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Associations between environmental variables and flatfish catch rates in Manukau Harbour and Kaipara Harbour

New Zealand Fisheries Assessment Report 2023/20

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ISSN 1179-5352 (online)
ISBN 978-1-991080-35-6 (online)

April 2023



Te Kāwanatanga o Aotearoa
New Zealand Government

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Please cite this report as:

Moore, B.R.; McKenzie, J.R. (2023). Associations between environmental variables and flatfish catch rates in Manukau Harbour and Kaipara Harbour. *New Zealand Fisheries Assessment Report 2023/20*. 30 p.

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EXECUTIVE SUMMARY

Moore, B.R.¹; McKenzie, J.R. (2023). Associations between environmental variables and flatfish catch rates in Manukau Harbour and Kaipara Harbour.

New Zealand Fisheries Assessment Report 2023/20. 30 p.

Manukau Harbour and Kaipara Harbour, on the west coast of the North Island of New Zealand, support significant commercial, recreational, and customary fisheries for flatfish, with commercial catches in these harbours totalling around 150 t in 2020–21. These fisheries are considered to comprise primarily yellowbelly flounder, *Rhombosolea leporina*. Declines in flatfish catch per unit effort have been observed in both harbours since the 1990s, indicative of declines in abundance.

Recruitment strength in short-lived species, such as yellowbelly flounder, can be highly influenced by environmental conditions, including water quality. We investigated the association between water quality and flatfish recruitment strength, as indexed by commercial catch data. Monthly water quality data were provided by Auckland Council. Data were obtained for three monitoring sites in the Manukau Harbour (Clarks Beach, Grahams Beach, and Weymouth) and six sites in the Kaipara Harbour (Shelly Beach Wharf, Kaipara River entrance, Makarau Estuary, Hoteo River mouth, Tauhoa Channel, and Oruawharo River). Water quality variables examined varied between harbours but included chlorophyll-*a* (chl-*a*), nitrates+nitrites, salinity, soluble phosphorus, total phosphorus, total suspended solids, turbidity, and water temperature. The influence of the Southern Oscillation Index (SOI) on catch rates was also examined for each harbour.

Environmental conditions in the Manukau and Kaipara harbours is likely to be most influential on flatfish abundance around the critical period when a year class is recruiting to settlement habitats, assumed to be October-February for both harbours. Accordingly, average logged water quality and SOI data between October and February were joined to catch and effort data time-lagged to correspond to the time when larvae settling in the respective harbours would be caught as adults in the commercial fishery. As catches in the Manukau Harbour have previously been shown to comprise predominantly two- and three-year-old fish, analyses were run with either a two- or three-year time lag (e.g., the average water quality data for the 1990 fishing year were joined to catch and effort data for the 1992 and 1993 fishing years, respectively). Generalised linear models (GLMs) were then used to assess the association between time-lagged individual water quality variables and catch rates. For the Manukau Harbour, for which a relatively long time series of data exists across all sites, a single series of models were run. Two series of models were run for the Kaipara Harbour: one exploring water quality from the Shelly Beach Wharf monitoring site, for which data were available from late 1991 onwards, and a second exploring the average water quality experienced across the six monitoring sites, for which data were available from 2009 onwards.

In the Manukau Harbour, significant positive associations between turbidity and total phosphorus and catch rates were evident under both two- and three-year time lags. For the Kaipara Harbour Shelly Beach Wharf site, GLMs indicated positive relationships between catch and several correlated variables, including chl-*a*, nitrates+nitrites, soluble phosphorus, total phosphorus, and total suspended solids for the model with a two-year time lag, and chl-*a*, nitrates+nitrites, soluble phosphorus, total phosphorus, total suspended solids, and turbidity for the model with a three-year time lag. No water quality variables were selected by the model using data for all sites from 2009 onwards when either a two-year or three-year time lag was applied.

When considered alongside the declining trends in flatfish abundance in both the Manukau and Kaipara harbours, these results suggest that turbid water conditions and elevated levels of total phosphorus

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observed in the Manukau and Kaipara harbours in the early to mid-1990s may have had a positive effect on flatfish recruitment and abundance, and, conversely, subsequent decreases in these variables with improved catchment management may have negatively affected flatfish abundance. Ongoing monitoring of trends in water quality and ecological characterisations in association with flatfish catch and effort data would be beneficial to further assess relationships between environmental variables, flatfish recruitment, and catch rates.

1. INTRODUCTION

Flatfish support significant commercial, recreational, and customary fisheries in New Zealand. Total annual commercial landings of flatfish in 2021–22 were 1814 t (Fisheries New Zealand 2022). New Zealand's Flatfish Individual Transferable Quota (ITQ) provides for the landing of eight species of flatfish in the QMS, namely brill (*Colistium guntheri*), lemon sole (*Pelotretis flavilatus*), New Zealand sole (*Peltorhamphus novaezeelandiae*), yellowbelly flounder (*Rhombosolea leporina*), sand flounder (*Rhombosolea plebeia*), black flounder, (*Rhombosolea retiaria*), greenback flounder (*Rhombosolea tapirina*) (Fisheries New Zealand 2022).

Significant fisheries for flatfish occur in Manukau Harbour and Kaipara Harbour, on the west coast of New Zealand's North Island and in flatfish Quota Management Area (QMA) FLA 1, with commercial catches in these harbours totalling around 150 t in 2020–21 (Moore et al. 2023). The status of stocks in these areas is assessed on the basis of trends in standardised catch per unit effort (CPUE). Although considerable fluctuation occurs among years, both the Manukau and Kaipara CPUE series show a long-term declining trend between the mid-1990s and about 2010. Since then, both series have been generally stable and are currently 54% and 67% below the respective peaks in the early to mid-1990s (Fisheries New Zealand 2022, Moore et al. 2023)

Catches of flatfish in the Manukau and Kaipara harbours are believed to predominantly comprise yellowbelly flounder (*R. leporina*; YBF). Yellowbelly flounder is a fast-growing, short-lived species, generally surviving to three to four years of age and rarely to five or six years (Colman 1974a, Pearks 1985, Stevens & Sutton 2006). In the Manukau Harbour, yellowbelly flounder spawn in late winter to spring, with recruitment of larvae to coastal fringes commencing in September, and peaking from October to February (Mutoro 2001).

Recruitment in short-lived species, such as yellowbelly flounder, can be highly variable from year to year and highly influenced by environmental conditions. For example, Beentjes & Renwick (2001) found that recruitment of red cod (*Pseudophycis bachus*) into commercial fisheries off the east and west coasts of New Zealand's South Island is related to sea temperature and weather conditions experienced during their early life history. In Western Australia, recruitment of the western rock lobster (*Panulirus cygnus*) is highly correlated with water temperature and the strength of oceanographic currents, which in turn, results in considerable inter-annual catch variability (Caputi et al. 1996, 2001).

McKenzie et al. (2013) investigated whether annual fluctuation in environmental variables (suitably lagged) correlate with fluctuations in flounder commercial CPUE in the Manukau Harbour, by including water quality variables in CPUE standardisations. They found positive associations between catch and dissolved oxygen concentration, and negative correlations between catch and ammonia concentration and turbidity. They concluded that periods of high turbidity and ammonia, and low dissolved oxygen, may have negatively affected yellowbelly flounder recruitment success. Using a similar analytical framework to that of McKenzie et al. (2013), Parsons et al. (2015) found associations between flatfish catch rates, nitrate concentrations, and the occurrence of La Niña events in the Kaipara Harbour. When considered alongside the declining trends in flatfish abundance in FLA 1, McKenzie et al. (2013) and Parsons et al. (2015) concluded estuarine water quality and other environmental conditions may be significant factors affecting the sustainability of the flatfish fishery and recommended ongoing studies of the influence of water quality on flatfish recruitment be undertaken.

The objective of this report was to explore the association between water quality and commercial flatfish catch rates in the Manukau and Kaipara harbours, through the inclusion of water quality variables in the generalised linear models (GLMs) used to standardise flatfish catch rates. We extend the analyses of McKenzie et al. (2013) and Parsons et al. (2015), incorporating additional years of catch, effort, and water quality data.

2. METHODS

2.1 Study areas

This study focused on the Manukau and Kaipara harbours on the west coast of the North Island (Figure 1 and Figure 2). In addition to flatfish, both of these harbours support significant commercial, recreational, and customary fisheries for several fish and elasmobranch species including grey mullet (*Mugil cephalus*), kahawai (*Arripis trutta*), parore (*Girella tricuspidata*), rig (*Mustelus lenticulatus*), school shark (*Galeorhinus galeus*), and snapper (*Chrysophrys auratus*), and a range of bivalve molluscs including cockles (Veneridae), oysters, pipi (*Paphies australis*), and scallops (*Pecten novaezelandiae*) (Hewitt & Funnell 2005, Morrison et al. 2014, Fisheries New Zealand 2022).

The Manukau Harbour is an ecologically significant coastal embayment, covering approximately 365 km² with over 450 km of shoreline. The harbour is relatively shallow, with over 60% of its area being intertidal (Auckland Council 2021), and opens to the Tasman Sea via a narrow, shallow (2.2 km wide and 30 m deep) channel (Mutoro 2001). The main channel has four branches (Papakura, Parakau, Waiuku, and Wairopa). Nutrient concentrations in the harbour are elevated compared to regional reference guidelines and are highest in the Māngere Inlet, a weakly flushed, deep embayment in the north east of the harbour, and near the Māngere Wastewater Treatment Plant (Auckland Council 2021). An upgrade to the treatment plant in 2001 led to significant improvements in coastal water quality, particularly in levels of ammoniacal nitrogen, dissolved reactive phosphorus, total phosphorus, and turbidity, and particularly in the Māngere Inlet and surrounding areas. Further upgrades to improve the removal of nutrients, pathogens, and bacteria were completed in 2018 (Auckland Council 2021).

The Kaipara Harbour is New Zealand's largest harbour, covering an area of approximately 743 km², of which approximately 40% is intertidal (Morrison et al. 2014). Much of the shoreline has mangrove swamps and marsh, while the catchment principally comprises farming and forest areas (Mutoro 2001, Morrison et al. 2014). However, there are a few urban settlements around the harbour, and horticulture, urbanisation, and other forms of land use have continued to intensify in recent decades (Makey 2010, Morrison et al. 2014).

2.2 Data used in this study

2.2.1 Catch and effort data

Catch and effort data used in this study were derived from those used in the most recent characterisation and CPUE standardisation analyses of FLA 1 fisheries (Moore et al. 2023). Data grooming and aggregation to the daily effort stratum for the CPUE standardisations, including selection of core vessels, followed the approach of Moore et al. (2023).

2.2.2 Environmental data

Water quality data for the Manukau and Kaipara harbours were provided by Auckland Council (AC). These data derive from AC's Marine Water Quality Monitoring Programme, which has monitored water quality monthly near-continuously since 1987 in the Manukau Harbour (although the water quality parameters and sites monitored have changed over time) (Foley et al. 2018, Auckland Council 2021, Ingley 2021). For the Manukau Harbour, data were obtained for three monitoring sites: 1) Clarks Beach (AC monitoring site 43506); 2) Grahams Beach (AC monitoring site 43507); and 3) Weymouth (AC monitoring site 43904) (Figure 1). These sites were selected as they had the longest time series of available data (dating back to 1987) and were considered representative of juvenile flatfish settlement habitats in the harbour. Data from Wairopa at Māngere Bridge (AC monitoring site 43905) and Puketutu Island (AC monitoring site 43906) dating back to 1987 were also obtained, but early water quality variables for these sites were considered not to be representative of the harbour as a whole and were excluded from the analyses.

For the Kaipara Harbour, water quality data were obtained for six monitoring sites: 1) Shelly Beach Wharf (AC monitoring site 45214); 2) Kaipara River entrance (AC monitoring site 45374); 3) Makarau Estuary (AC monitoring site 45506); 4) Hoteo River mouth (AC monitoring site 45700); 5) Tauhoa Channel (AC monitoring site 45801); and 6) Oruawharo River (AC monitoring site 109663) (Figure 2).

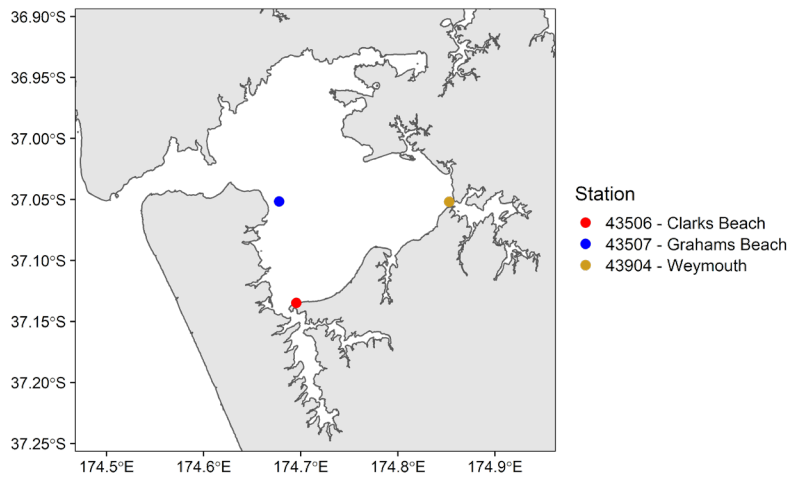


Figure 1: Location of the Manukau Harbour water quality monitoring sites used in this study.

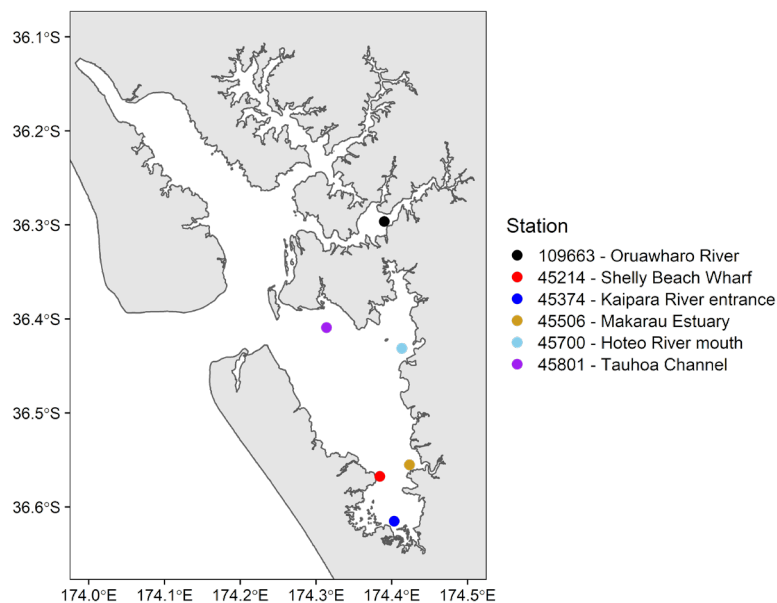


Figure 2: Location of the Kaipara Harbour water quality monitoring sites used in this study.

Analyses focused on those variables that have been previously demonstrated to influence recruitment in estuarine species (Beentjes & Renwick 2001, McKenzie et al. 2013), and for which a relatively long time series of reliable data were available. For the Manukau Harbour, this initially included:

- Ammonia as N – total (mg/L) ($\text{NH}_3 + \text{NH}_4$)
- Dissolved oxygen (ppm)
- Salinity (ppt)
- Soluble phosphorus (mg/L)
- Total phosphorus (mg/L)
- Total suspended solids (mg/L)
- Turbidity (NTU)
- Water temperature (degrees Celsius)

For the Kaipara Harbour, ten variables were initially assessed:

- Ammonia as N – total (mg/L) (NH_3+NH_4)
- Chlorophyll-*a* (mg/L) (hereafter chl-*a*)
- Dissolved oxygen (ppm)
- Nitrate + nitrite as N (mg/L)
- Salinity (ppt)
- Soluble phosphorus (mg/L)
- Total phosphorus (mg/L)
- Total suspended solids (mg/L)
- Turbidity (NTU)
- Water temperature (degrees Celsius)

In addition, the influence of the Southern Oscillation Index (SOI) on catch rates was examined for each harbour. SOI indices were extracted from the *rsoi* package (Albers 2022) in R version 4.0.5 (R Core Team 2022).

2.3 Statistical analysis

2.3.1 Matching environmental and catch and effort data

Water quality and climate conditions in the Manukau and Kaipara harbours are likely to be most influential on flatfish abundance around the critical period when a year class recruits to settlement habitats (McKenzie et al. 2013). Accordingly, water quality data were time-lagged to correspond to the time when larvae settling in the respective harbours would be caught as adults in the commercial fishery. Although the early life history of yellowbelly flounder is poorly understood, peak settlement time of juveniles is considered to commence in September, peaking from October to February (Mutoro 2001). Age sampling data indicate that the Manukau Harbour fishery is almost entirely composed of two- and three-year-old fish in approximately equal proportion by weight (McKenzie et al. 2013). Given the similarities in species targeted and gear used, a similar assumption was made for the Kaipara Harbour. Catch and effort data for a given year were therefore matched with the average water quality and SOI indices over the recruitment period (i.e., October-February) experienced two years previously (i.e., a two-year lag) and three years previously (i.e., a three-year lag). Models were also run using the average of the previous 2–3 years combined, but showed largely similar results as the models including either two- or three-year lags, and are thus not presented here.

2.3.2 Model fitting and selection

Prior to model fitting, data exploration was carried out to identify correlated covariates. Co-linearity among water quality variables averaged over the recruitment period was assessed using Pearson's correlation coefficient, with values of greater than or equal to 0.6 considered to indicate co-linearity.

Following McKenzie et al. (2013), GLMs were used to assess the influence of environmental variables on flatfish CPUE. Environmental variables were added to the GLM framework used to derive standardised CPUE indices for each harbour by Moore et al. (2023). Given the small proportion of zero catch records in targeted flatfish set net fishing (Moore et al. 2023) GLMs for both harbours were based on positive estimated catch data (i.e., zero catch events were not included). All GLMs used a log-normal error distribution. The fishing operational covariates offered to each GLM included fishing month, vessel, total net length, and fishing duration. Following McKenzie et al. (2013), fishing year was excluded from all GLMs, as year and values for a given water quality parameters were associated. Due to differences in temporal resolution of fishing duration data collected on different forms over the period examined here, fishing duration data were aggregated into one-hour bins. Total net length, (binned) fishing duration, and all water quality variable data were log-transformed prior to inclusion in models. Fishing month and vessel were supplied to all GLMs as factors, while (log) total net length, (log) fishing duration, and all (logged) water quality variables were provided as cubic splines with a low number of

degrees of freedom. The use of cubic splines allowed the relationship between catch and a given water quality variable to be non-linear.

For the Manukau Harbour, models were built using data for all available years. For the Kaipara Harbour, two series of models were developed, one exploring water quality from the Shelly Beach Wharf monitoring site, for which data were available from late 1991 onwards, and a second exploring the average water quality values experienced across the six monitoring sites, using data from 2009 onwards. Dissolved oxygen and ammonia were excluded from all models due to a change in monitoring equipment and laboratory service provider in 2009 and 2017 respectively, which may have influenced trends over time (Ingleby 2021; see Results).

A forward stepwise selection procedure was used to identify the best-fitting model from the provided explanatory variables. Here, (log) estimated catch was regressed against the full set of explanatory variables, selecting variables one at a time until the improvement in the model R^2 was less than 1%. The order of the variables in the selection process was based on the variable with the lowest Akaike Information Criterion (AIC) so that the degrees of freedom were minimised (Moore et al. 2023). Separate models were run for correlated variables, with the best-fitting model identified using AIC. For the Kaipara Harbour dataset, this necessitated adding each variable into the models individually, due to the large number of correlated variables for this harbour (see Results). All GLMs were fitted using the `stepAIC` function of NIWA's *CPUE* package (Manning 2021) in R version 4.0.5 (R Core Team 2022). To evaluate the shape of the relationship between water quality and catch for any water quality variables retained by the model, predictions were run across each observed level of the given water quality variable, with the other retained model terms held at constant values (mean values for continuous variables and modal values for factors). Results from these predictions were then compared against those from models run excluding water quality but including a year effect, to evaluate the association between year and water quality, and to assess how well the water quality variable predicted annual catch rates.

3. RESULTS

3.1 Summary of water quality

3.1.1 Manukau Harbour

Water quality data for the Manukau Harbour were available from the late 1980s (Figure 3). There was general agreement in the trends observed for a given variable among sites, although observed values were often at quite different magnitudes of scale. Total phosphorus, soluble phosphorus, and turbidity showed a marked decrease over time. Water temperature at all sites showed a progressive increase, particularly from around 2004. Dissolved oxygen was highly variable in the early years of the time series but increased in 2009 coinciding with a change in monitoring equipment (Ingleby 2021). Thereafter, dissolved oxygen has remained relatively stable across all monitoring sites, albeit with a slight decrease over time (Figure 3). For a given year, concentrations of ammonia, total phosphorus, and soluble phosphorus, as well as turbidity were higher at the Weymouth site than at either Clarks Beach or Grahams Beach.

Considerable correlation was evident among several water quality variables for the Manukau Harbour. Turbidity was highly correlated (Pearson correlation coefficient > 0.6) with total phosphorus and total suspended solids. Total phosphorus and soluble phosphorus were also correlated (Figure 4).

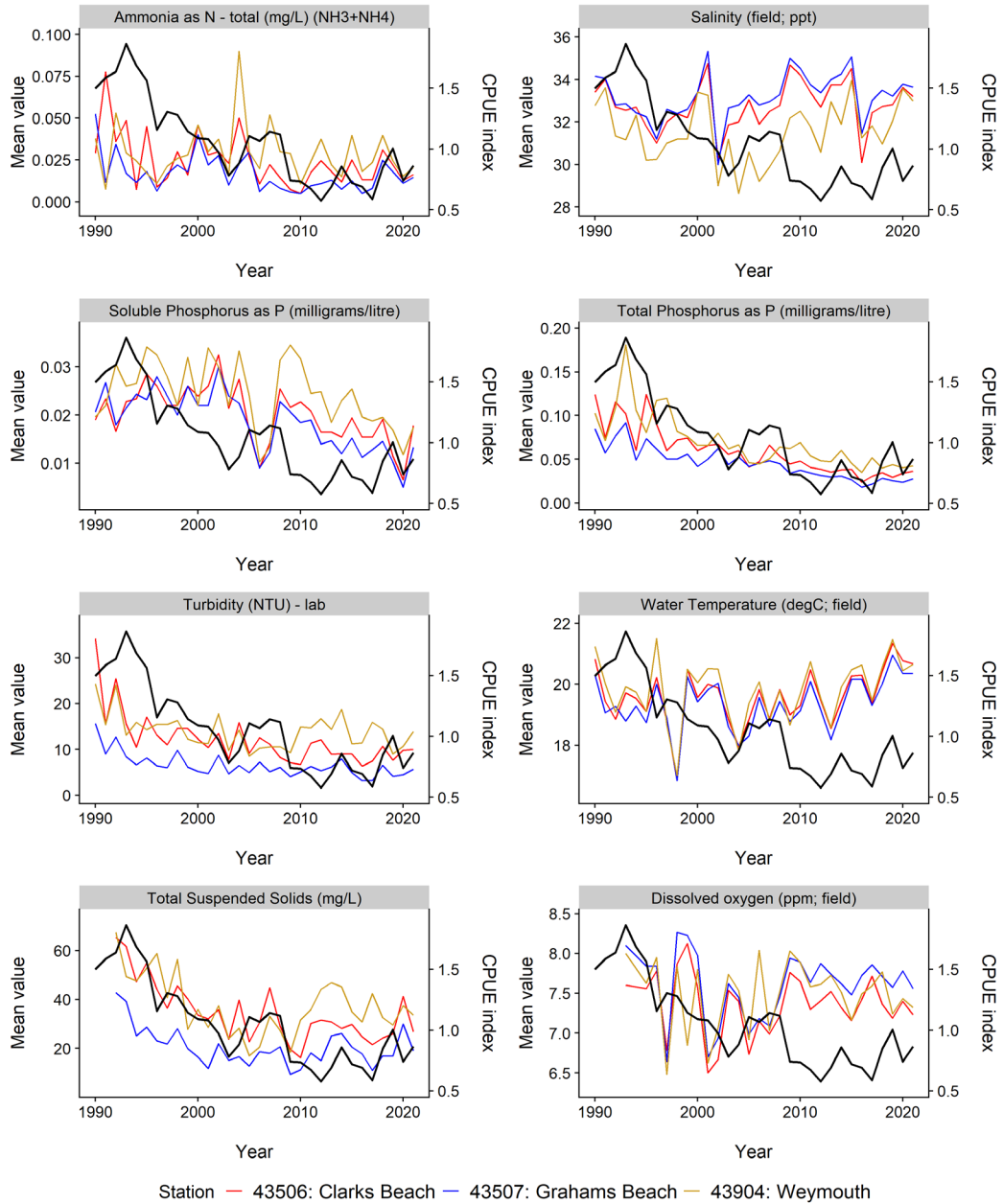


Figure 3: Mean annual water quality for the assumed peak yellowbelly flounder recruitment period (October-February) for monitoring sites within the Manukau Harbour. The final standardised catch per unit effort time series used to indicate stock status is plotted in black (from Moore et al. 2023).

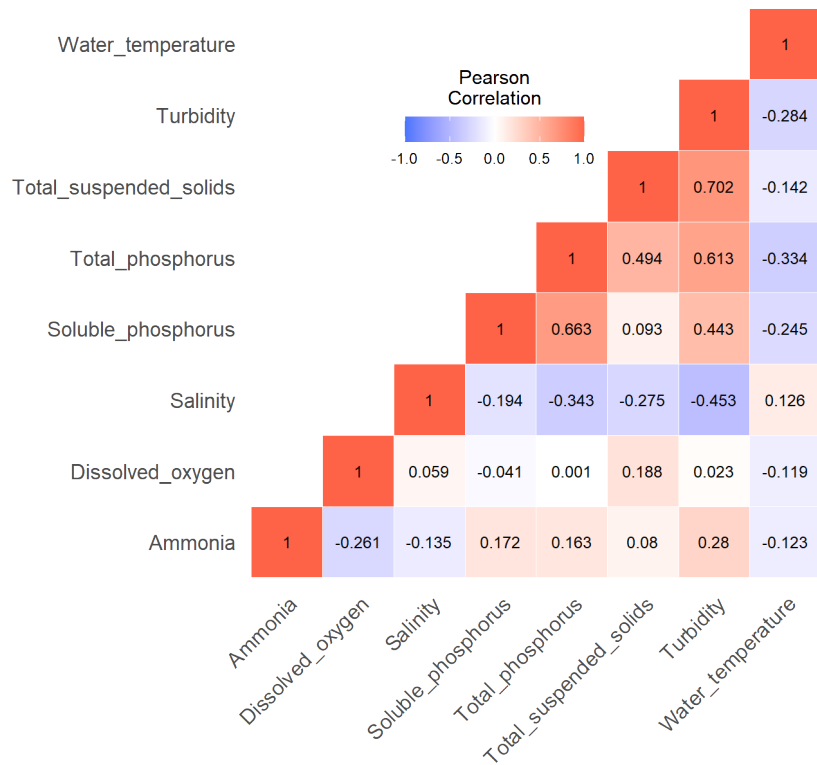


Figure 4: Pearson correlation coefficients between average water quality variables over the assumed peak yellowbelly flounder recruitment period (October-February) in the Manukau Harbour (all years).

3.1.2 Kaipara Harbour

Water quality monitoring by AC commenced in the Kaipara Harbour in the early 1990s, at Shelly Beach Wharf. Other monitoring sites were added to the programme in 2009 (Figure 5). The Oruawharo River site was monitored for only a short period (2009–2014) but was included in the analyses as resulting data were largely comparable with other sites, and thus were considered representative of the harbour at large.

Decreases over time (albeit with significant inter-annual fluctuations) in chl-*a*, nitrates+nitrites, soluble phosphorus, total phosphorus, total suspended solids, and turbidity were evident across all sites, although chl-*a* and soluble phosphorus concentrations increased at all sites in 2021 (Figure 5). Average water temperatures over the assumed peak recruitment period showed similar inter-annual fluctuations but have increased progressively since the mid-2000s (Figure 5). Dissolved oxygen was highly variable at the Shelly Beach Wharf site in the early years of the time series but increased in 2009 coinciding with a change in monitoring equipment (Ingleby 2021) and have remained relatively stable across all monitoring sites thereafter (Figure 5).

Considerable correlation was evident among water quality variables for the Kaipara Harbour. For the Shelly Beach Wharf dataset, nitrates+nitrites, soluble phosphorus, total phosphorus, total suspended solids, and turbidity were all highly correlated (Figure 6). Concentrations of chl-*a* were highly correlated with soluble phosphorus, total phosphorus, total suspended solids, and turbidity, while ammonia concentrations were highly correlated with total phosphorus, total suspended solids, and turbidity (Figure 6). Water temperature was negatively correlated with concentrations of nitrates+nitrites, total phosphorus, total suspended solids, and turbidity (Figure 6). For the ‘all sites’ dataset (i.e., using data from 2009 onwards), total phosphorus, total suspended solids, and turbidity were again highly correlated (Figure 7). Concentrations of chl-*a* were negatively correlated with salinity, and dissolved oxygen was negatively correlated with water temperature (Figure 7).

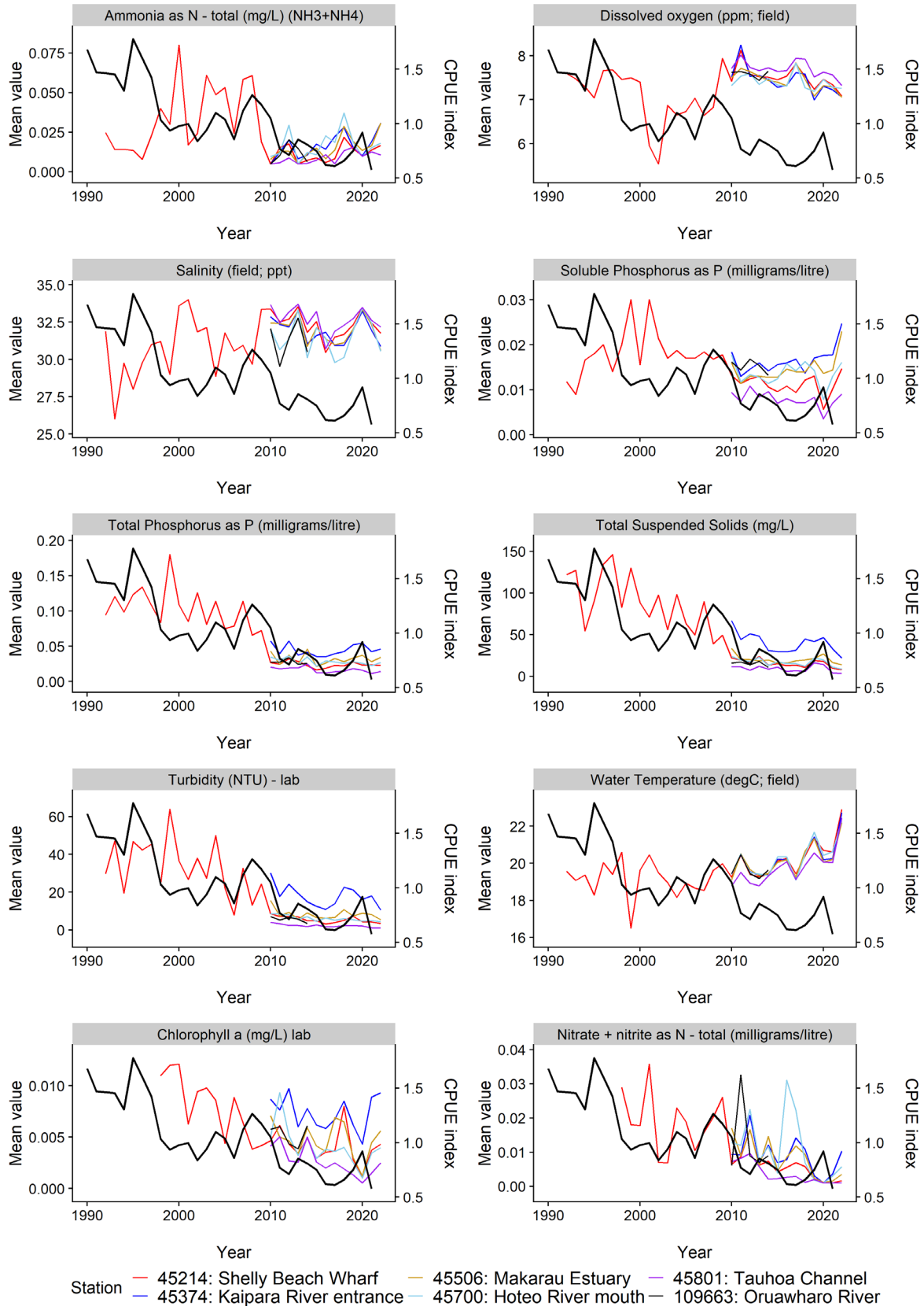


Figure 5: Mean annual water quality for the assumed peak yellowbelly flounder recruitment period (October-February) for monitoring sites within the Kaipara Harbour. The final standardised catch per unit effort time series used to indicate stock status is plotted in black (from Moore et al. 2023).

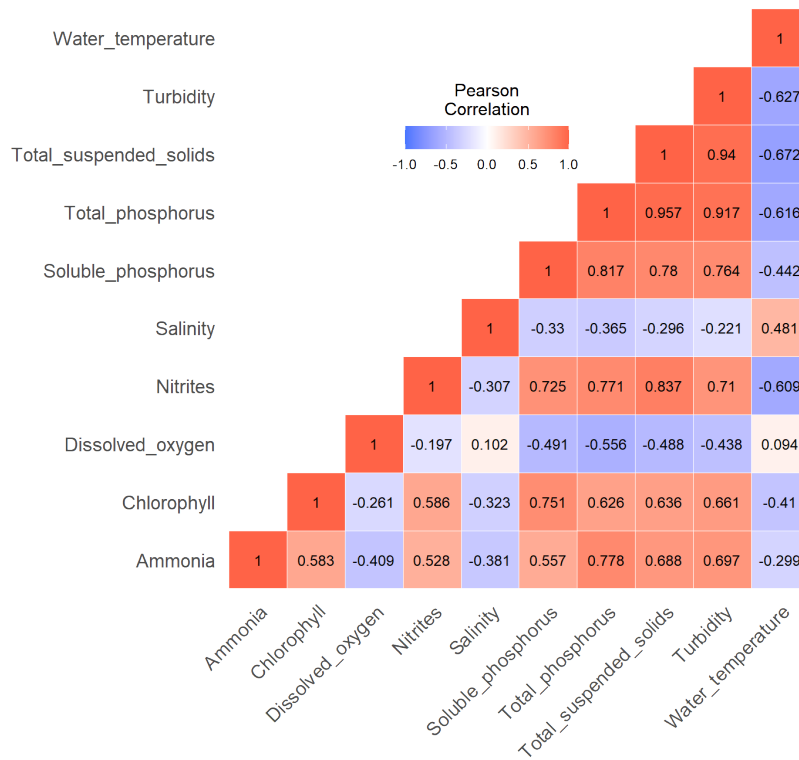


Figure 6: Pearson correlation coefficients between average water quality variables over the assumed peak yellowbelly flounder recruitment period (October-February) in the Kaipara Harbour (Shelly Beach Wharf site).

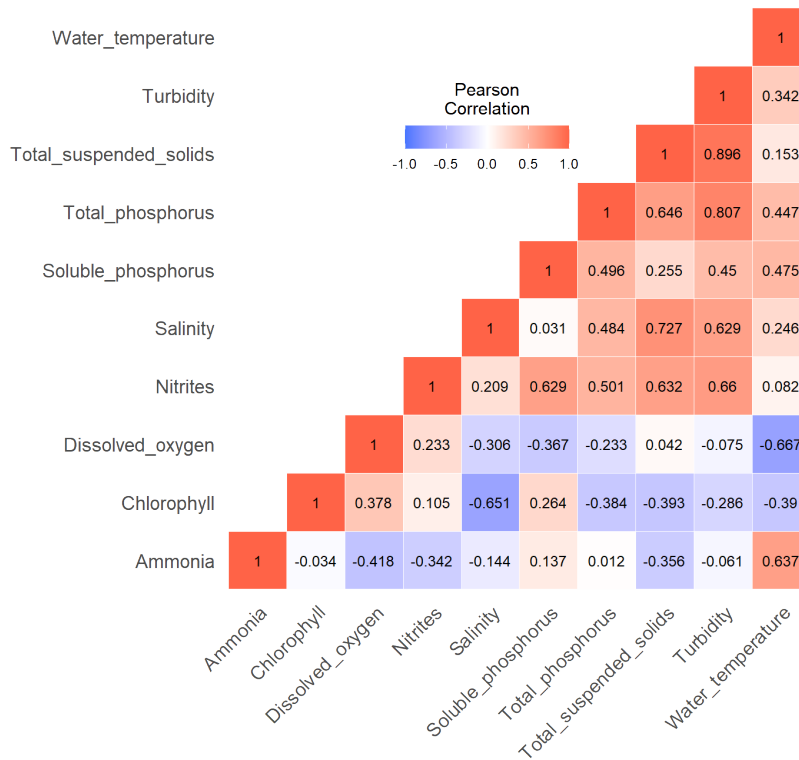


Figure 7: Pearson correlation coefficients between average water quality variables over the assumed peak yellowbelly flounder recruitment period (October-February) in the Kaipara Harbour (all sites from 2009 onwards).

3.2 Catch per unit effort standardisations incorporating water quality

3.2.1 Manukau Harbour

When water quality variables corresponding to the peak recruitment period with a two-year time lag were offered to the GLMs instead of fishing year, the correlated variables (log) total phosphorus and (log) turbidity were selected, with the model including total phosphorus having a slightly lower AIC than the model including turbidity (Table 1 and Table 2). Once the effects of vessel, month, net length, and fishing duration were standardised for, positive associations between catch in a given set and time-lagged total phosphorus concentration or turbidity was evident, with highest (log) catches per set associated with years with highest total phosphorus concentrations and turbidity (Figure 8 and Figure 9). Residuals from the two models were similar and generally showed no influential outliers and good residual patterns (Figure A1 and Figure A2).

Table 1: Selected predictors for the lognormal CPUE model including total phosphorus for the Manukau Harbour with a two-year time lag, showing the order of acceptance of variables into the model, and the residual deviance, R^2 , and AIC values following the variable's inclusion.

Variable	Residual deviance	R^2	AIC
vessel	19 711	0.225	73 948
log_total_net_length	18 102	0.288	71 319
log_duration	17 540	0.310	70 349
month	17 007	0.331	69 416
log_total_phosphorus	16 666	0.344	68 792

Table 2: Selected predictors for the lognormal CPUE model including turbidity for the Manukau Harbour with a two-year time lag, showing the order of acceptance of variables into the model, and the residual deviance, R^2 , and AIC values following the variable's inclusion.

Variable	Residual deviance	R^2	AIC
vessel	19 711	0.225	73 948
log_total_net_length	18 102	0.288	71 319
log_duration	17 540	0.310	70 349
month	17 007	0.331	69 416
log_turbidity	16 747	0.341	68 944

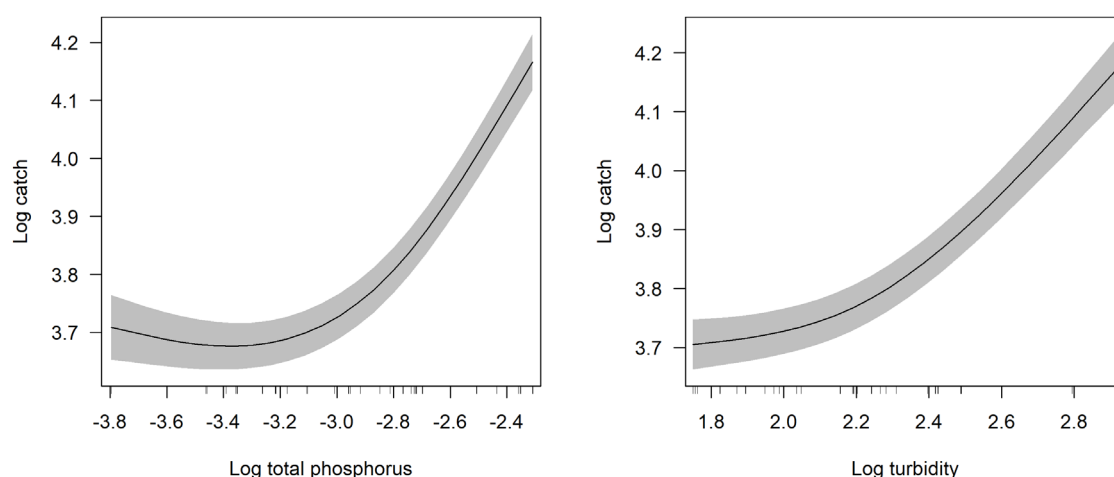


Figure 8: Effects plots for water quality variables retained in generalised linear models examining catch per set in the Manukau Harbour. Plots show the predicted catch per set predicted from the (log) total phosphorus and (log) turbidity terms for models with a two-year time lag when all other variables were held at constant values (mean values for continuous variables, modal values for factors). Shaded areas represent 95% confidence intervals.

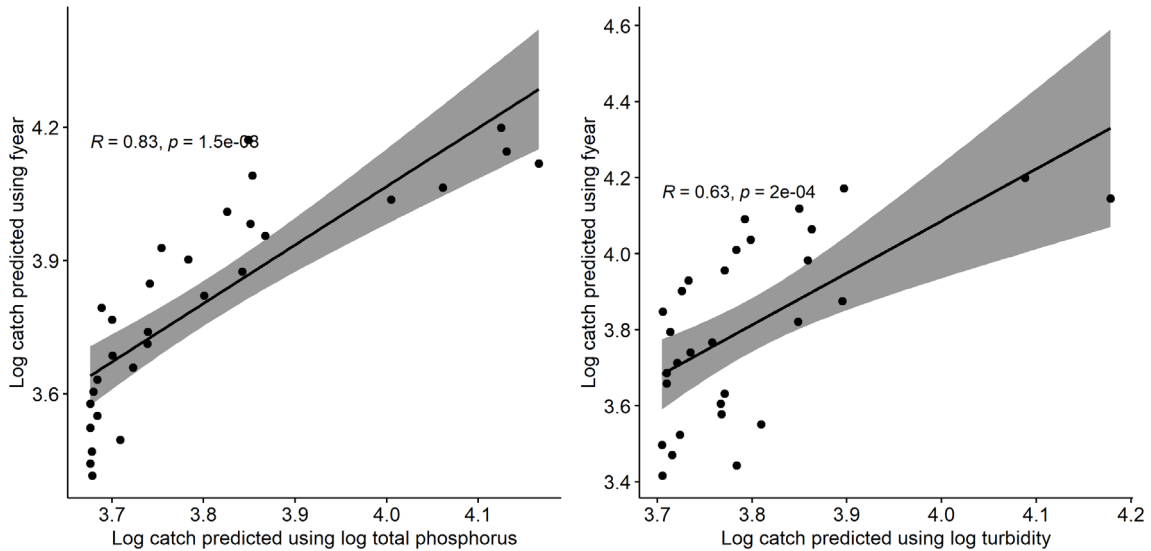


Figure 9: Correlations between predicted catch per set from models using (log) total phosphorus concentration and fishing year (year) (left) and (log) turbidity and fishing year (right) from the selected generalised linear models linking water quality to catch with a two-year time lag in the Manukau Harbour. Shaded areas represent 95% confidence intervals.

Results from models with a three-year lag were nearly identical to those from the models with a two-year lag, with (log) total phosphorus and (log) turbidity selected, with the model including turbidity having a slightly lower AIC than the model including total phosphorus (Table 3 and Table 4). Both of these models gave a slightly improved fit compared with the model with a two-year lag, as evidenced by a larger R^2 value and smaller residual deviance and AIC values (*cf* Tables 1 and 2 with Tables 3 and 4). Once the effects of vessel, month, net length, and fishing duration were standardised for, positive associations between catch in a given set and time-lagged turbidity and total phosphorus were evident, with highest catches per set associated with years with highest turbidity and total phosphorus concentrations (Figure 10 and Figure 11). Residuals from the models were similar, and generally showed no influential outliers and good residual patterns (Figure A3 and Figure A4).

Table 3: Selected predictors for the lognormal CPUE model including turbidity for the Manukau Harbour with a three-year time lag, showing the order of acceptance of variables into the model, and the residual deviance, R^2 , and AIC values following the variable's inclusion.

Variable	Residual deviance	R^2	AIC
vessel	19 711	0.225	73 948
log_total_net_length	18 102	0.288	71 319
month	17 540	0.310	70 349
log_duration	17 007	0.331	69 416
log_turbidity	16 018	0.348	66 427

Table 4: Selected predictors for the lognormal CPUE model including total phosphorus for the Manukau Harbour with a three-year time lag, showing the order of acceptance of variables into the model, and the residual deviance, R^2 , and AIC values following the variable's inclusion.

Variable	Residual deviance	R^2	AIC
vessel	19 711	0.225	73 948
log_total_net_length	18 102	0.288	71 319
month	17 540	0.310	70 349
log_duration	17 007	0.331	69 416
log_total_phosphorus	16 128	0.344	66 631

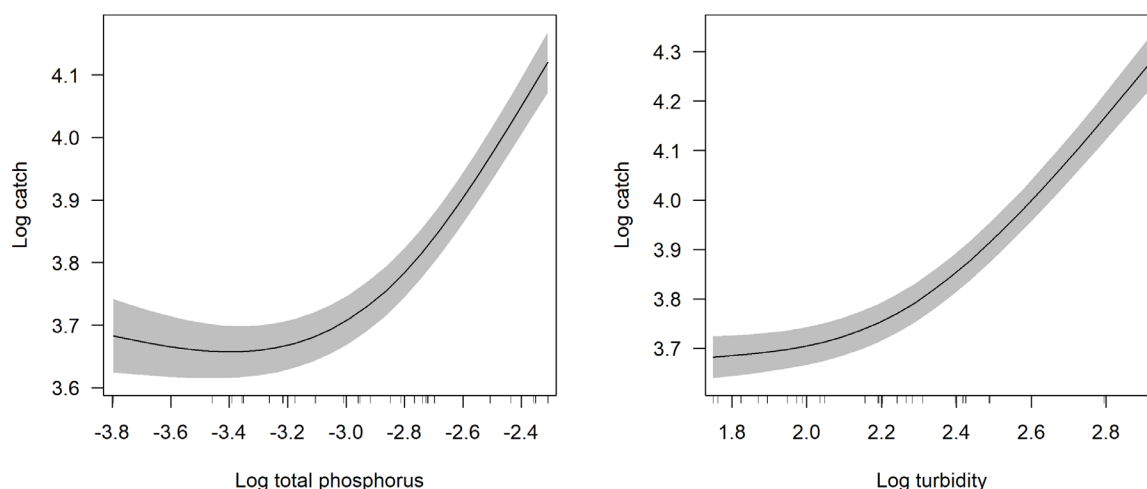


Figure 10: Effects plots for water quality variables retained in generalised linear models examining catch per set in the Manukau Harbour. Plots show the predicted catch per set predicted from the (log) total phosphorus and (log) turbidity terms for models with a three-year time lag when all other variables were held at constant values (mean values for continuous variables, modal values for factors). Shaded areas represent 95% confidence intervals.

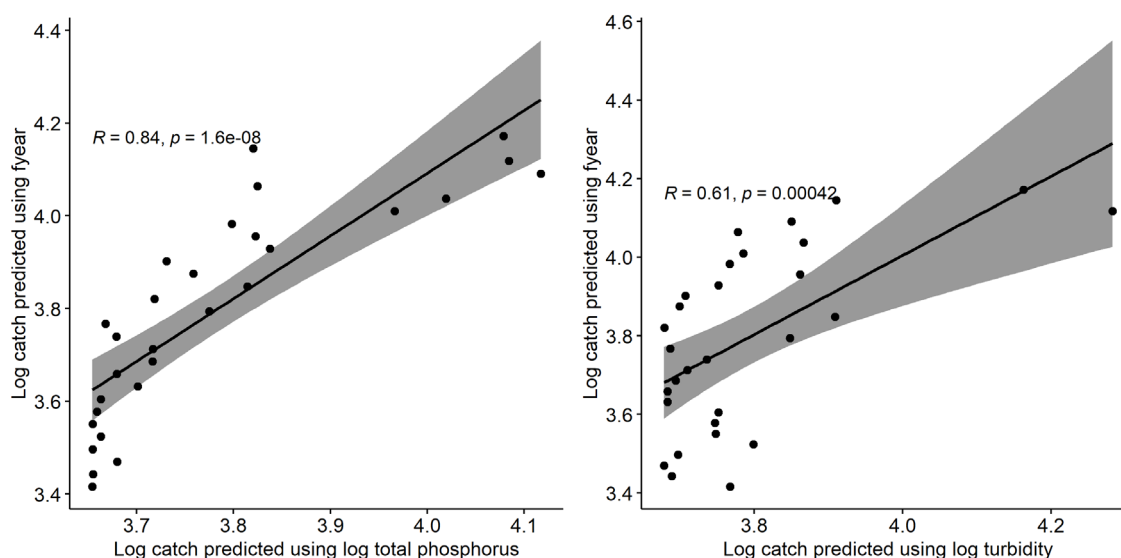


Figure 11: Correlations between predicted catch per set from models using (log) total phosphorus concentration and fishing year (left) and (log) turbidity and fishing year (right) from the selected generalised linear models linking water quality to catch with a three-year time lag in the Manukau Harbour. Shaded areas represent 95% confidence intervals.

3.2.2 Kaipara Harbour

When water quality variables for the Shelly Beach Wharf dataset were added individually with a two-year time lag, chl-*a*, nitrates+nitrites, soluble phosphorus, total phosphorus, and total suspended solids were all retained by the model (in addition to the terms for vessel, month, net length, and fishing duration). Of these, the model including a term for (log) total phosphorus had the lowest overall AIC and residual deviance values, followed by the model incorporating total suspended solids (Appendix B, Tables B1–B5). The variables retained in the models showed similar responses, with an approximately positive association with catch after standardising for the effects of vessel, month, net length, and fishing duration (Figure 12 and Figure 13). Slight decreases in catch were associated with the highest values of most of the retained variables (Figure 12). Residuals from the models were largely similar

and generally showed no influential outliers and good residual patterns (note: residual diagnostic plots for the model including (log) total phosphorus (i.e., the best fitting model) are provided as Figure B1).

When water quality variables for the Shelly Beach Wharf dataset were added individually with a three-year time lag, chl-*a*, nitrates+nitrites, soluble phosphorus, total phosphorus, total suspended solids, and turbidity were all retained by the model, with the model including a term for total suspended solids having the lowest overall AIC and residual deviance values (Appendix B, Tables B6–B11). The variables retained in the model again showed similar responses, with a general positive association with catch, and a slight decrease in catch associated with the highest values of most of the retained variables (i.e., tending towards a ‘ Ω ’ shape; Figure 14 and Figure 15). Residuals from the models were largely similar and generally showed no influential outliers and good residual patterns (note: residual diagnostic plots for the model including (log) total suspended solids (i.e., the best fitting model) are provided as Figure B2).

For the 2009+ dataset (i.e., incorporating water quality data from multiple monitoring sites from 2009 onwards), no water quality variables were selected by the model with either a two- or three-year time lag (i.e., the model retained only the terms for vessel, (log) total net length, (log) fishing duration, and month of the fishing event).

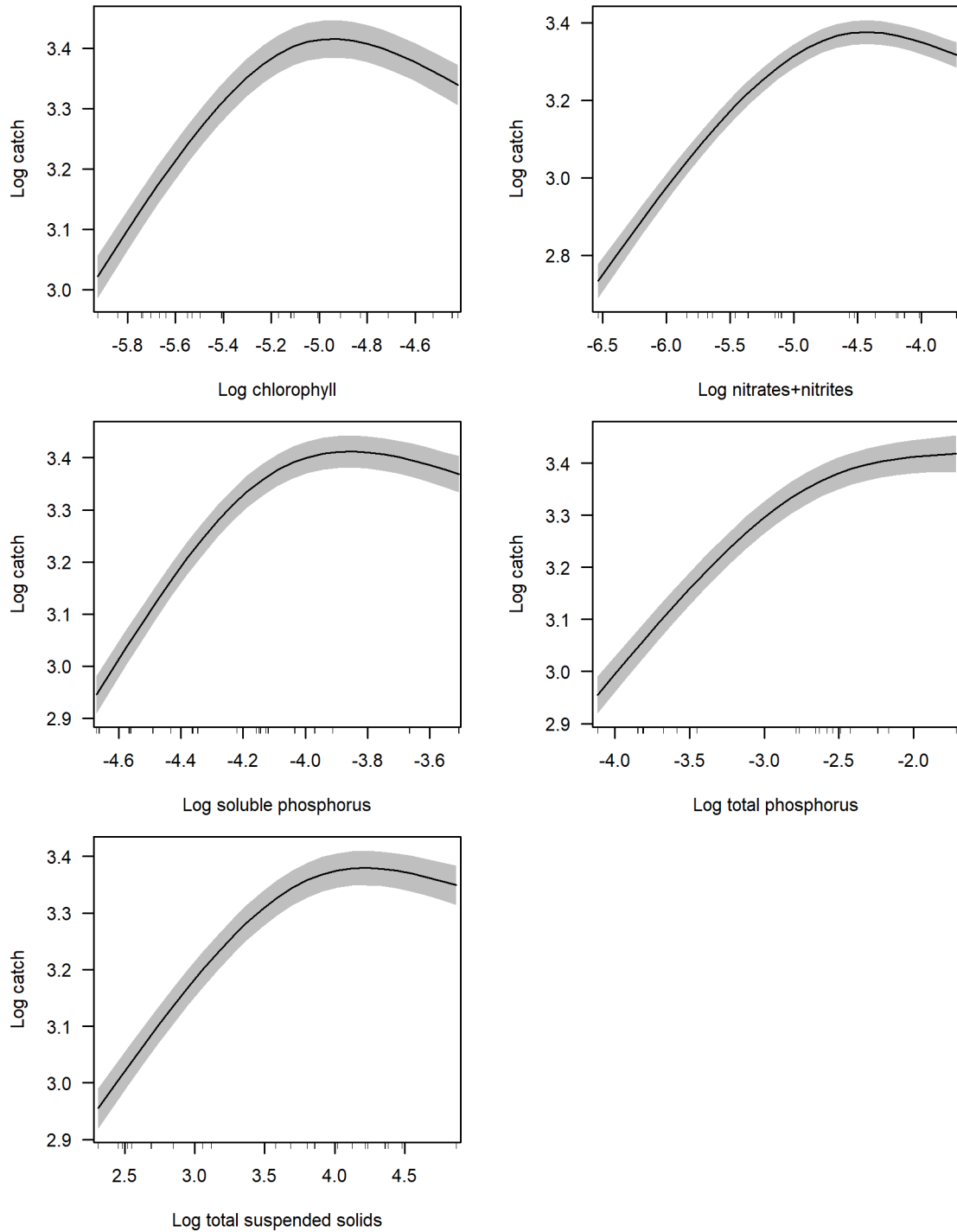


Figure 12: Effects plots for water quality variables retained in generalised linear models examining catch per set in the Kaipara Harbour. Plots show the predicted catch per set predicted from terms retained in models with a two-year time lag when all other variables were held at constant values (mean values for continuous variables, modal values for factors). Shaded areas represent 95% confidence intervals.

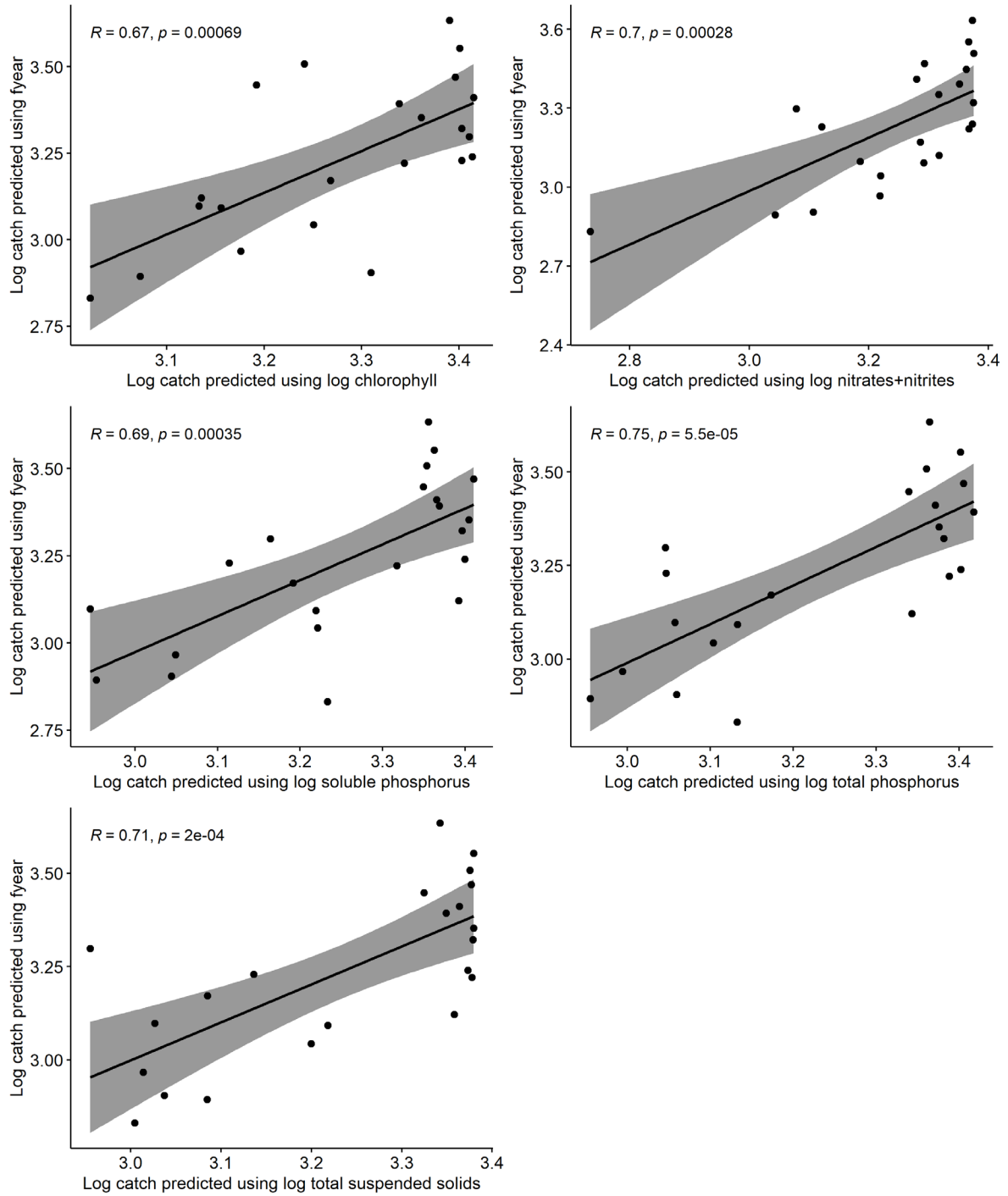


Figure 13: Correlations between predicted catch per set from water quality variables and fishing year from the selected GLMs linking water quality to catch with a two-year time lag in the Kaipara Harbour (Shelly Beach Wharf site). Shaded areas represent 95% confidence intervals.

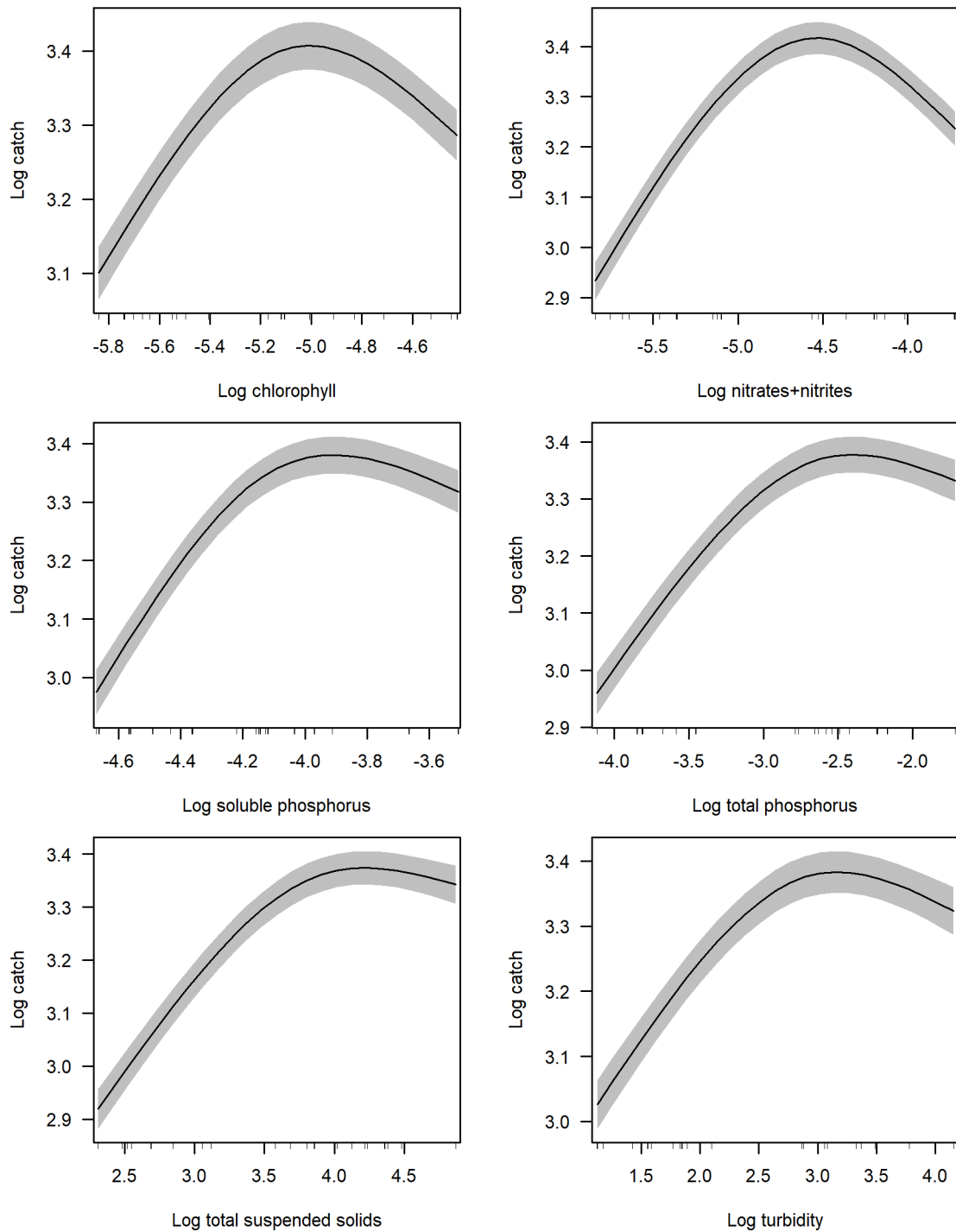


Figure 14: Effects plots for water quality variables retained in generalised linear models examining catch per set in the Kaipara Harbour. Plots show the predicted catch per set predicted from terms retained in models with a three-year time lag when all other variables were held at constant values (mean values for continuous variables, modal values for factors). Shaded areas represent 95% confidence intervals.

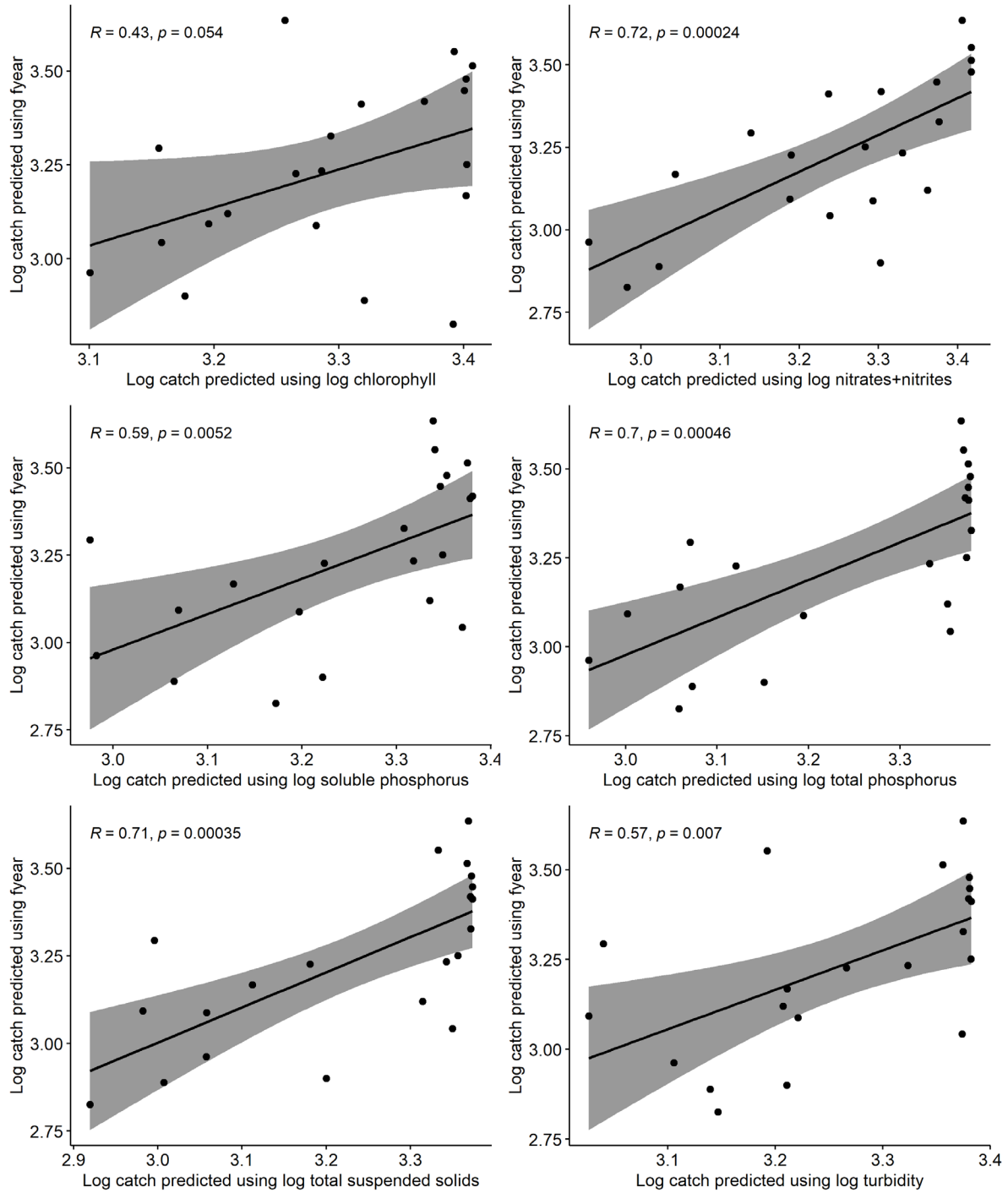


Figure 15: Correlations between predicted catch per set from water quality variables and fishing year (fyear) from the selected GLMs linking water quality to catch with a three-year time lag in the Kaipara Harbour (Shelly Beach Wharf site). Shaded areas represent 95% confidence intervals.

4. DISCUSSION

This report examined the association between flatfish catch per set and time-lagged water quality variables in the Manukau and Kaipara harbours, on the west coast of New Zealand's North Island. In the Manukau Harbour, positive associations were observed between flatfish catch per fishing set and mean total phosphorus concentrations and turbidity during the assumed peak recruitment period. Similar associations were observed in the Kaipara Harbour. These results suggest that turbid water conditions and elevated levels of total phosphorus observed in the Manukau and Kaipara harbours in the early to mid-1990s may have had a positive effect on flatfish recruitment and abundance, and, conversely, subsequent decreases in these variables with improved catchment management may have negatively affected flatfish abundance. Ongoing monitoring of trends in water quality in association with flatfish catch and effort data would be beneficial to further assess relationships between water quality, flatfish recruitment, and catch rates.

The strong correlations among several water quality variables in the Kaipara Harbour precluded the ability to associate catch rates per set with any individual water quality variable for this location. Similarly, in the Manukau Harbour, total phosphorus and turbidity were correlated, again making it difficult to ascribe the association to any one individual variable. In reality, however, it is likely that in both harbours, water quality variables operate as proxies, or in synergy. For example, in both harbours, a positive association was observed between total phosphorus and catch. Phosphorus is a key nutrient that can stimulate the growth of algae and plants in aquatic systems, occurring in both dissolved and particulate forms (with total phosphorus, as used in these analyses, being a measure of both forms) (Ingley 2021). Thus, high phosphorus concentrations may result in high phytoplankton growth, and thus elevated concentrations of chl-*a*. High chl-*a* concentrations, such as observed in algal blooms, can subsequently result in secondary changes in water clarity and dissolved oxygen (Plew et al. 2020). In addition, phosphorus is also associated with total suspended solids and turbidity (Villa et al. 2019, Ingley 2021), while turbidity has been widely used as a proxy to predict concentrations of total suspended solids (Bilotta & Brazier 2008, Villa et al. 2019).

GLMs were used here as a modelling framework to predict catch rates as a function of a set of possible covariates. GLMs are powerful modelling tools that allow one to characterise relationships between the response variable of interest and model covariates. However, GLMs are not always able to select the main covariate driving the response variable when model covariates are correlated, even if the overall prediction remains accurate. This issue also applies to the identified shape of the individual relationship between the response variable and each of the correlated covariates. Of note, unreliable inference with co-linear model covariates is not just linked to GLMs; other models that use a correlative modelling framework (e.g. Generalised Additive Models) encounter the same problem (Tredennick et al. 2021). As such, the relationships reported here should be interpreted with caution.

The positive association between turbidity and catch observed in the Manukau Harbour was initially unexpected, as this result contrasts with the findings of McKenzie et al. (2013), who observed a negative association between turbidity and annual flatfish catch rates in the Manukau Harbour based on data collected between 1990 and 2009. The study of McKenzie et al. (2013) used water quality data from a single site (Weymouth) that may not have been representative of the harbour as a whole. Similarly, Parsons et al. (2015) found an overall negative association between flatfish catch rates and nitrate concentrations in the Kaipara Harbour, in contrast to the generally positive, but tending Ω -shape association observed between catch rates and nitrates+nitrites for the Kaipara Harbour in the current study. Examination revealed these differences largely resulted from the inclusion of additional years of data. This highlights the importance of ongoing monitoring to improve the long-term characterisation of the relationship between water quality and catch rates.

High concentrations of nutrients such as phosphorus and high levels of total suspended solids and turbidity can be lethal to marine species (Able & Kaiser 1994). For estuarine species such as yellowbelly flounder, however, moderate levels of total suspended solids / turbidity and nutrients such as phosphorus may be beneficial, while low levels may be detrimental. For example, increased phosphorus

may have increased primary productivity, leading to increases in prey availability and thus juvenile flatfish survival. Similarly, increased total suspended solids or turbidity levels may have a positive effect on flatfish recruitment by either reducing mortality associated with predation due to increased predator avoidance, or by increasing juvenile survival through increased feeding success, either by increasing prey availability or by providing greater opportunity for camouflage while foraging. Yellowbelly flounder are ambush predators that rely on non-visual, chemosensory-based approaches to locate food and feed nocturnally on a wide variety of benthic epifauna and infauna (in particular crustaceans, annelids, molluscs, and small fishes) (Livingston 1981, 1987, Mutoro 2001). In support of the latter hypothesis, larvae of the closely-related greenback flounder (*R. tapirina*) showed improved feeding ability in turbid versus clear water across various prey densities (Shaw et al. 2006). Alternately, the effect might be driven by a third unaccounted for covariate correlated with these variables. Controlled experiments, with yellowbelly flounder larvae reared under different water quality regimes, would be required to test this hypothesis.

Based on available information, declines in catch rates of flatfish in the Manukau and Kaipara harbours do not appear to be related to changes in sediment characteristics. Sediment monitoring conducted by AC in the Manukau Harbour revealed no significant change in the proportions of gravel/shell (> 2000 µm), sand (coarse 63 µm), and silt/clay (i.e., mud) between 1987 and 2018, while benthic chl-*a* concentration and sediment organic content have similarly remained constant since monitoring of these variables commenced in 2000 (Greenfield et al. 2019). Similarly, in the Kaipara Harbour, sediment particle sizes, organic content, and chl-*a* concentrations have generally remained stable since AC commenced monitoring of these characteristics in the southern Kaipara Harbour in 2009 (Hailes & Carter 2015, RIMU 2018).

It is unclear from available data whether changes in flatfish abundance, as indexed by standardised CPUE, relate to the extent of available habitat. In the Kaipara Harbour, the cover of mangroves has increased in recent years, along with non-indigenous biogenic species such as Asian date mussels and Pacific oysters. These increases are associated with declines in the extent of bare tidal mudflats, the preferred habitat for yellowbelly flounder (Morrison et al. 2014).

Water temperature has previously been observed to influence flatfish recruitment and survivorship. For example, Dou et al. (2005) found a significant negative effect of water temperature on survival of Japanese flounder, *Paralichthys olivaceus*, reared under controlled conditions, with rearing in higher temperatures (18 °C and 21 °C) leading to accelerated yolk exhaustion and growth and reduced starvation tolerance and survival compared with when larvae were reared in lower temperatures (15 °C). Water temperatures in both the Manukau and Kaipara harbours have steadily increased since the mid-2000s (Foley et al. 2018, Ingley 2021, this study); however water temperature was not retained in models for either harbour, under either a two- or three-year time lag. It may be that the increases in temperature observed in both harbours are not sufficient to result in increased larval mortality. Alternatively, changes in temperature may act at finer spatial scales than the coarse resolution of the analysis. Again, controlled experiments, with yellowbelly flounder larvae reared under different temperature regimes, are required to test this hypothesis.

A key assumption made in this study, and in monitoring trends in abundance of flatfish in the Manukau and Kaipara harbours in general, is that single stocks of flatfish occur in each of these areas. In the Manukau Harbour, tagging data and fisheries-independent surveys suggest yellowbelly flounder undertake cyclical migrations to deeper waters of the main channel in winter and spring to spawn, with larvae then recruiting to sheltered inshore areas (Mutoro 2001). A similar dynamic has been proposed for yellowbelly flounder and sand flounder in the Hauraki Gulf (Colman 1973, 1974a, 1974b). This would suggest that yellowbelly flounder in Manukau Harbour and Kaipara Harbour represent 'closed' populations. Conversely, Constable (2014) demonstrated genetic similarity of yellowbelly flounder among northern North Island sampling locations, suggesting a degree of connectivity among areas. The spawning behaviour and relatively long pelagic larval durations (~70 days, Constable 2014) of yellowbelly flounder may provide a mechanism for the advection and dispersal of eggs and larvae among areas. Studies into the connectivity of populations between the Manukau and Kaipara harbours

and adjacent harbours on the west coast of the North Island, including the Hokianga and Kawhia harbours, would be of benefit to confirm the assumptions made for these analyses, as well as to determine the spatial scale of assessment and management of flatfish stocks in FLA 1.

In addition to a negative association between catch and turbidity, McKenzie et al. (2013) found a positive correlation between dissolved oxygen concentration and flatfish catch rates, and a negative correlation between ammonia and flatfish catch rates in the Manukau Harbour. We opted not to include ammonia or dissolved oxygen in the current analyses. For ammonia, an abrupt step increase was observed in 2017, coinciding with a change in laboratory service provider, while a change in the equipment used to measure dissolved oxygen in 2009 resulted in discrepancies in the time series (Ingle 2021). Since 2009, AC has also been recording dissolved oxygen saturation (%), while data on a suite of benthic ecological variables and contaminants have been collected since 1987. These data were not analysed in the current study due to resource constraints and, for dissolved oxygen saturation, their relatively short time series, but should be explored in future analyses as the time series develops.

5. ACKNOWLEDGEMENTS

This work was funded by Fisheries New Zealand under project FLA2021–01. We thank Auckland Council Research and Evaluation Unit (RIMU), especially Janine Kamke, for providing the water quality data. Members of the Inshore Fisheries Working Group provided constructive feedback that improved the analyses. Steven Holmes and Richard O’Driscoll (NIWA) and Marc Griffiths (Fisheries New Zealand) provided useful comments on the draft report.

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APPENDIX A SUPPORTING TABLES AND FIGURES FOR MANUKAU HARBOUR ANALYSES

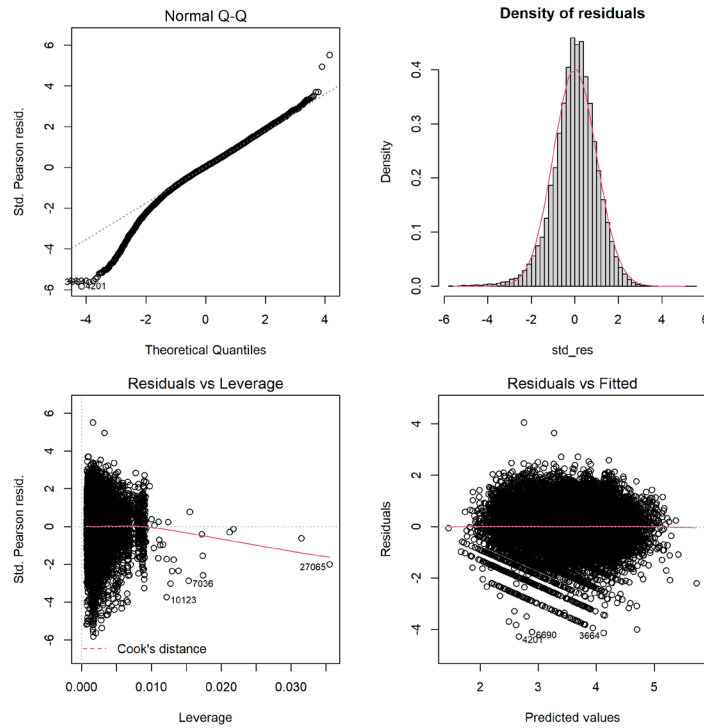


Figure A1: Diagnostic plots for the fit of the lognormal model for the Manukau Harbour FLA CPUE series incorporating (log) total phosphorus with a two-year time lag. Upper left panel, Q-Q plot of standardised Pearson residuals; upper right panel, histogram of standardised residuals compared to lognormal distribution (red line); lower left panel, standardised Pearson residuals versus leverage plot; lower right panel, residuals plotted against the predicted model catch.

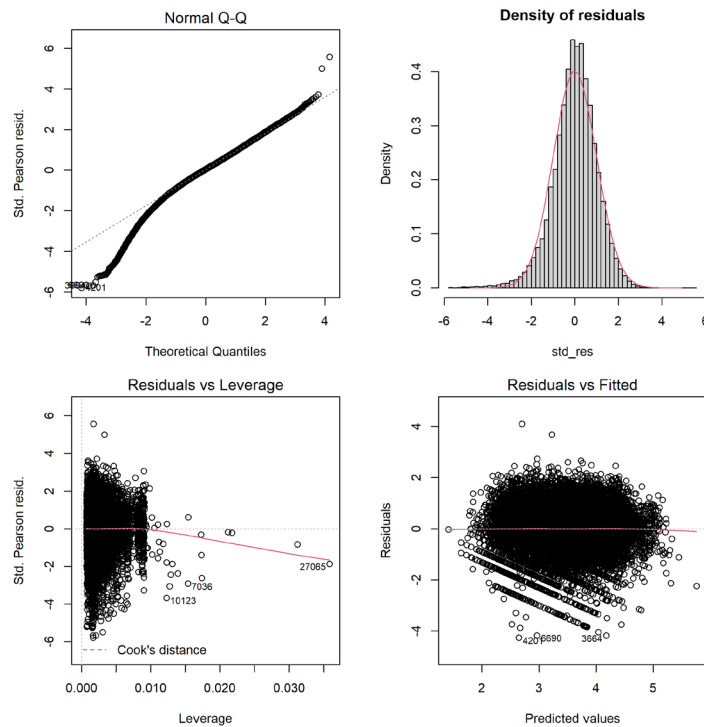


Figure A2: Diagnostic plots for the fit of the lognormal model for the Manukau Harbour FLA CPUE series incorporating (log) turbidity with a two-year time lag. See the caption for Figure A1 for information on the plot types presented.

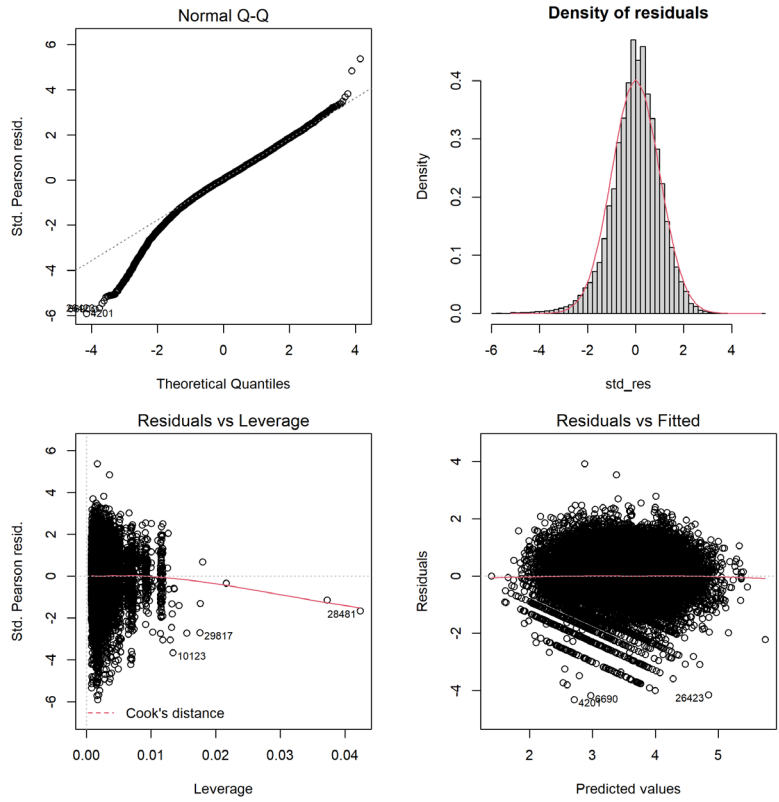


Figure A3: Diagnostic plots for the fit of the lognormal model for the Manukau Harbour FLA CPUE series incorporating (log) turbidity with a three-year time lag. See the caption for Figure A1 for information on the plot types presented.

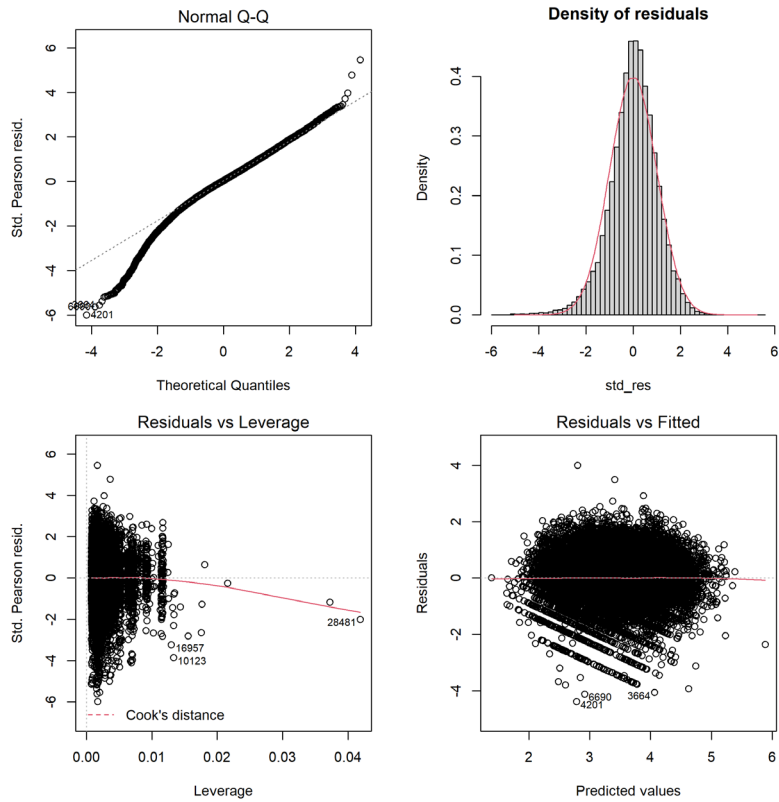


Figure A4: Diagnostic plots for the fit of the lognormal model for the Manukau Harbour FLA CPUE series incorporating (log) total phosphorus with a three-year time lag. See the caption for Figure A1 for information on the plot types presented.

APPENDIX B SUPPORTING TABLES AND FIGURES FOR KAIPARA HARBOUR ANALYSES

Table B1: Selected predictors for the lognormal CPUE model including chl-*a* (Shelly Beach Wharf site) for the Kaipara Harbour with a two-year time lag, showing the order of acceptance of variables into the model, and the residual deviance, R², and AIC values following the variable's inclusion.

Variable	Residual deviance	R ²	AIC
Vessel	27 468	0.216	115 748
Log total net length	26 349	0.248	113 547
Month	25 683	0.267	112 212
Log duration	25 109	0.284	111 019
Log chl- <i>a</i>	24 582	0.299	109 898

Table B2: Selected predictors for the lognormal CPUE model including nitrates+nitrates as N (Shelly Beach Wharf site) for the Kaipara Harbour with a two-year time lag, showing the order of acceptance of variables into the model, and the residual deviance, R², and AIC values following the variable's inclusion.

Variable	Residual deviance	R ²	AIC
Vessel	27 468	0.216	115 748
Log total net length	26 349	0.248	113 547
Month	25 683	0.267	112 212
Log duration	25 109	0.284	111 019
Log nitrates+nitrites	24 454	0.302	109 620

Table B3: Selected predictors for the lognormal CPUE model including soluble phosphorus (Shelly Beach Wharf site) for the Kaipara Harbour with a two-year time lag, showing the order of acceptance of variables into the model, and the residual deviance, R², and AIC values following the variable's inclusion.

Variable	Residual deviance	R ²	AIC
Vessel	27 468	0.216	115 748
Log total net length	26 349	0.248	113 547
Month	25 683	0.267	112 212
Log soluble phosphorus	25 083	0.284	110 963
Log duration	24 420	0.303	109 547

Table B4: Selected predictors for the lognormal CPUE model including total phosphorus (Shelly Beach Wharf site) for the Kaipara Harbour with a two-year time lag, showing the order of acceptance of variables into the model, and the residual deviance, R², and AIC values following the variable's inclusion.

Variable	Residual deviance	R ²	AIC
Vessel	27 468	0.216	115 748
Log total net length	26 349	0.248	113 547
Month	25 683	0.267	112 212
Log total phosphorus	24 990	0.287	110 764
Log duration	24 293	0.307	109 271

Table B5: Selected predictors for the lognormal CPUE model including total suspended solids (Shelly Beach Wharf site) for the Kaipara Harbour with a two-year time lag, showing the order of acceptance of variables into the model, and the residual deviance, R^2 , and AIC values following the variable's inclusion.

Variable	Residual deviance	R^2	AIC
Vessel	27 468	0.216	115 748
Log total net length	26 349	0.248	113 547
Month	25 683	0.267	112 212
Log total suspended solids	25 102	0.284	111 001
Log duration	24 406	0.304	109 516

Table B6: Selected predictors for the lognormal CPUE model including chl-*a* (Shelly Beach Wharf site) for the Kaipara Harbour with a three-year time lag, showing the order of acceptance of variables into the model, and the residual deviance, R^2 , and AIC values following the variable's inclusion.

Variable	Residual deviance	R^2	AIC
Vessel	25 445	0.216	107 301
Log total net length	24 346	0.249	105 136
Month	23 631	0.271	103 692
Log duration	23 102	0.288	102 583
Log chl- <i>a</i>	22 767	0.298	101 868

Table B7: Selected predictors for the lognormal CPUE model including nitrates+nitrites (Shelly Beach Wharf site) for the Kaipara Harbour with a three-year time lag, showing the order of acceptance of variables into the model, and the residual deviance, R^2 , and AIC values following the variable's inclusion.

Variable	Residual deviance	R^2	AIC
Vessel	25 445	0.216	107 301
Log total net length	24 346	0.249	105 136
Month	23 631	0.271	103 692
Log nitrates+nitrites	23 029	0.290	102 426
Log duration	22 415	0.309	101 103

Table B8: Selected predictors for the lognormal CPUE model including soluble phosphorus (Shelly Beach Wharf site) for the Kaipara Harbour with a three-year time lag, showing the order of acceptance of variables into the model, and the residual deviance, R^2 , and AIC values following the variable's inclusion.

Variable	Residual deviance	R^2	AIC
Vessel	25 445	0.216	107 301
Log total net length	24 346	0.249	105 136
Month	23 631	0.271	103 692
Log duration	23 102	0.288	102 583
Log soluble phosphorus	22 621	0.303	101 553

Table B9: Selected predictors for the lognormal CPUE model including total phosphorus (Shelly Beach Wharf site) for the Kaipara Harbour with a three-year time lag, showing the order of acceptance of variables into the model, and the residual deviance, R², and AIC values following the variable's inclusion.

Variable	Residual deviance	R ²	AIC
Vessel	25 445	0.216	107 301
Log total net length	24 346	0.249	105 136
Month	23 631	0.271	103 692
Log total phosphorus	23 067	0.289	102 507
Log duration	22 439	0.308	101 154

Table B10: Selected predictors for the lognormal CPUE model including total suspended solids (Shelly Beach Wharf site) for the Kaipara Harbour with a three-year time lag, showing the order of acceptance of variables into the model, and the residual deviance, R², and AIC values following the variable's inclusion.

Variable	Residual deviance	R ²	AIC
Vessel	25 445	0.216	107 301
Log total net length	24 346	0.249	105 136
Month	23 631	0.271	103 692
Log total suspended solids	23 035	0.290	102 438
Log duration	22 399	0.309	101 068

Table B11: Selected predictors for the lognormal CPUE model including turbidity (Shelly Beach Wharf site) for the Kaipara Harbour with a three-year time lag, showing the order of acceptance of variables into the model, and the residual deviance, R², and AIC values following the variable's inclusion.

Variable	Residual deviance	R ²	AIC
Vessel	25 445	0.216	107 301
Log total net length	24 346	0.249	105 136
Month	23 631	0.271	103 692
Log duration	23 102	0.288	102 583
Log turbidity	22 701	0.300	101 725

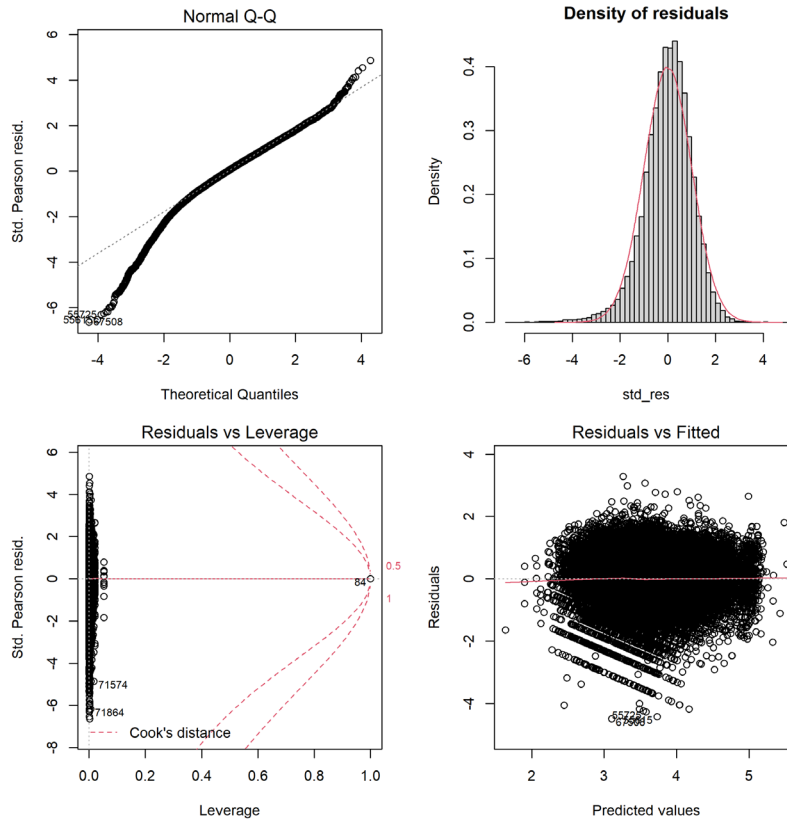


Figure B1: Diagnostic plots for the fit of the lognormal model for the Kaipara Harbour FLA CPUE series incorporating (log) total phosphorus from Shelly Beach Wharf with a two-year time lag. See the caption for Figure A1 for information on the plot types presented.

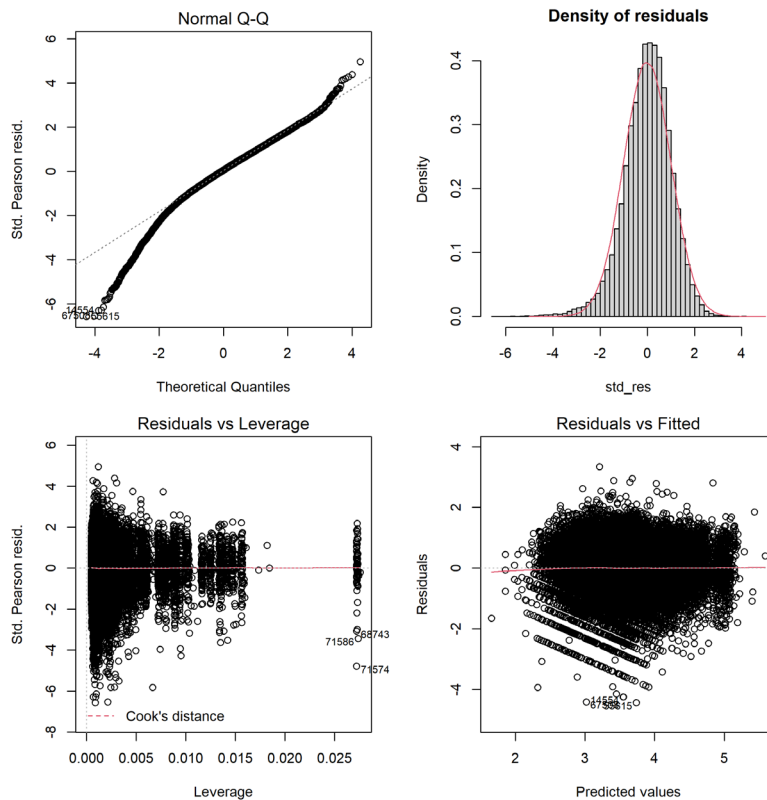


Figure B2: Diagnostic plots for the fit of the lognormal model for the Kaipara Harbour FLA CPUE series incorporating (log) total suspended solids from Shelly Beach Wharf with a three-year time lag. See the caption for Figure A1 for information on the plot types presented.