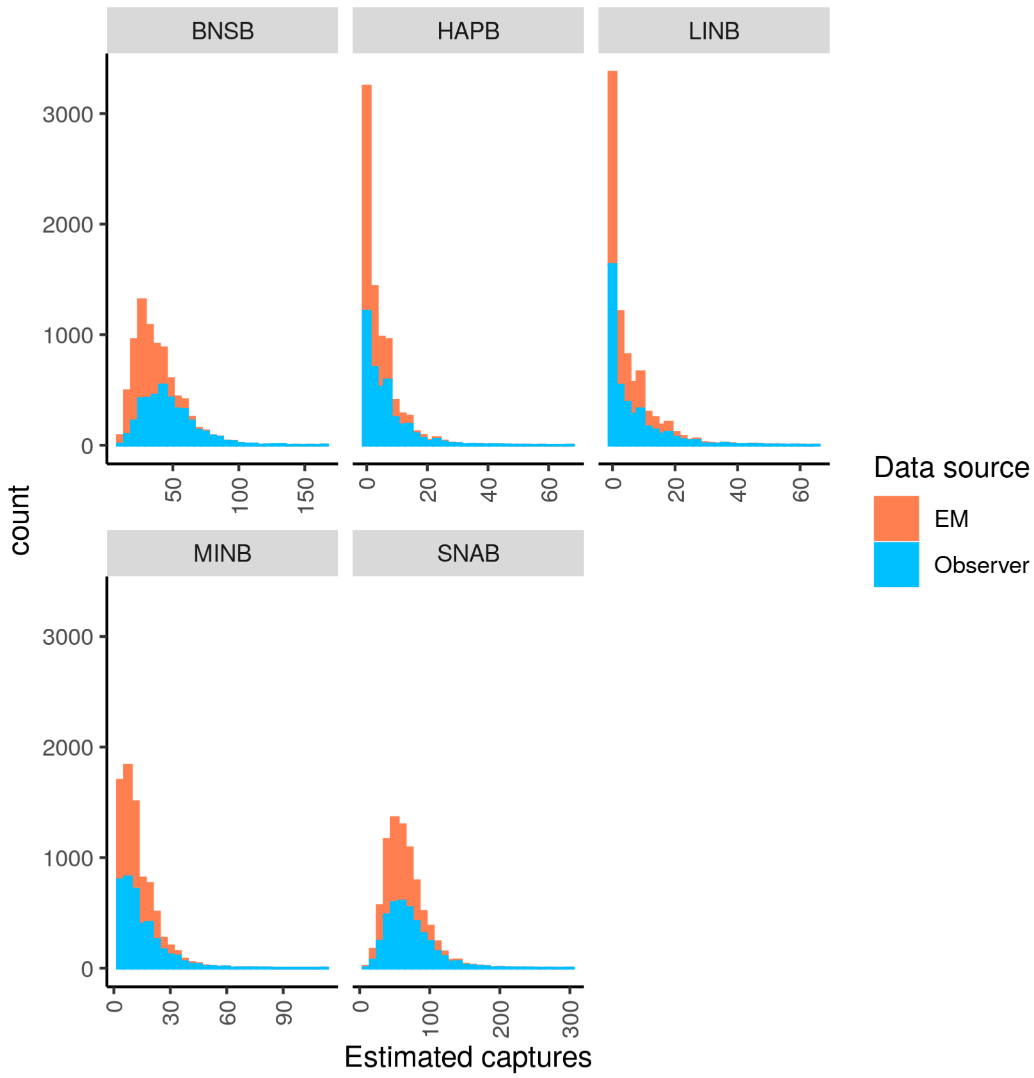

Figure 5: Histograms of MCMC samples for black petrel captures during the 2016–17 fishing year in small-vessel bottom longline fisheries in FMA 1 based on the original PSC database in blue and the expanded PSC database with additional electronic monitoring (EM) data shown in red. Fisheries are shown in different panels: BNSB bluenose (*Hyperoglyphe antarctica*); HAPB hāpuku (*Polyprion oxygeneios*) and bass (*P. americanus*); LINB ling (*Genypterus blacodes*); SNAB snapper (*Chrysophrys auratus*); MINB all other target species (Table E-1).

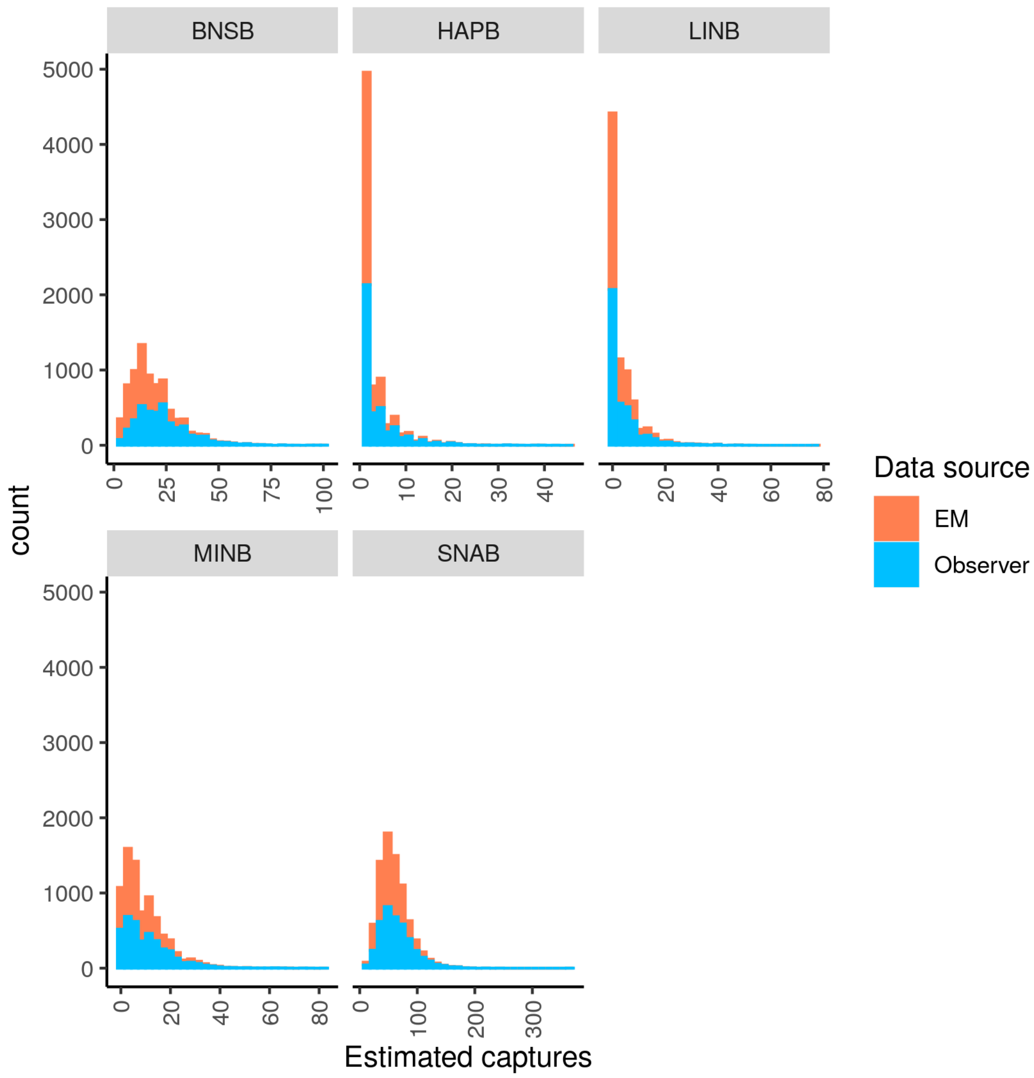

Figure 6: Histograms of MCMC samples for black petrel captures during the 2017–18 fishing year in small-vessel bottom longline fisheries in FMA 1 based on the original PSC database in blue and the expanded PSC database with additional electronic monitoring (EM) data shown in red. Fisheries are shown in different panels: BNSB bluenose (*Hyperoglyphe antarctica*); HAPB hāpuku (*Polyprion oxygeneios*) and bass (*P. americanus*); LINB ling (*Genypterus blacodes*); SNAB snapper (*Chrysophrys auratus*); MINB all other target species (Table E-1).

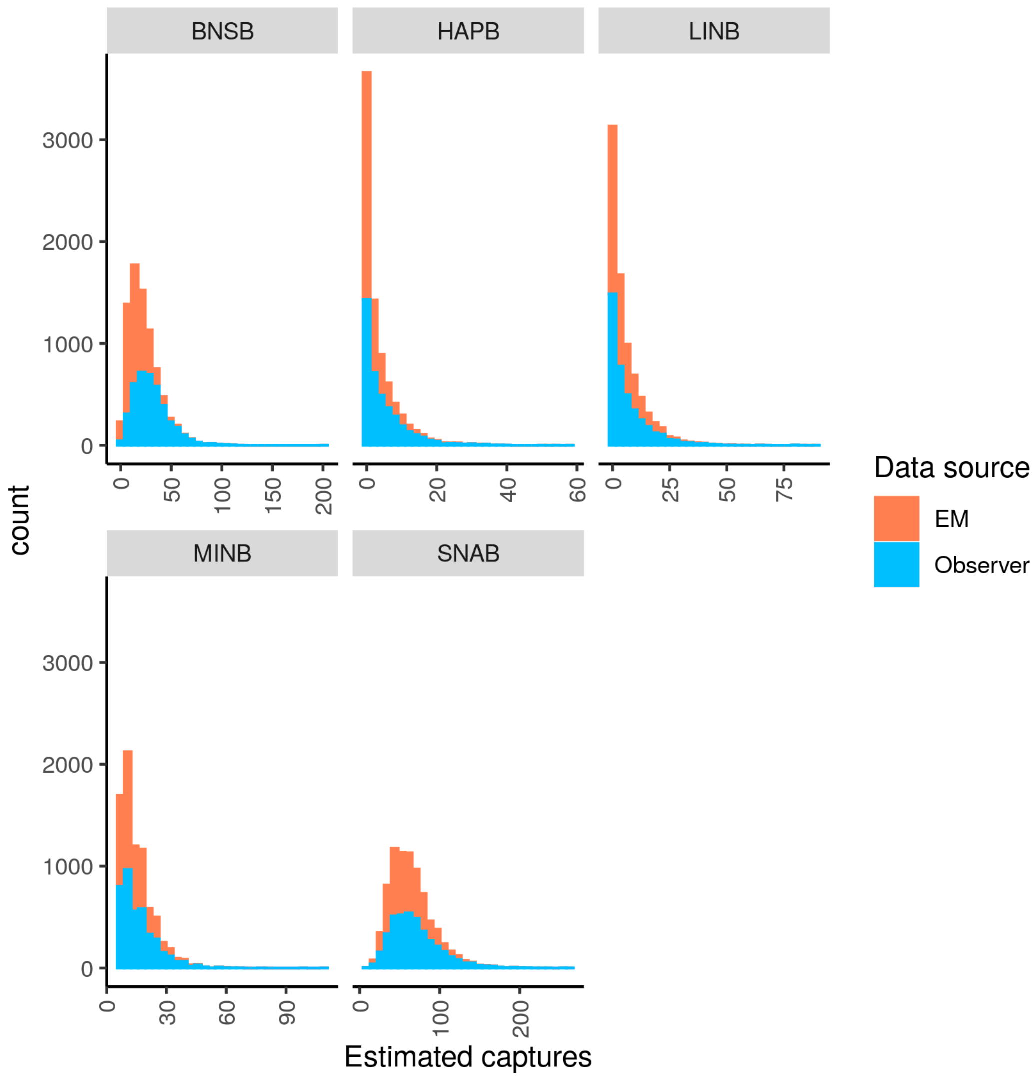

Figure 7: Histograms of MCMC samples for black petrel captures during the 2018–19 fishing year in small-vessel bottom longline fisheries in FMA 1 based on the original PSC database in blue and the expanded PSC database with additional electronic monitoring (EM) data in red. Fisheries are shown in different panels: BNSB bluenose (*Hyperoglyphe antarctica*); HAPB hāpuku (*Polyprion oxygeneios*) and bass (*P. americanus*); LINB ling (*Genypterus blacodes*); SNAB snapper (*Chrysophrys auratus*); MINB all other target species (Table E-1).

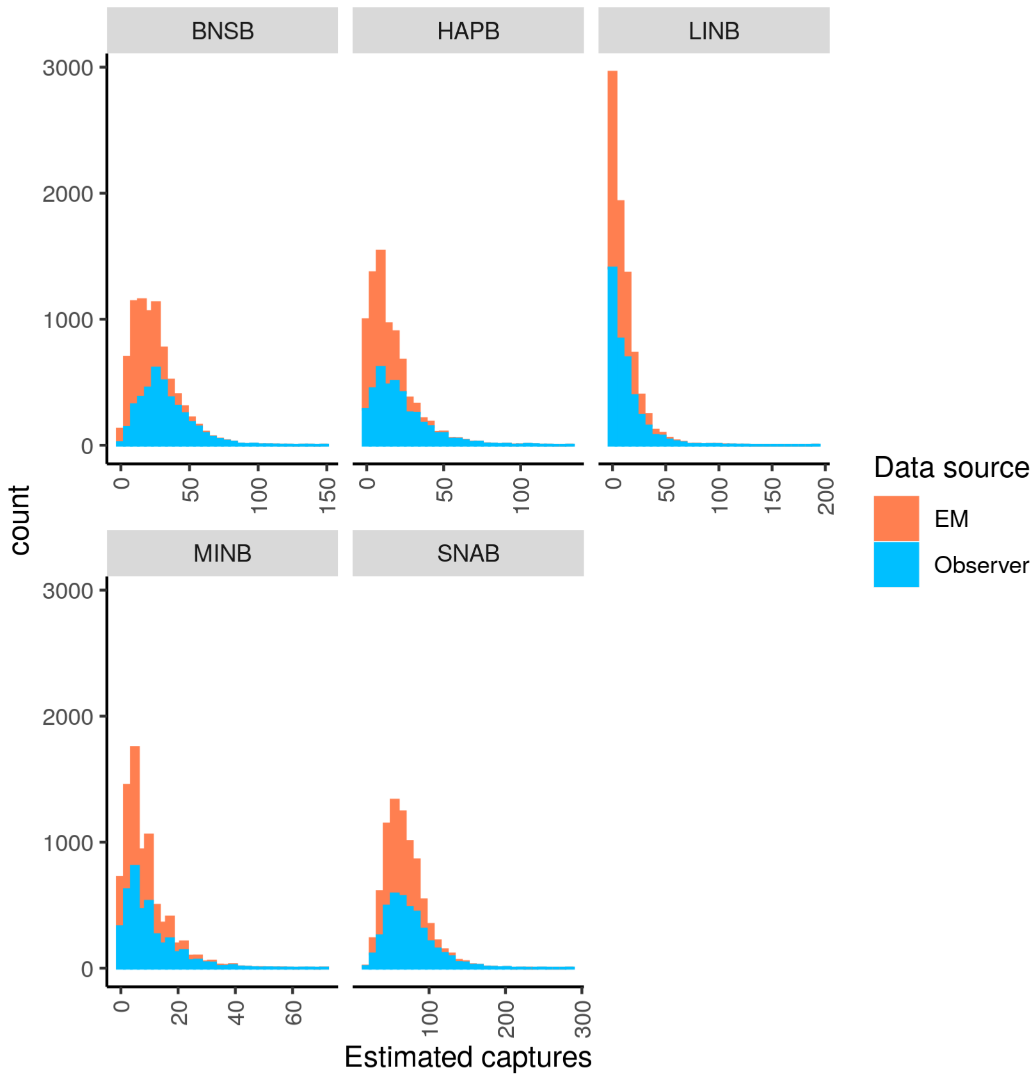

Figure 8: Histograms of MCMC samples for black petrel captures during the 2019–20 fishing year in small-vessel bottom longline fisheries in FMA 1 based on the original PSC database in blue and the expanded PSC database with additional electronic monitoring (EM) data in red. Fisheries are shown in different panels: BNSB bluenose (*Hyperoglyphe antarctica*); HAPB hāpuku (*Polyprion* oxygeneios) and bass (*P. americanus*); LINB ling (*Genypterus blacodes*); SNAB snapper (*Chrysophrys auratus*); MINB all other target species (Table E-1).

3.3 Expected black petrel estimates for different proportion of reviewed video footage (Objective 2)

Table 4 shows the expected value of the posterior mean (expected mean) and expected posterior SD of black petrel captures in an additional fishing year (i.e., model fitting was informed by historical data from 1998–99 to 2019–20 fishing years based on observer data and simulated data for an additional fishing year with assessed camera footage) for model fits against bootstrapped data with different proportions of assessed video footage. Also shown for the different model fits is the RMSE of estimated captures, which allows both the expected bias and precision of the methods to be evaluated in a single metric. For the RMSE calculation, the 'true' number of captures was the expected mean captures with 100% coverage. The total number of fishing events in the additional fishing year for 1000 bootstrapped samples combined was 5 494 000, and the average known number of black petrel captures in the additional year was 73.69 (i.e., there were 73 690 black petrel captures in the additional year for all 1000 bootstrapped samples combined) (Table 4).

Table 4: Summary statistics of estimated black petrel captures and fishing events from model fits against simulated datasets with different percentages of assessed video footage from EM. Shown are expected mean and expected standard deviation (SD) of estimated black petrel captures in a simulated additional fishing year. The Root Mean Square Error (RMSE) is based on differences in expected means of estimated and known black petrel captures for a full dataset that was created via bootstrapping black petrel captures from observer and EM data (see Methods). The number of observed and total fishing events are for all 1000 bootstrap samples combined.

	Estimated captures			Number of fishing events	
Assessed	Expected Mean	Expected SD	RMSE	Observed	Total
1%	89.48	17.61	23.65	54 000	5 494 000
10%	88.77	16.63	22.45	549 000	5 494 000
20%	84.21	14.64	18.03	1 099 000	5 494 000
30%	83.62	14.00	17.16	1 648 000	5 494 000
40%	81.86	12.55	14.98	2 197 000	5 494 000
50%	79.57	11.23	12.68	2 746 000	5 494 000
60%	77.93	9.86	10.73	3 295 239	5 494 000
70%	77.16	8.75	9.41	3 842 912	5 494 000
80%	75.77	6.83	7.14	4 392 616	5 494 000
90%	74.86	4.84	4.98	4 943 302	5 494 000
Full dataset	73.69	–	0.00	5 494 000	5 494 000

The results from this simulation analysis suggest that the current proportion of vessels with assessed video footage is insufficient to reliably estimate black petrel captures in small-vessel BLL fisheries in FMA 1. The observer coverage (i.e., based on human observers only) between the 2016–17 and 2019–20 fishing years ranged from 2.61 to 5.96% and was at times 0% in previous fishing years (Table 1). Here, the expected mean and SD of black petrel captures for model fits against data with 1% of assessed video footage were 89.48 (21% bias compared with the 'true' number of black petrel captures) and 17.61, respectively (Table 4). In comparison, the expected mean based on 100% observed footage was 73.69 black petrel captures, implying that with 1% of assessed video footage, estimated black petrel captures are both highly uncertain and strongly biased. This is also reflected in the relatively high RMSE of 23.65, which is 26% of the expected mean (89.48) for model fits with 1% assessed video footage (Table 4).

After including assessed video footage from EM, the percentage of all fishing events that were observed and/or EM ranged from 11.22 to 16.05% (Table 1). The model fitted with 10% assessed video footage yielded an expected mean and SD of 88.77 (20% bias compared with the 'true' number of black petrel captures) and 16.63, respectively, and an RMSE of 22.45 (Table 4). Hence, 10% assessed footage resulted in only minor improvements of both precision and bias. Model estimates improved noticeably when 20% of video footage was assessed. The corresponding expected mean and SD of black petrel captures was 84.21 (14% bias compared with the 'true' number of black petrel captures) and 14.64, respectively. However, the RMSE was 18.03, which was 21.41% of the expected mean, implying poor precision of estimated captures despite improvements in bias. Conversely, the expected mean and SD for the model fitted with 90% of assessed video footage was 74.86 and 4.84, respectively, and the RMSE was 4.98 (Table 4). The expected mean, SD, and RMSE for predicted black petrel captures from simulated data decreased as the percentage of assessed footage used to fit the models increased.

These results reflect expected means of black petrel captures from a single model fitted to combined data from multiple bootstrap iterations. Model fits against each of these bootstrapped datasets separately might yield slightly different results. Further, only data with known captures (i.e., those being observed and/or with EM) could be used for bootstrapping, which is less than 20% of all fishing events. Thus, results based on higher percentages of assessed video footage might be more suitable to guide upcoming assessments of EM data. For example, based on the results here, with 40% assessed video footage, the expected mean and SD were 81.86 (11% bias compared with the 'true' number of black petrel captures) and 12.55, respectively. The corresponding RMSE was 15.98 which is 18% of the expected mean (Table 4).

3.4 Fisher-reported captures vs. model estimates (Objective 3)

Estimated black petrel captures from the model fit against data including captures from both observers and assessed video footage are shown in Table 5 for human-observed (some of these could have cameras deployed as well), camera-monitored (no observer present) and assessed video footage, camera-monitored (no observer present) but unassessed video footage, and unobserved (no human observer and no camera present) fishing events. Shown are fishing effort, the number of fishing events, and posterior median and mean plus the 95% credible interval (CrI). Also shown are (where applicable) reported captures (for black petrels and all seabirds combined) based on observers or camera footage, and fishers, as well as corresponding captures rates per 10 000 hooks. Captures and captures rates for all seabirds combined are to assist with assessing differences in capture rates across observed, camera monitored, and unmonitored events. This was done because some fishers could have misidentified seabird species and thus the capture rate for black petrels could be biased due to species misidentification.

These results suggest that the current modelling approach might overpredict black petrel captures on unobserved fishing events. However, the results also suggest that fishers are more likely to report captures when either observers or cameras were present during a fishing trip. For fishing events with observer or cameras on-board (Observed), there was reasonable alignment between estimated captures and those reported by both observers and fishers. That is, the model has a good predictive ability for captures on observed fishing events (but note that actual observed captures of these observed fishing events were also used for model fitting). For example, for observed fishing events in the 2019–20 fishing year, there were 5 (95% CrI: 0–18) estimated black petrel captures and both observer and fishers each reported two black petrel captures (Table 5). For fishing events with only camera on-board and assessed video footage (Camera only (assessed)), the reported captures based on both video footage and fishers were also within the 95% CrI of estimated black petrel captures. For example, in the 2019–20 fishing year, the estimated captures were 15 (95% CrI: 2–39) black petrels on purely camera-monitored fishing events and based on video footage and fishers there were each 11 and 7 reported black petrel captures, respectively. One exception was the 2016–17 fishing year, when the estimated black petrel captures were 13 (95% CrI: 1–34) but the fisher-reported data had zero black petrel captures (based on video footage there were four reported) (Table 5). For both, observed (and/or camera-monitored) and purely electronically monitored fishing events, raw capture rates for black petrels were within the same order of magnitude and mostly comparable with captures rates based on fisher-reported black petrel captures. Further, when only cameras were present, but video footage was not assessed, then fisher-reported black petrel captures were still within the 95% CrI of estimated black petrel captures and raw captures rates were comparable with those calculated for observed and camera-monitored fishing events with assessed video footage (Table 5). For all unobserved fishing events between the 2016–17 and 2019–20 fishing years, the number of fisher-reported black petrel captures were below the 95% CrI of estimated black petrel captures and fisher-reported capture rates differed by an order of magnitude compared with those events that were either observed or camera monitored (Table 5). For example, for unobserved fishing events in the 2019–20 fishing year, the estimated captures were 89 (95% CrI: 42–161) black petrels. In contrast, fishers only reported 11 black petrels on unobserved fishing events in the same fishing year (Table 5).

When assessing raw capture rates for all seabirds caught in small-vessel BLL fisheries in FMA 1 between the 2016–17 and 2019–20 fishing years, the effect of observers and cameras on bycatch reporting by fishers was not obvious. For example, in the 2016–17 and 2017–18 fishing years, capture rates for all seabirds were in a similar order of magnitude when either based on fisher-reported captures on fishing events with cameras (but unassessed video footage) or fisher-reported captures on unobserved fishing events. However, in the 2018–19 and 2019–20 fishing years, capture rates for fisher-reported seabird captures were considerably higher on unobserved fishing events (Table 5). In other words, there existed no obvious pattern or trend in rates of fisher-reported seabird captures across the different monitoring categories (e.g., observed vs. unobserved).

Table 5: Summary of total small-vessel (< 34 m) bottom longlining effort (total number of hooks), number of fishing events, estimated black petrel captures (mean and 95% credible interval (CrI)), and reported captures by observers, based on camera footage, or by fishers, in FMA 1 between the 2016–17 and 2019–20 fishing years; results are separate for observed events, only camera-monitored (i.e., EM) with assessed video footage, only camera-monitored (i.e., EM) but without assessed video footage, and unobserved events (i.e., no observer on-board or camera deployed).

		Estimated black petrel captures				Reported captures			Reported rates (per 10 000 hooks)		
Fishing year	Effort	No. of events	Posterior median	Posterior mean	95% CrI	Observer/camera (black petrels)	Fisher (black petrels)	Fisher (all seabirds)	Observer/camera (black petrels)	Fisher (black petrels)	Fisher (all seabirds)
Observed											
2016–17	568 046	228	7	8	0–25	13	12	50	0.229	0.211	0.88
2017–18	329 516	159	3	4	0–17	2	0	38	0.061	0.000	1.153
2018–19	315 235	156	3	4	0–17	2	2	19	0.063	0.063	0.603
2019–20	802 843	377	3	5	0–18	2	2	104	0.025	0.025	1.295
Camera only (assessed)											
2016–17	1 291 654	441	11	13	2–35	4	0	10	0.031	0.000	0.077
2017–18	1 380 926	437	11	13	1–34	7	6	46	0.051	0.043	0.333
2018–19	1 629 770	572	15	17	3–42	9	7	29	0.055	0.043	0.178
2019–20	1 705 310	639	14	15	2–39	11	7	64	0.065	0.041	0.375
Camera only (unassessed)											
2016–17	2 608 380	870	15	17	3–44	–	7	37	–	0.027	0.142
2017–18	2 473 110	920	15	16	3–41	–	6	26	–	0.024	0.105
2018–19	1 650 764	550	7	9	0–27	–	1	5	–	0.006	0.03
2019–20	2 101 425	724	6	7	0–25	–	4	27	–	0.019	0.128
Unobserved											
2016–17	8 314 983	4164	73	77	36–136	–	2	85	–	0.002	0.102
2017–18	7 706 884	3795	56	59	25–114	–	3	55	–	0.004	0.071
2018–19	8 863 532	4692	75	79	37–143	–	2	117	–	0.002	0.132
2019–20	7 664 987	4589	85	89	42–161	–	11	223	–	0.014	0.291

4. DISCUSSION

These results provide empirical evidence of the effectiveness of EM to improve the estimation of black petrel captures and the compliance of commercial fishers to report protected species captures. Findings show that on-board cameras designed to either supplement or substitute data collected by human observers contribute a wider range of monitored small-vessel BLL fishing activity in FMA 1. This in turn reduced the upward bias in estimated black petrel captures when solely based on data collected by human observers. Electronic monitoring, however, has yet to be formally integrated into models that estimate seabird bycatch. In conclusion, estimated black petrel captures in New Zealand's commercial fishery were likely overpredicted in at least recent years.

Studies on the distribution of black petrels show that their at-sea abundance peaks at the shelf break (around 1000 m water depth) north of Great Barrier Island (e.g., Abraham et al. 2015). The overlap between BLL fisheries and black petrel distribution is high within that area but decreases in the Hauraki Gulf (Abraham et al. 2015). This study showed that fishing activity towards the north of Great Barrier Island had a higher proportion of human-observed fishing events than those operating further inshore, including the Hauraki Gulf. Hence, observations of black petrel captures were upwardly biased because of disproportionate allocation of observers to fishing vessels operating further offshore in areas of high black petrel activity. In other words, data collected by human observers did not represent a random sample of small-vessel BLL fishing activity in FMA 1. Rather, observer allocation to fishing vessels might have been driven by logistical factors; for example, better communication with specific vessel operators, vessels with planned longer trips resulting in less down time, or more comfortable vessels offering a better working environment.

Camera deployment, however, is independent of the logistical challenges associated with assigning observers to fishing trips, although other challenges might apply. For the 2016–17 and 2017–18 fishing years, EM data for this study were collected from 24.2% and 23.9%, respectively, of FMA 1 BLL fishing events, with 15.6% and 12.3% of fishing events having reviewed video footage (Middleton & Guard 2021). For the 2018–19 and 2019–20 fishing years, video footage was obtained for 25.8% and 26.2% of hooks set, respectively, and with 23.8% and 24.7% being reviewed for seabird captures (Middleton & Abraham 2023). Consequently, a more representative sample of small-vessel BLL fishing activity within FMA 1 was obtained, especially when combined with existing data collected by observers. Including capture observations from the EM study in the models lowered the estimated black petrel captures, implying that previous estimates were upwardly biased because of non-random sampling of capture data and potential factors that have not been accounted for in existing models for seabird bycatch. Note that the model was fitted to data that included simulated camera-assessed fishing events and 22 years of human-observed fishing events, the latter containing a spatial bias in observer allocation. Hence, a remaining bias in predicted black petrel captures caused by biased historical data is expected. Additional years of camera-monitoring (with sufficient proportion of assessed video footage) should reduce that bias.

Despite the overprediction of black petrel captures, the results of this analysis suggest that fishers reported black petrel captures more accurately when either an observer was present or cameras deployed. New Zealand commercial fishers have been legally obliged to report protected species captures since October 2008. However, fishers might not accurately report bycatch as shown in other fisheries, such as the California halibut trawl fishery (Matthews et al. 2022), and this could be due to factors such as the fisher not observing bycatch while working on the deck. Conversely, electronic monitoring has shown to provide better bycatch data than by fishers in other fisheries (e.g., Danish gillnetting in the North Sea as shown by Kindt-Larsen et al. 2012). In this study, the results also suggest that fisher compliance to report bycatch improves when either observers or cameras were present but that only few captures were reported in the absence of cameras. The mismatch in fisher-reported captures for unobserved vessels could partially be linked to the identified upwards bias in estimated black petrel captures. However, simulations conducted here have shown that the fisher-reported captures and model estimates would still differ by at least one order of magnitude. Some mismatch could be owed to fishers' inability to correctly identify black petrels or other bird species. Nonetheless, given that the mismatch between estimated black petrel captures and those reported by fishers was only obvious for entirely unobserved events suggests that most of that discrepancy was caused by under-reporting. A statistical model applied to fishery-reported seabird captures in the presence (and absence) of cameras also showed an increased probability that the fisher-reporting rate will increase when cameras were present (Tremblay-Boyer & Abraham 2020).

Fisher-reported captures of black petrel were close to those reported by observers, however slightly lower than those identified via camera footage. This suggests that some communication occurred between observers and fishers, although both have to report captures independently from each other. That would have resulted in fishers being able to report captures to species level when observers were present. In contrast, when no observers were on-board and only cameras were present then fishers might not be able to fully identify all species and are more likely to report higher level species identification codes. These issues would be exacerbated for fully unobserved events, which would explain the strong mismatch between fisher-reported captures of black petrels and model predictions on unobserved fishing events.

The identified bias in estimated black petrel captures due to low observer coverage and non-random sampling of fishing events, and the further potential for bycatch underreporting by fishers, emphasizes the importance of EM. Based on the results of this study, bias and precision of estimated black petrel captures are expected to improve by increasing the proportion of fishing vessels that are equipped with cameras. However, captured video footage needs to be assessed first before EM data are available for statistical modelling, and reviewing large amounts of footage might be unfeasible due to costs if they are to be reviewed manually. This study and previously published studies regarding EM monitoring and fisher-reported captures are important steps towards improving the management of protected species captures in commercial fisheries. Nevertheless, further significant steps are required to obtain robust model estimates of protected species captures and reliable bycatch reporting by commercial fishers. One step forward could be to equip all BLL fishing vessels with cameras and to assess 100% of the video footage for several consecutive fishing seasons to inform the development of new and species-specific bycatch models. As per Fisheries Change Plan, all BLL inshore vessels in New Zealand will be equipped with cameras between 2022 and 2024 (other methods include surface longlining, purse seine, Danish seine, trawling vessels ≤ 32 metres and set net vessels ≥ 8 metres)[7]. However, only a fraction of the collected video footage will be reviewed for captures. Alternatively, artificial intelligence tools could be used to review video footage. These data would also improve the predictive ability of protected species captures models and determine the proportion of reviewed video footage (and how this needs to be sampled from the existing footage) that is required for robust bycatch predictions.

Like observers in New Zealand's fisheries, fishers also need to be trained in bird species (and other taxa) identification. To underpin the need to train fishers in seabird species identification, further research should investigate how the proportion of species level identification to higher level species identification codes differs between events with fisheries observers, cameras only, and unobserved fishing events. While EM should continue across all fishing activity, bycatch reporting could be based on fisher-reported captures (that are confirmed by necropsies as done for observer-reported captures) on vessels with cameras, since the presence of cameras yields better fisher reporting. Partially assessed video footage (after a full census) could be used for model fitting. Differences between model predictions and fisher-reported captures could provide the incentive to either identify bycatch misreporting by fishers or to reparametrise models to respond to changes in, for example, fishing practice or environmental factors driving bycatch.

[7] On-board cameras for commercial fishing vessels | New Zealand Government (mpi.govt.nz)

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APPENDIX A: SUMMARY OF FISHING ACTIVITY IN FMA 1 BETWEEN THE 2016–17 AND 2019–20 FISHING YEARS

Table A-1: Reported commercial catch for all fishing methods operating in FMA 1 between the 2016–17 and 2019–20 fishing years (data retrieved from https://fs.fish.govt.nz/Page.aspx?pk=41&tk=99&ey=2017, https://fs.fish.govt.nz/Page.aspx?pk=41&tk=99&ey=2018, https://fs.fish.govt.nz/Page.aspx?pk=41&tk=99&ey=2019, https://fs.fish.govt.nz/Page.aspx?pk=41&tk=99&ey=2020).

Species code	Name	Reported commercial catch (kg)
SNA	Snapper Auckland (East)	18 085 974
TRE	Trevally Auckland (East)	5 918 386
TAR	Tarakihi Auckland (East)	4 420 809
KAH	Kahawai Auckland (East)	4 047 137
GMU	Grey Mullet Auckland (East) & (West) combined	3 333 773
GUR	Gurnard Auckland (East)	3 097 124
SCH	School Shark Auckland (East)	2 255 493
FLA	Flatfish 1 & 9 Combined	1 630 073
JDO	John Dory Auckland (East)	1 215 970
SPO	Rig Auckland (East)	1 090 479
HPB	Hāpuku & Bass 1 & 9 Combined	1 072 799
BNS	Bluenose Auckland (East)	947 141
PIL	Pilchards Auckland(East)	787 285
SUR	Kina Hauraki Gulf and Bay of Plenty	555 905
CRA	Spiny red rock lobster Northland	503 771
KIN	Kingfish Auckland(East)	337 102
SUR	Kina East Northland	149 762
RSN	Red Snapper Auckland(East)	109 683
SCA	Scallop Coromandel scallop fishery	88 735
GAR	Garfish Auckland(East)	85 112
YEM	Yellow Eyed Mullet Auckland(East)	57 249
PAD	Paddle Crab Auckland(East)	39 852
BCO	Blue Cod Auckland (East)	36 582
OCT	Octopus Auckland(East)	33 653
SCA	Scallop Northland scallop fishery	26 750
BMA	Blue Maomao Auckland(East)	16 378
SCC	Sea cucumber Hauraki Gulf and Bay of Plenty	5679
POY	Oysters Pacific Auckland(East)	4425
PAU	Pāua Auckland	1833
SCC	Sea cucumber East Northland	498
GLM	Green-lipped mussel Auckland (East)	233
KWH	Knobbed whelk Auckland (East)	1
BYA	Frilled Venus Shell Auckland (East)	0
COC	Cockle Whangarei Harbour cockle fishery	0
COC	Cockle East Northland	0
COC	Cockle Hauraki Gulf and Bay of Plenty	0
DAN	Ringed Dosinia Auckland (East)	0

Table A-1: continued.

DSU	Silky dosinia Auckland (East)	0
HOR	Horse Mussel Auckland (East)	0
MDI	Trough Shell Auckland (East)	0
MMI	Large trough shell Auckland (East)	0
OYS	Dredge Oyster Auckland (East)	0
PDO	Deepwater tuatua Auckland (East)	0
PPI	Pipi Whangarei Harbour fishery	0
PPI	Pipi East Northland	0
PPI	Pipi Hauraki Gulf and Bay of Plenty	0
PZL	Deepwater clam Auckland (East)	0
SAE	Triangle shell Auckland (East)	0
SCA	Scallop Eastern Bay of Plenty	0
TUA	Tuatua East Northland	0
TUA	Tuatua Hauraki Gulf and Bay of Plenty	0

Table A-2: Number of fishing events per method in FMA 1 between the 2016–17 and 2019–20 fishing years. Data were retrieved from the Protected Species Captures Database (PSCDB) version 6.

Fishing method	Description	Number of fishing events
SN	Set net	70 029
Trawl	Trawl	19 888
BLL	Bottom longline	18 002
CRP	Crab pots	9 198
DS	Danish Seining - Single	6 930
RLP	Rock Lobster Potting	4 437
RN	Ring Net	4 099
T	Trolling	2 989
BS	Beach Seining/Drag Netting	2 479
HL	Hand Lining	2 400
SLL	Surface longline	2 355
PS	Purse seine	2 020
DL	Drop/Dahn Lines	1 902
DPN	Dip netting	750
DV	Diving	253
DN	Inshore Drift Netting	118
OCP	Octopus pots	102
L	Lampara	92
CP	Cod Potting	82
PL	Pole and Line	21
SCN	Scoop netting	8
SJ	Squid jigging	2

Table A-3: Number of fishing events per target species for small-vessel (< 34 metres) bottom longline fisheries operating in FMA 1 between the 2016–17 and 2019–20 fishing years. Acronyms for target species are described in Table E-1; data were retrieved from the Protected Species Captures Database (PSCDB) version 6.

Target species	Number of fishing events
SNA	14 323
BNS	1 070
LIN	1 061
HPB	473
TAR	416
RSN	176
HAP	144
BAS	97
RRC	77
GUR	65
SWO	34
SCH	19
KAH	16
RIB	14
KIN	7
TRE	4
SNX	2
SNI	1
SKI	1
RBY	1
AER	1

APPENDIX B: MODEL PARAMETERS

Table B-1: Combination of fishing method and vessel class.

Fishing method	Vessel class	Method_class
BLL	L	BLL_L
BLL	S	BLL_S
SLL	L	SLL_L
SLL	S	SLL_S
Trawl	L	Trawl_L
Trawl	S	Trawl_S

Table B-2: Target fisheries in final data used for seabird captures modelling. Names were anticipated by matching acronyms against target fishery names listed by Abraham & Richard (2020).

Acronym	Name
ALBS	Albacore SLL
BIGS	Bigeye SLL
BNSB	Bluenose BLL
DPWT	Deepwater trawl
FLAT	Flatfish trawl
HAKT	Hake trawl
HAPB	Hāpuku trawl
HOKT	Hoki trawl
INST	Inshore trawl
LINB	Ling BLL – vessel ≤ 34 m
LINB IWL	Ling BLL with integrated weight line – vessel > 34 m
LINB NOIWL	Ling BLL without integrated weight line – vessel > 34 m
LINT	Ling trawl
MACT	Mackerel trawl
MIDT	Middle depth trawl
MINB	Minor targets BLL
MINS	Minor surface longline
SBWT	Southern blue whiting trawl
SCIT	Scampi trawl
SNAB	Snapper BLL
SQUT	Squid trawl
STNS	Southern bluefin SLL
SWOS	Swordfish SLL

Table B-3: Customised fishing areas by Abraham & Richard (2020) and assigned region.

Acronym	Name	Region
AUCK5	Auckland Islands	South
COOKE8	Cook Strait	South
EAST2	East of North Island	North
ECHAT	Eastern Chatham Rise	South
ESUBA	East Subantarctic	South
FIOR	Fjordland	South
KERM10	Kermadec Islands	North
NORTH1	North East	North
SSUBA	South Subantarctic	South
STEW5	Stewart Snared Shelf	South
WCHAT4	Western Chatham Rise	South
WCNI9	West Coast North Island	North
WCSI	West Coast South Islands	South

Table B-4: Season definition used for seabird capture estimation.

Season	Months
Summer	Jan, Feb, Mar
Autumn	Apr, May, Jun
Winter	Jul, Aug, Sep
Spring	Oct, Nov, Dec

Table B-5: Description of prior distributions for estimating seabird captures including the 2019–20 fishing year.

Parameter	Type	Prior distribution	Parameters
α	Intercept	Log-normal	Mean: -3 (on log scale) SD: 5 (on log scale)
$M_{m,v,i}$	Fixed effect	Log-normal	Mean: -3 (on log scale) SD: 5 (on log scale)
R_i	Fixed effect	Log-normal	Mean: -3 (on log scale) SD: 5 (on log scale)
S_i	Fixed effect	Log-normal	Mean: -3 (on log scale) SD: 5 (on log scale)
F_i	Random effect	Gamma	Mean: 1 (shape=rate) SD: log-normal with Mean: 0 (on log-scale) SD: 1 (on log-scale) Truncation: [10^{-8}, 10]
A_i	Random effect	Gamma	Mean: 1 (shape=rate) SD: log-normal with Mean: 0 (on log-scale) SD: 1 (on log-scale) Truncation: [10^{-8}, 10]
$Y_{m,v,y,i}$	Random effect	Gamma	For each fishing method: Mean: 1 (shape=rate) SD: log-normal with Mean: 0 (on log-scale) SD: 1 (on log-scale) Truncation: [10^{-8}, 10]
Φ	Overdispersion	Log-normal	Mean: 0 SD: 5 (on log-scale) Truncation: [1/400, 400]
v	Overdispersion scaling	uniform	Range: [0, 2]

APPENDIX C: STAN CODE

```
data{
	/* Captures */
	int NOBS;
	int ROWS;
	int COUNT[NOBS];
	int EVENTS[ROWS];

	int AREA_SEABIRDS[ROWS];
	int FISHERY_SEABIRDS[ROWS];
	int AREA_SEABIRDS_UNIQUE;
	int FISHERY_SEABIRDS_UNIQUE;
	int FISHING_YEAR[ROWS];
	int FISHING_YEAR_UNIQUE;
	int METHOD_UNIQUE;
	int METHOD[ROWS];
	int VESSEL_CLASS[ROWS];
	int METHOD_CLASS[ROWS];
	int REGION_SEABIRD[ROWS];
	int SEASON[ROWS];
	int VESSEL_CLASS_SUMMARY[ROWS];
	int METHOD_CLASS_NOTFIXED_N;
	int REGION_SEABIRD_NOTFIXED_N;
	int SEASON_NOTFIXED_N;
	int VESSEL_CLASS_SUMMARY_NOTFIXED_N;
	int METHOD_CLASS_FIXED_i;
	int REGION_SEABIRD_FIXED_i;
	int SEASON_FIXED_i;
	int VESSEL_CLASS_SUMMARY_FIXED_i;
	int METHOD_CLASS_NOTFIXED_i[METHOD_CLASS_NOTFIXED_N];
	int REGION_SEABIRD_NOTFIXED_i;
	int SEASON_NOTFIXED_i[SEASON_NOTFIXED_N];
	int VESSEL_CLASS_SUMMARY_NOTFIXED_i;
}

parameters {
	/* intercept */
	real log_beta0;

	/* fixed effects */
	real log_beta_METHOD_CLASS_v[METHOD_CLASS_NOTFIXED_N];
	real log_beta_REGION_SEABIRD_v[REGION_SEABIRD_NOTFIXED_N];
	real log_beta_SEASON_v[SEASON_NOTFIXED_N];
	real log_beta_VESSEL_CLASS_SUMMARY_v[VESSEL_CLASS_SUMMARY_NOTFIXED_N];

	/* sd for random effects */
	real <lower=1E-8, upper=5> sd_eta_AREA_SEABIRDS;
	real <lower=1E-8, upper=5> sd_eta_FISHERY_SEABIRDS;

	/* random effects */
	real <lower=1E-8, upper=10> eta_AREA_SEABIRDS[AREA_SEABIRDS_UNIQUE];
	real <lower=1E-8, upper=10> eta_FISHERY_SEABIRDS[FISHERY_SEABIRDS_UNIQUE];

	/* sd for nested random effects */
	real <lower=1E-8, upper=5> sd_eta_FISHING_YEAR[METHOD_UNIQUE];

	/* nested random effects */
	vector <lower=1E-8, upper=10>[FISHING_YEAR_UNIQUE] eta_FISHING_YEAR[METHOD_UNIQUE];

	/* overdispersion */
	real <lower=0.0025, upper=400> phi[METHOD_UNIQUE];
	real<lower=0.0, upper=2.0> nu;
}

 transformed parameters {
```

```
	real beta [ROWS]; // total of fixed effects
	vector [ROWS] mustar; // random and fixed effects combined

	/* fixed effects */
	vector[METHOD_CLASS_NOTFIXED_N + 1] log_beta_METHOD_CLASS;
	vector[REGION_SEABIRD_NOTFIXED_N + 1] log_beta_REGION_SEABIRD;
	vector[SEASON_NOTFIXED_N + 1] log_beta_SEASON;
	vector[VESSEL_CLASS_SUMMARY_NOTFIXED_N + 1] log_beta_VESSEL_CLASS_SUMMARY;

	/* nested random effects */
	real eta_FISHING_YEAR_METHOD_UNIQUE [ROWS];

	/* other constraints: if no constraints exist then it will just create a copy of the original effect without constraints */
	real eta_FISHING_YEAR_METHOD_UNIQUE_c [ROWS]; // random effects
	real eta_AREA_SEABIRDS_c [ROWS]; // random effects
	real eta_FISHERY_SEABIRDS_c [ROWS]; // random effects

	/* Fixed effects */
	log_beta_METHOD_CLASS[METHOD_CLASS_FIXED_i] = 0.0;  // base case
	for (i in 1:METHOD_CLASS_NOTFIXED_N) {
	    log_beta_METHOD_CLASS[METHOD_CLASS_NOTFIXED_i[i]] = log_beta_METHOD_CLASS_v[i]; //
subsequent fixed effects
	}

	log_beta_REGION_SEABIRD[REGION_SEABIRD_FIXED_i] = 0.0;  // base case
	log_beta_REGION_SEABIRD[REGION_SEABIRD_NOTFIXED_i] = log_beta_REGION_SEABIRD_v[1]; //
subsequent fixed effects

	log_beta_SEASON[SEASON_FIXED_i] = 0.0;  // base case
	for (i in 1:SEASON_NOTFIXED_N) {
	    log_beta_SEASON[SEASON_NOTFIXED_i[i]] = log_beta_SEASON_v[i]; // subsequent fixed effects
	}

	log_beta_VESSEL_CLASS_SUMMARY[VESSEL_CLASS_SUMMARY_FIXED_i] = 0.0;  // base case
	log_beta_VESSEL_CLASS_SUMMARY[VESSEL_CLASS_SUMMARY_NOTFIXED_i] =
log_beta_VESSEL_CLASS_SUMMARY_v[1]; // subsequent fixed effects

	/* nested random effects */
	for (k in 1:ROWS) {
	   eta_FISHING_YEAR_METHOD_UNIQUE[k] = eta_FISHING_YEAR[METHOD[k], FISHING_YEAR[k]]; //
Nested random year effects combined into one vector
	}

	/* other constraints: if no constraints exist then it will just create a copy of the original effect without constraints */
	for (k in 1:ROWS) {
	    eta_FISHING_YEAR_METHOD_UNIQUE_c[k] = ((VESSEL_CLASS[k] == 2) ? 1 :
eta_FISHING_YEAR_METHOD_UNIQUE[k]);
	    eta_AREA_SEABIRDS_c[k] = (eta_AREA_SEABIRDS[AREA_SEABIRDS[k]]);
	    eta_FISHERY_SEABIRDS_c[k] = (eta_FISHERY_SEABIRDS[FISHERY_SEABIRDS[k]]);
	}


	/* Mean catch rate (equation 1 in Abraham & Richard 2019) */
	for (k in 1:ROWS) {
	  beta[k] = exp(log_beta0 + log_beta_METHOD_CLASS[METHOD_CLASS[k]] +
log_beta_REGION_SEABIRD[REGION_SEABIRD[k]] + log_beta_SEASON[SEASON[k]] +
log_beta_VESSEL_CLASS_SUMMARY[VESSEL_CLASS_SUMMARY[k]]);
	mustar[k] = beta[k] * eta_FISHING_YEAR_METHOD_UNIQUE_c[k] * eta_AREA_SEABIRDS_c[k] *
eta_FISHERY_SEABIRDS_c[k];
	}

 }

  model {
	/* INTERCEPT */
	log_beta0 ~ normal(-3,5);
```

```
            /* fixed effects */
            log_beta_METHOD_CLASS_v ~ normal(0,5);
            log_beta_REGION_SEABIRD_v ~ normal(0,5);
            log_beta_SEASON_v ~ normal(0,5);
            log_beta_VESSEL_CLASS_SUMMARY_v ~ normal(0,5);

            /* sd for random effects */
            sd_eta_AREA_SEABIRDS ~ lognormal(0,1);
            for (i in 1:AREA_SEABIRDS_UNIQUE){
              eta_AREA_SEABIRDS[i] ~ gamma(pow(sd_eta_AREA_SEABIRDS, -2), pow(sd_eta_AREA_SEABIRDS, -
2));
            }

            /* sd for random effects */
            sd_eta_FISHERY_SEABIRDS ~ lognormal(0,1);
            for (i in 1:FISHERY_SEABIRDS_UNIQUE){
              eta_FISHERY_SEABIRDS[i] ~ gamma(pow(sd_eta_FISHERY_SEABIRDS, -2),
pow(sd_eta_FISHERY_SEABIRDS, -2));
            }

            /* nested random effect */
            for (i in 1:METHOD_UNIQUE){
              sd_eta_FISHING_YEAR[i] ~ lognormal(0,1);
              for (j in 1:FISHING_YEAR_UNIQUE) {
                eta_FISHING_YEAR[i, j] ~ gamma(pow(sd_eta_FISHING_YEAR[i], -2), pow(sd_eta_FISHING_YEAR[i], -
2));
              }
            }

            /* Overdispersion parameter */
            for (i in 1:METHOD_UNIQUE) {
                phi[i] ~ lognormal(0,1);
            }

            nu ~ uniform(0, 2);

            /* Likelihood: negative binomial model for observed captures */
            for (k in 1:NOBS) {
                COUNT[k] ~ neg_binomial_2(EVENTS[k] * mustar[k], EVENTS[k] * phi[METHOD[k]]  * (mustar[k] ^ nu));
            }
}
```

APPENDIX D: R CODE FOR INDIVIDUAL FISHING EVENT CAPTURE PREDICTIONS

```
## Load MCMCs
load(file = 'model_out.Rdata')

## Extract estimated captures and append model variables
# extract model output
model_out_extract <- rstan::extract(model_out)
model_out_extract_names <- names(model_out_extract)

# loop across yrs
for(t in yrs){
all_bird_groups_t <- all_bird_groups[fishing_year==t,]

estimate <- array(NA, dim=c(length(model_out_extract$log_beta0), dim(all_bird_groups_t)[1]))
for(k in 1:dim(all_bird_groups_t)[1]){
    beta = exp(model_out_extract$log_beta0 +
        model_out_extract$log_beta_METHOD_CLASS[,all_bird_groups_t$method_class_stan[k]] +
        model_out_extract$log_beta_REGION_SEABIRD[,all_bird_groups_t$region_seabird_stan[k]] +
        model_out_extract$log_beta_SEASON[,all_bird_groups_t$season_stan[k]]);

    eta_FISHING_YEAR_c <-
model_out_extract$eta_FISHING_YEAR[,all_bird_groups_t$method_stan[k],all_bird_groups_t$fishing_year_stan[k]]

    if(all_bird_groups_t$vessel_class[k]=='S'){
      eta_FISHING_YEAR_c[ ] <- 1
    }

    mustar = beta *
    model_out_extract$eta_AREA_SEABIRDS[,all_bird_groups_t$area_seabirds_stan[k]] *
    model_out_extract$eta_FISHERY_SEABIRDS[,all_bird_groups_t$fishery_seabirds_stan[k]] *
    eta_FISHING_YEAR_c;

   # // captures
   size=all_bird_groups_t$effort_num[k] * model_out_extract$phi[,all_bird_groups_t$method_stan[k]]  *
(mustar^model_out_extract$nu)
    prob=size/(size+all_bird_groups_t$effort_num[k] * mustar)
    estimate[,k] = unlist(map2(size, prob, rnbinom, n=1))
}

saveRDS(all_bird_groups_t, paste0('/all_bird_groups_t_',str_sub(t, 1, 4),'.rds')
saveRDS(estimate, paste0('/estimate_',str_sub(t, 1, 4),'.rds')

  }
}

# merge yr-specific data sets and predictions
for(t in yrs){
  dt <- readRDS(paste0('all_bird_groups_t_',str_sub(t, 1, 4),'.rds'))
  est <-  readRDS(paste0('estimate_',str_sub(t, 1, 4),'.rds')) %>%
    t() %>%
    as.data.table()

    names(est) <- paste0('sample_', 1:dim(est)[2])

    dt2 <- cbind(dt, est)

  if(t==yrs[1]){
    dt3 <- dt2
  } else {
    dt3 <- rbind(dt3, dt2)
  }
}

## summarise predicted captures structures by years, observed and camera-monitors (Objective 3)
sum_samples <- function(samples){
  eval(parse(text=paste0('
```

```
  tmp<-dt3[, .(', samples, ' = sum(', samples, ')), by = c("obs", "em", "camera", "fishing_year")]; #
  setkey(tmp, obs, em, fishing_year)
  return(tmp$', samples, ')
  ')))
}
out<- map(paste0('sample_', 1:4002), sum_samples)
mtrx <- matrix(unlist(out), ncol = 4002, nrow = 47)

# create summary table
dt3_summary<-dt3[, .(sum(sample_1)), by =  c("obs", "em", "camera", "fishing_year")]; # the template
setkey(dt3_summary, obs, em, fishing_year)
dt3_summary[, V1 := NULL]

library(matrixStats)
dt3_summary[, median :=  rowMedians(mtrx) %>% t() %>% t() %>% round(0)]
dt3_summary[, mean :=  rowMeans(mtrx) %>% t() %>% t() %>% round(0)]
dt3_summary[, lower :=  rowQuantiles(mtrx, probs=0.025) %>% t() %>% t() %>% round(3)]
dt3_summary[, upper :=  rowQuantiles(mtrx, probs=0.975) %>% t() %>% t() %>% round(3)]

obs_summary <- dt3[, .(sum(black_petrel)), by =  c("obs", "em", "camera", "fishing_year")];
setkey(obs_summary, obs, em, fishing_year)

dt3_summary$reported <- obs_summary$V1
```

APPENDIX E: TARGET SPECIES CODES

Table E-1: Target species classified as MINB fisheries.

MPI species code	Common name	Scientific Name
ABR	Short snouted lancetfish	*Alepisaurus brevirostris*
JMA	Jack mackerel	*Trachurus declivis, T. murphyi, T. novaezelandiae*
BMA	Blue maomao	*Scorpis violacea*
JDO	John dory	*Zeus faber*
NSD	Northern spiny dogfish	*Squalus griffini*
GMU	Grey mullet	*Mugil cephalus*
POR	Pōrae	*Nemadactylus douglasii*
RIB	Ribaldo	*Mora moro*
SCI	Scampi	*Metanephrops challengeri*
BUT	Butterfish	*Odax pullus*
BWH	Bronze whaler shark	*Carcharhinus brachyurus*
SHL	Shovel nosed lobster	*Scyllarus* sp.
EMA	Blue mackerel	*Scomber australasicus*
RSK	Rough skate	*Zearaja nasuta*
SHA	Shark	
SWA	Silver warehou	*Seriolella punctata*
BAS	Bass groper	*Polyprion americanus*
RAT	Rattails	*Macrouridae*
TRE	Trevally	*Pseudocaranx georgianus*
SUN	Sunfish	*Mola mola*
SPD	Spiny dogfish	*Squalus acanthias*
NTU	Northern bluefin tuna	
KOH	Kōheru	*Decapterus koheru*
ALB	Albacore tuna	*Thunnus alalunga*
JGU	Spotted gurnard	*Pterygotrigla picta*
BIG	Bigeye tuna	*Thunnus obesus*
HAK	Hake	*Merluccius australis*
TAR	Tarakihi	*Nemadactylus macropterus & N. rex*
BCA	Barracudina	*Magnisudis prionosa*
SKJ	Skipjack tuna	*Katsuwonus pelamis*
PTO	Patagonian toothfish	*Dissostichus eleginoides*
SND	Shovelnose spiny dogfish	*Deania calcea*
BSH	Seal shark	*Dalatias licha*
STA	Giant stargazer	*Kathetostoma* spp.
KTA	King tarakihi	*Nemadactylus rex*
KIN	Kingfish	*Seriola lalandi*
ELE	Elephantfish	*Callorhinchus milii*
OSD	Other sharks and dogs	Selachii
SNI	Snipefish	*Macroramphosus scolopax*
TUR	Turbot	*Colistium nudipinnis*
YFN	Yellowfin tuna	*Thunnus albacares*
SNX	Snapper (Undersized)	*Chrysophrys auratus*

Table E-1 continued.

PMA	Pink maomao	*Caprodon longimanus*
SPO	Rig	*Mustelus lenticulatus*
RPE	Red perch	
HOK	Hoki	*Macruronus novaezelandiae*
OCT	Octopus	*Pinnoctopus cordiformis*
SUR	Kina	*Evechinus chloroticus*
SPE	Sea perch	*Helicolenus spp.*
GAR	Garfish	*Hyporhamphus ihi*
BAR	Barracouta	*Thyrsites atun*
LDO	Lookdown dory	*Cyttus traversi*
RRC	Red scorpion fish	*Scorpaena cardinalis & S. papillosus*
ROC	Rock cod	*Lotella rhacinus*
BYX	Alfonsino & long-finned beryx	*Beryx splendens & B. decadactylus*
BRC	Northern bastard cod	*Pseudophycis breviuscula*
BWS	Blue shark	*Prionace glauca*
RBY	Rubyfish	*Plagiogeneion rubiginosum*
KAH	Kahawai	*Arripis trutta, A. xylabion*
SWO	Broadbill swordfish	*Xiphias gladius*
SNS	Sunset shell	*Psammobiidae*
BRA	Short-tailed black ray	*Dasyatis brevicaudata*
RBM	Ray’s bream	*Brama brama*
SCA	Scallop	*Pecten novaezelandiae*
SSK	Smooth skate	*Dipturus innominatus*
GUR	Gurnard	*Chelidonichthys kumu*
SCH	School shark	*Galeorhinus galeus*
CDL	Cardinalfish	*Epigonidae*
SKI	Gemfish	*Rexea spp.*
WAR	Common warehou	*Seriolella brama*
YEM	Yelloweye mullet	*Aldrichetta forsteri*
PAU	lack paua & yellowfoot paua	*Haliotis iris & H. australis*
CRA	Rock lobster	*Jasus edwardsii*
NIL	No catch	
FRO	Frostfish	*Lepidopus caudatus*
LIM	Limpets	
RCO	Red cod	*Pseudophycis bachus*
AER	*Aeneator recens*	*Aeneator recens*
SKA	Skate	Rajidae Arhynchobatidae
SCG	Scaly gurnard	*Lepidotrigla brachyoptera*
PAD	Paddle crab	*Ovalipes catharus*
TRU	Trumpeter	*Latris lineata*
FLY	Flying fish	Exocoetidae
RSN	Red snapper	*Centroberyx affinis*
FLA	Flatfish	
SNH	???	
MAK	Mako shark	*Isurus oxyrinchus*
BCO	Blue cod	*Parapercis colias*
LSO	Lemon sole	*Pelotretis flavilatus*

APPENDIX F: MODEL ESTIMATES

Table F-1: Summary of model estimates for model fitted against black petrel captures from observer data plus EM data between the 1998–99 and 2019–20 fishing years (EM data ranged 2016–17 and 2019–20 fishing years).

Parameter	Mean	SD	2.50%	97.50%	n_eff	Rhat
log_beta0	-3.671	0.806	-5.079	-1.862	4091.013	1.000
sd_eta_AREA_SEABIRDS	1.232	0.414	0.612	2.217	3820.042	0.999
sd_eta_FISHERY_SEABIRDS	0.779	0.284	0.337	1.451	4015.824	1.001
eta_AREA_SEABIRDS[1]	0.901	1.087	0.001	3.818	3539.611	1.001
eta_AREA_SEABIRDS[2]	0.983	1.172	0.001	4.247	3649.266	1.000
eta_AREA_SEABIRDS[3]	0.205	0.174	0.016	0.646	3829.384	1.000
eta_AREA_SEABIRDS[4]	0.922	1.120	0.001	4.160	3845.350	1.000
eta_AREA_SEABIRDS[5]	0.964	1.166	0.001	4.233	4182.723	0.999
eta_AREA_SEABIRDS[6]	0.939	1.160	0.001	4.247	3641.577	1.000
eta_AREA_SEABIRDS[7]	0.937	0.843	0.057	3.155	3961.748	1.000
eta_AREA_SEABIRDS[8]	2.876	1.686	0.505	7.172	3821.119	1.000
eta_AREA_SEABIRDS[9]	0.923	1.088	0.001	3.944	3816.290	1.000
eta_AREA_SEABIRDS[10]	0.877	1.051	0.000	3.754	4125.818	1.000
eta_AREA_SEABIRDS[11]	0.926	1.133	0.001	3.909	3797.985	1.000
eta_AREA_SEABIRDS[12]	0.319	0.243	0.033	0.945	3967.151	1.000
eta_AREA_SEABIRDS[13]	0.912	1.084	0.001	3.922	3863.588	1.001
eta_FISHERY_SEABIRDS[1]	1.642	1.041	0.381	4.339	3681.109	0.999
eta_FISHERY_SEABIRDS[2]	0.942	0.473	0.239	2.065	4085.943	1.000
eta_FISHERY_SEABIRDS[3]	1.830	0.884	0.656	3.964	4045.904	1.000
eta_FISHERY_SEABIRDS[4]	0.941	0.631	0.119	2.443	4189.335	1.000
eta_FISHERY_SEABIRDS[5]	0.963	0.766	0.036	2.862	3706.471	1.000
eta_FISHERY_SEABIRDS[6]	1.013	0.844	0.036	3.053	3651.783	1.000
eta_FISHERY_SEABIRDS[7]	1.140	0.670	0.259	2.803	3726.932	0.999
eta_FISHERY_SEABIRDS[8]	0.810	0.621	0.026	2.358	4061.704	1.000
eta_FISHERY_SEABIRDS[9]	1.371	0.764	0.386	3.261	4009.226	1.000
eta_FISHERY_SEABIRDS[10]	0.779	0.600	0.024	2.215	3938.452	1.000
eta_FISHERY_SEABIRDS[11]	0.991	0.813	0.038	3.053	4023.378	1.000
eta_FISHERY_SEABIRDS[12]	0.994	0.812	0.038	3.123	4071.446	1.001
eta_FISHERY_SEABIRDS[13]	0.964	0.783	0.032	2.890	4182.870	1.000
eta_FISHERY_SEABIRDS[14]	0.557	0.466	0.012	1.683	3911.434	1.000
eta_FISHERY_SEABIRDS[15]	0.725	0.567	0.020	2.188	4080.937	1.000
eta_FISHERY_SEABIRDS[16]	1.012	0.511	0.315	2.232	4122.324	1.000
eta_FISHERY_SEABIRDS[17]	1.134	0.649	0.203	2.745	3992.621	0.999
eta_FISHERY_SEABIRDS[18]	0.994	0.802	0.044	2.999	4024.609	1.000
eta_FISHERY_SEABIRDS[19]	0.904	0.601	0.125	2.451	3964.414	1.000
eta_FISHERY_SEABIRDS[20]	0.437	0.215	0.135	0.954	4119.593	1.000
eta_FISHERY_SEABIRDS[21]	1.648	1.174	0.295	4.951	4120.781	1.000
eta_FISHERY_SEABIRDS[22]	0.277	0.263	0.003	0.949	4101.127	1.001
eta_FISHERY_SEABIRDS[23]	0.936	0.499	0.188	2.120	4112.118	1.000
sd_eta_FISHING_YEAR[1]	0.880	0.570	0.127	2.179	1879.225	1.000
sd_eta_FISHING_YEAR[2]	0.803	0.529	0.123	2.115	1945.781	1.000

Table F-1 continued.

sd_eta_FISHING_YEAR[3]	0.725	0.489	0.118	1.937	1967.446	1.000
phi[1]	0.417	0.249	0.132	1.051	4223.491	1.000
phi[2]	1.617	1.111	0.443	4.481	4112.017	1.000
phi[3]	0.672	0.745	0.094	2.409	4254.870	1.001
log_beta_METHOD_CLASS[1]	-3.104	3.529	-10.836	2.575	3871.006	1.000
log_beta_METHOD_CLASS[2]	0.000	0.000	0.000	0.000	NA	NA
log_beta_METHOD_CLASS[3]	-0.232	1.201	-2.606	2.050	3958.860	1.000
log_beta_METHOD_CLASS[4]	0.732	0.713	-0.554	2.242	4111.346	1.000
log_beta_METHOD_CLASS[5]	-2.725	0.958	-4.678	-0.839	4125.853	1.001
log_beta_METHOD_CLASS[6]	-2.737	0.790	-4.321	-1.166	4098.558	1.000
log_beta_REGION_SEABIRD[1]	0.000	0.000	0.000	0.000	NA	NA
log_beta_REGION_SEABIRD[2]	-7.133	2.559	-12.970	-3.034	4249.562	1.000
log_beta_SEASON[1]	0.000	0.000	0.000	0.000	NA	NA
log_beta_SEASON[2]	-0.541	0.291	-1.112	0.013	4023.400	1.000
log_beta_SEASON[3]	-3.678	1.113	-6.255	-1.893	3590.064	1.000
log_beta_SEASON[4]	-0.506	0.260	-1.026	-0.009	4008.375	1.000