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Location Choice Modelling of BLL Vessels Operating in the Hauraki Gulf Marine Park Region

Report to Ministry for Primary Industries (MPI), New Zealand

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Executive summary

Ensuring the sustainable use of resources whilst attempting to manage them in the context of multiple and often competing stakeholder groups has contributed towards increased interest in the application of spatial management measures. As these measures have the potential to result in both benefits and costs it is desirable to understand how these may vary under alternative management scenarios and to be able to address them up front, prior to implementation. From the perspective of commercial fisheries, spatial measures that may restrict where commercial vessels are permitted to operate can impose additional costs on the fishery as a result of increased travel or reduced catches. Displaced effort also has the potential to impose broader environmental costs, or conflict with other stakeholder groups.

Location choice models can be developed utilising data on how vessels have been observed to behave in the past, and then used to make predictions around how fishing effort will redistribute under alternative management scenarios in the future. This can provide managers with guidance on the issues of where vessels may end up fishing, the impacts this would have on their operating costs and revenues, and allows the tradeoffs of alternative management scenarios to be explicitly accounted for at the planning stage. Random utility modelling has been widely applied for this purpose in the fisheries context and assumes that the expected utility of fishing in an area influences the probability of effort being allocated there.

This assessment uses the random utility modelling approach to develop a set of location choice models for bottom longline (BLL) vessels operating in and around the Hauraki Gulf Marine Park (HGMP) in New Zealand. Logbook data was used to identify BLL vessels that were financially dependent on the HGMP region and was then combined with additional data relating to factors such as weather conditions and fuel prices to explain their choice making behaviour. A set of independent port level models were developed alongside a single model that incorporates all ports simultaneously. The ability of both approaches to predict observed, out of sample, effort distributions across the HGMP region were tested and compared, with the level of correlation between predicted and observed effort distributions ranging between 0.70 to 0.98 at the annual level and 0.67 to 0.95 at the monthly level.

The utility of the models for predicting how effort would redistribute following a management change was demonstrated with a set of hypothetical closure scenarios. The effects of closures on vessel revenues and costs were simulated and compared at both the port and HGMP level. When viewed at the HGMP level impacts were anticipated to be relatively small in all cases from a revenue perspective, but the cost proxy was predicted to increase by just below 25% under one of the scenarios. At the port level, impacts on revenues and costs were predicted to have greater variability, with some ports being more affected than others under the same scenarios, highlighting the need to be cognisant of the potential for management measures to have distributional effects.

The models developed indicate that expectations of value per unit of effort in an area (vpue) and where a vessel operated in the previous time period (LR) generally have positive a influence on effort allocation in the HGMP BLL fishery. Strong westerly winds, variability in vpue and cost factors have negative influences. This was used to estimate where effort is likely to eventuate under given sets of conditions for vessels from different ports. The outputs of this assessment, in the form of RUM models and r code, may also be utilised by resource managers to test more targeted questions surrounding the impacts of spatial management questions.

In summary:

- Effort allocation models were developed for BLL vessels that logbook data indicates are dependent upon fishing in the HGMP.
    - The anticipated value per unit of effort (vpue) and where vessels had been operating recently generally had positive relationships with the probability of vessels operating in a given area.

- Strong winds from the west, high variability in the vpue of an area, and the costs associate with getting there generally had a negative relationship with the probability of vessels operating in an area.
- The distribution of fishing effort was modelled and effort redistribution under hypothetical closure scenarios was then tested at the HGMP level and for individual ports.
- The effects of these hypothetical management changes were generally seen to be relatively minor in most cases at the HGMP level but more mixed at the port level, demonstrating a need to consider impacts at the port level.
- Additional factors for consideration that cannot be directly accounted for in the models, and their potential effects on the results, were then considered along with possible areas for model development.

1 Introduction

Maintaining the sustainable use of resources whilst simultaneously balancing the multiple objectives of competing groups is an ongoing challenge for many marine resource managers and has contributed towards increasing interest in spatial management as a tool to manage resource extraction, recreational use and biodiversity. A significant factor that management bodies are required to account for when considering the use of area closures, or variations of these such as zoned marine reserves, is the associated cost borne by stakeholders such as commercial fishers and also potentially by the management authority.

Location choice modelling utilises information on the attributes of individual choice making entities, typically at the vessel level, and the conditions in the full set of locations they have available to them to better understand what drives them to operate in certain locations. This can in turn be used to simulate situations and provide guidance as to where fishers are likely to fish under given sets of circumstances, and consequently how effort will redistribute across a given area. The development of these types of models can thus contribute to the decision making process by allowing alternative management scenarios to be tested and considered and the potential consequences of each explored prior to implementation. This capability may be particularly useful when considering the use of management measures that will change the costs or benefits of fishing in certain locations or restrict fishery access (e.g. marine reserves or area closures). The redistribution of effort that typically comes about as a result of spatial management measures is an important factor for consideration, the expected consequences of which should be explicitly incorporated at the planning stage.

This work was commissioned by the Ministry of Primary Industries (MPI), New Zealand, in response to them increasingly being called to advise on the economic impacts of closing fishing grounds due to growing competition for the use of marine space. The location of most fishing in New Zealand is reported at a fine spatial resolution (event start positions to within 1-2 nm) so spatial fishing patterns of fleets and individuals can be summarised to assess value and quality of fishing grounds under threat of closure. However, MPI needs better understanding of what happens to displaced fishing to evaluate the net effects of spatial closures on fishing revenue and costs and other effects of displacing fishing effort. The objectives of this work were threefold:

1) Develop a location choice model for one of the fisheries in the Hauraki Gulf Marine Park (HGMP) using a random utility modelling approach
2) Engage with commercial fishers in order to characterise individual choice making behaviours, obtain information on catch plans, operating costs, and other drivers of location choice, to help validate the models
3) Document the process so that it may be transferred to the MPI.

The Hauraki Gulf bottom longline sector was chosen for modelling as these vessels currently operate throughout the majority of the HGMP's range and logbook data indicates that a number of vessels in the fishery obtain the majority of their landings, and thus revenues, from the region. The relatively high levels of dependence on the HGMP these vessels exhibit suggests that there is also the potential for them to be impacted as a result of any changes to the spatial management of the region and developing location choice models of the fishery allows this issue to be investigated and alternative management scenarios to be considered.

2 Methodology

The HGMP BLL fishery was modelled using discrete choice random utility (RUM) models. These are a probabilistic modelling approach that allows for heterogeneity in attributes of the decision makers. The probability that a decision making entity (e.g. vessel / fisher) will choose to fish in a given location is estimated as a function of both area (e.g. values per unit of effort (vpue), distance from port, weather) and individual (e.g. vessel size, gear, areas fished before) specific characteristics. One underlying assumption when using RUMs is that the decisions of individuals are independent over time, i.e. the decision on where to fish today is not directly dependent upon where the vessel fished on the previous trip. However, the effects of past decisions on current decisions can be included explicitly in the model, and is commonly done so in fisheries applications to capture "habits" or behaviour based on past experiences.

Random utility models are the most widely applied method of modelling fisher location choice (Andersen et al. 2012; Bockstael and Opaluch 1983; Eales and Wilen 1986; Holland and Sutinen 1999; Holland and Sutinen 2000; Hutton et al. 2004; Marchal et al. 2009; Pascoe et al. 2013; Schnier and Felthoven 2011; Smith 2002; Smith et al. 2010; Wilen et al. 2002) and, when applied in this context, are typically developed using revealed preference data, i.e. previously observed behaviour with respect to choice of fishing location. These observed choices, and the conditions under which they were made, are then used to identify what is likely to be most influential in driving these decisions.

Most economically oriented applications of choice modelling have the underlying assumption that the choices made by a rational decision maker reflect an attempt to maximise the utility they expect to derive given the choices available to them (and as such the attributes of the other possible choices in the choice set all have lower expected utilities). As fisheries are mostly commercial enterprises expectations of the profit associated with choices are typically used as a proxy for expected utility.

RUM models are comprised of a deterministic component and a random component. The utility associated with any one choice is usually defined as a linear combination of a set of observable explanatory variables that together are believed to form the deterministic (i.e. non-random) components of the utility, and a stochastic error component that accounts for any unobserved effects.

$$U_{ij} = \beta_j z_{i,j} + \varepsilon_{ij}$$

where for a given choice maker time-event i, (such as a fishing trip) choice j (i.e. fishing location) is made. The explanatory variables z_{ij} may be comprised of attributes of the choice, x_{ij}, and choice maker's individual characteristics, w_i, while β_j is the estimate parameter vector. Estimating the utility associated with each individual choice within the possible set thus allows the relative probability of being chosen to be determined for each and every alternative.

2.1.1 MULTINOMIAL LOGIT (MNL) MODELS

The basic multinomial logit model (Louviere et al. 2000) is widely used in general choice modelling and is the starting point when developing more complex forms of RUMs, such as the nested logit (NL). Choice probabilities in the MNL model may be given by

$$Pr_{(i|j)} = \frac{e^{\sum \beta x_{ij}}}{\sum_{j=1}^{J} e^{\sum \beta x_{ij}}}$$

where the choice maker time-event i chooses choice j, and x_{ij} is a vector of choice specific attributes. In this instance the choice maker is the individual fishing vessel.

Whilst this functional form is widely used, it also requires that a relatively strict set of assumptions are maintained. These are that the variances and covariances of alternative choices error terms are independent and identically distributed (IID) and have a type 1 extreme value distribution (exp(-exp(-ε_{ij}))); observed choices are independent of one another; and, that preferences are homogeneous. From a practical modelling perspective IID is often discussed in the context of choices being independent of irrelevant alternatives (IIA), as this is the behavioural outcome of the IID assumption and must hold if the relative probabilities are to remain unchanged if there is a change in the choice set (Hensher et al. 2005). The reliance on this assumption essentially makes the MNL model inappropriate for testing the impact of changing the choice set decision makers face i.e. the closure of fishing location (Smith 2002; Wilen et al. 2002).

2.1.1 NESTED LOGIT (NL) MODELS

Nested Logit Models allow subsets of alternatives to share unobserved characteristics (i.e. some correlation between error terms of sub-sets, relaxation of assumptions around IIA), something that has been demonstrated as potentially problematic when applying the MNL form (Schnier and Felthoven 2011). The nested logit is probably the most widely applied functional form in fisheries location choice modelling (Bucaram et al. 2013; Curtis and Hicks 2000; Curtis and McConnell 2004; Holland and Sutinen 1999; Holland and Sutinen 2000; Kahui and Alexander 2008; Morey et al. 1993; Pascoe et al. 2013; Smith 2002). It partially relaxes the strict assumption of IIA as imposed by the multinomial logit model by allowing for correlation between subsets of alternatives. In the nested model, the probability of choice *j* is conditional upon choosing branch *k* (i.e. *j*|*k*) and *j* is given by

$$Pr_{(j|k)} = \frac{exp\left(\beta_j' z_{j|k}\right)}{\sum_{j \in k} \exp\left(\beta_j' z_{j|k}\right)} = \frac{exp\left(\beta_j' z_{j|k}\right)}{exp K_k}$$

and

$$K_k = \ln\left[\sum_{j \in k} \exp\left(\beta_j' z_{j|k}\right)\right]$$

where $K_k$is the inclusive value (IV) for *k*, and represents the composite utility of the choices within the branch. The probability of choosing any given *k* is given by

$$\Pr(k) = \frac{exp(\tau_k K_k)}{\sum_k \exp(\tau_k K_k)}$$

where τ_k is the IV value relating to branch *k*. The unconditional probability of choice *j* is thus given by Pr(*k*) *Pr(*j*|*k*).

3 The Hauraki Gulf Marine Park Bottom Longline (BLL) Fishery

3.1 Data sources

Detailed logbook data was supplied by the NZ MPI and contained information on catch and effort for all vessels that had at some point recorded at least one fishing event inside the Hauraki Gulf Marine Park (HGMP) over the period 2007-08 to 2012-13. Additional data, relating to vessels characteristics (e.g. length), fuel prices, fish prices (annual) and weather conditions over the same period were also supplied by the MPI. Data on the operating costs of vessels was not available.

The value of landings for each fishing event was calculated using annual price data supplied by the MPI and all prices were normalised to 2012 values.

3.2 Definition of the fleet

When defining what constituted the BLL fleet for the purposes of this assessment a number of factors and practical considerations were taken into account. Central to these was the question of how dependent a vessel was on fishing grounds situated within the HGMP, as this is directly related to the potential for them to be impacted if some of the area was no longer available to commercial fishing. Preliminary analysis of the data therefore focused on the proportion of revenue vessels had derived from areas within the HGMP and the extent to which this was obtained using BLL gear. The boundary of the HGMP is marked in yellow on Figure 1.

To allow for the fact that a number of the vessels operating within the gulf also utilise the areas adjacent to the gulf landings from areas 003 to 009, excluding 009H, (Figure 1) were considered when calculating the proportion of a vessel's revenue deemed as coming from the HGMP region. Histograms illustrating the proportion of total vessel revenue (gvp) obtained using BLL within the HGMP region are plotted in Figure 2. These plots demonstrate a clear bimodal pattern in the vessels considered, with some exhibiting high levels of financial dependence on the use of BLL gear in the HGMP region, obtaining over 75% of their revenue from this gear/area. At the same time there were also a large number of vessels that obtained less than 5% of their revenue in this manner. Based on the observed patterns of vessel dependence a cut off point of 50% was imposed. In addition to this vessels that had an estimated catch value of less than NZ$30,000 in the last year of data (2012-13) were also excluded from the analysis on the basis that they were unlikely to be operating on a full time basis. The latter constraint is imposed due to the fact that formally accounting for any alternative options the fisher may have outside of the fishery will not be possible at the modelling stage.

- ≥ 50% annual revenue using BLL in the HGMP
- ≥ NZ$30,000 annual revenue

Finally, one vessel had not been fishing in the region of the gulf prior to the 2012-13 fishing season and was consequently excluded from the dataset as it would have dropped out of the analysis later in any case when the last year of data was reserved for testing purposes. The final group consisted of 25 vessels; the average characteristics of which are set out in Table 1.

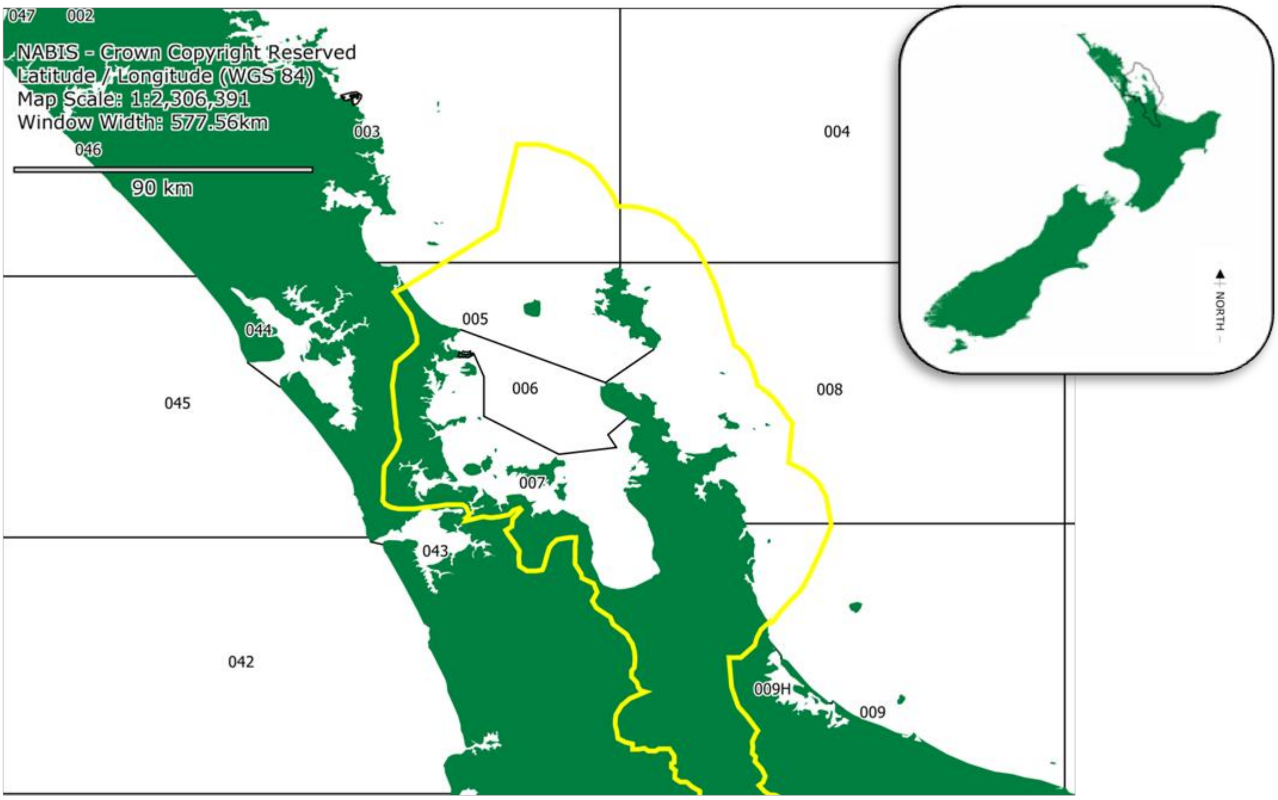

Figure 1. The Hauraki Gulf region, New Zealand statistical management areas outlined in black, Hauraki Gulf marine park boundary in yellow

Source: [www.nabis.qovt.nz]

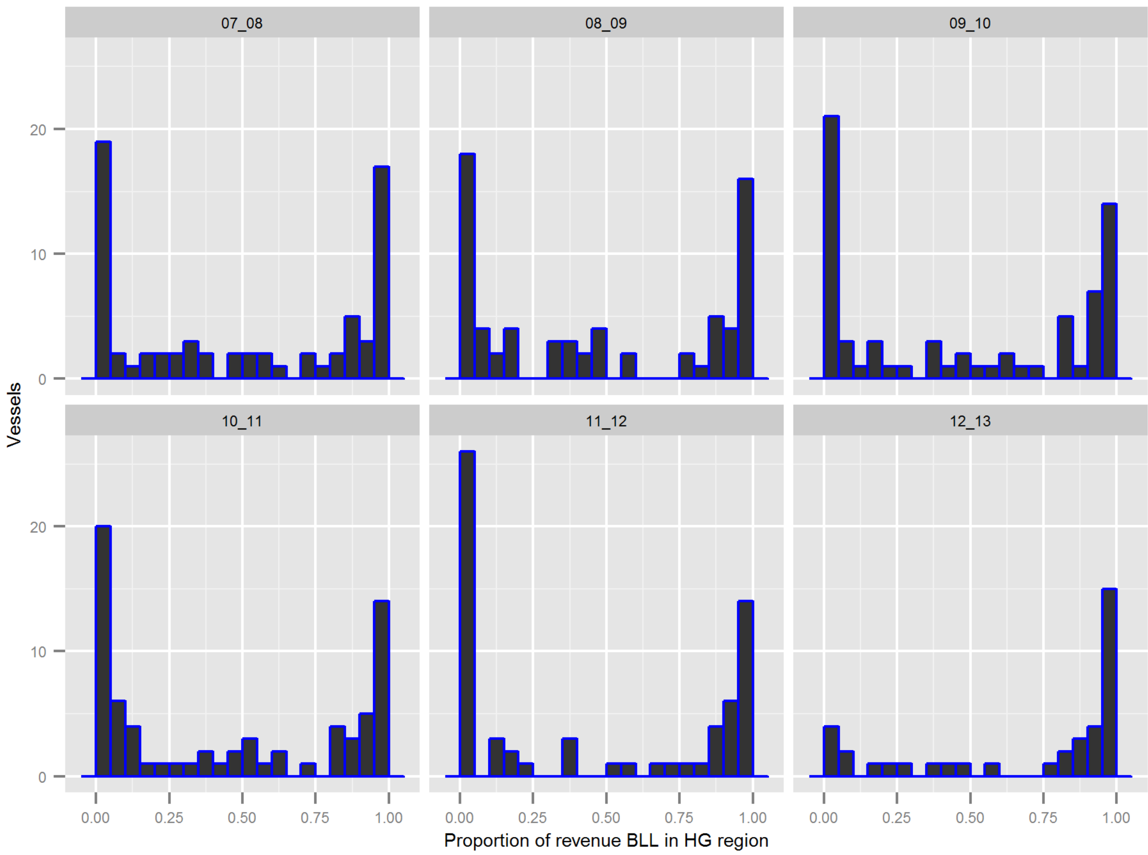

Figure 2 Proportion of total revenue obtained using BLL gear within the HGMP region at the vessel level (for the 82 vessels identified as having used BLL gear at some point in the HGMP region over the period 2007-8 to 2012-13)

Table 1 Characteristics of the HG BLL vessels

Variable	Mean	Sd
Length (m)	12.38	2.37
GrossTonnes	19.23	13.26
Kilowatts	136.38	73.45
DraughtMetres	1.52	0.42
BeamMetres	3.94	0.78
EventsperTrip	1.91	1.29
HooksperShot	1762	1030

3.3 Trip characteristics and data cleaning

Logbook data for the vessels identified in section 3.2 was then examined more closely and the characteristics of their BLL fishing trips defined. The data was also checked at this point for possible anomalies or errors as these are not uncommon in logbook data and have the potential to cause problems at the modelling stage when they may be harder to identify. In addition to the explanation in this section of how data was handled, Appendix A provides a catalogue of the R code used to undertake the analysis.

PORT NAMES

Trips where the name of the landing port was missing were removed and any obvious errors in the spellings of port names corrected. Trips where the port of landing was recorded as Viaduct Basin were assumed to be equivocal to Auckland in terms of distance travelled and three trips, to ports BLUFF 1 and KUPE BAY 2, were excluded as the distances to these locations were assumed to be exceptional and were possibly non-typical transitional type trips. Trips departing from/landing to OPUA were assigned the lat lon of WAITANGI, and trips departing from WHANGAREI and MARSDEN POINT were combined as they are in close proximity to one another and had relatively few observations in the dataset. Trips recorded as having had more than one landing were also not considered in the analysis as they are an infrequent occurrence in the fishery and potentially have a substantially different location choice decision making process underlying them.

INDIVIDUAL FISHING EVENTS WITHIN TRIPS

Trip level data was also checked to ensure that it conformed to some reasonable logical expectations. Trips that had more events recorded than indicated in the sequence numbers for that trip were assumed to be unreliable and omitted, for example one vessel had a record of 34 events in one trip when the maximum sequence length was 13. One trip that had gaps in the sequence numbers was also omitted. A small number of trips, where the number of fishing events were less than half the trip length in days (events< 0.5 * TripDays), were also not included in the analysis on the basis that they are atypical of the fishery as a whole and may reflect trips where problems were encountered.

As the hook count is an important factor in determining catch per unit of effort (cpue), errors here translate directly into the measures of value per unit of effort (vpue), used later in the analysis, so it important that the hook counts are reasonably representative of the fishery being considered. Effort data in terms of hooks shot per fishing event were therefore also checked and, on the basis of the distributions presented in Figure 3, the small number of trips that recorded shots with more than 5,000 hooks or less than 200 were excluded. A current HGMP BLL fisher advised that 1200-1500 hooks would be considered standard for a typical BLL vessel in the Hauraki Gulf and this appears to be supported by the data (Figure 3).

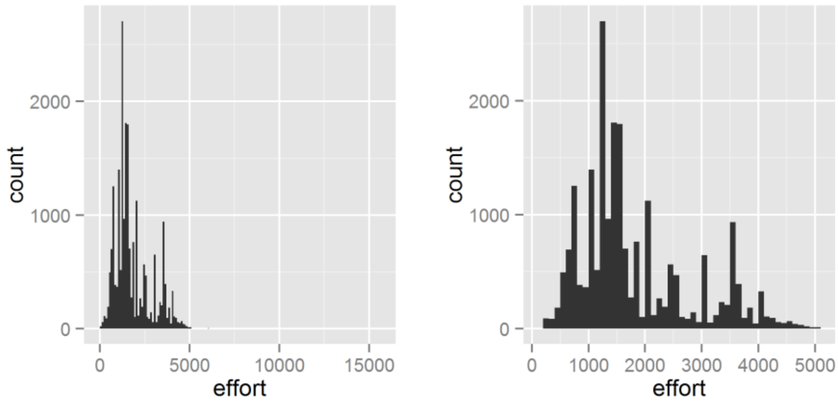

Figure 3 Effort (hooks set) by fishing event, left is plot prior to cleaning, right is after (max. 5,000 hooks)

DISTANCES TRAVELLED

A vessel’s registered home port is typically an unreliable means of determining where it actually departs from on any given fishing trip, as it not unusual for vessels to be based in and fish from ports other than that of registration. Port of departure is also not captured in logbook data so the last port of landing was assumed to be the point of departure on each trip. A trip sequence number was also derived for each vessel as the trip identification number (TripId) did not always appear to be in chronological order for some vessels and, for vessels that moved, the order that trips were undertaken in was needed when assigning their port of departure.

The distances vessels travelled within trips of differing lengths, measured in number of fishing events carried out, were calculated and the means are provided in Table 2 where they are also disaggregated to the average distances travelled at each stage of a trip. On average, the first (out) and last (in) legs of a trip were always the longest stages. These figures were also used to guide the identification of obvious outliers in the data when looking at the distances vessels travelled during trips (Figure 4).

Table 2 Mean distances (km) between fishing events within trips

Events	out	1to2	2to3	3to4	4to5	5to6	6to7	7to8	8to9	9to10	10to11	11to12	12to13	in
1	21.5													21.4
2	31.1	10.1												29.5
3	35.9	9.9	11.6											33.7
4	39.7	11.5	11.1	9.8										38.3
5	47.4	10.5	9.9	9.6	11.3									48.7
6	54.8	7.9	9.2	5.9	8.8	6.5								54.6
7	53.9	14.3	12.3	10.3	6.4	6.8	7.6							47.2
8	62.9	4.6	5.1	3.6	10.7	4.9	9.6	5.3						66.1
9	48.0	9.1	5.3	5.1	8.9	6.4	3.6	4.4	3.7					47.9
10	59.9	4.4	2.5	3.7	3.2	2.1	6.2	4.1	19.9	2.4				39.4
11	115.9	2.9	17.7	22.1	9.4	56.4	11.7	24.3	7.7	10.9	14.7			62.0
12	45.9	30.9	7.3	16.1	13.2	4.0	4.5	5.8	5.4	4.0	23.4	5.4		41.9
13	76.9	5.5	18.4	5.8	1.9	28.0	9.1	9.2	9.1	10.0	10.2	9.4	9.3	53.5

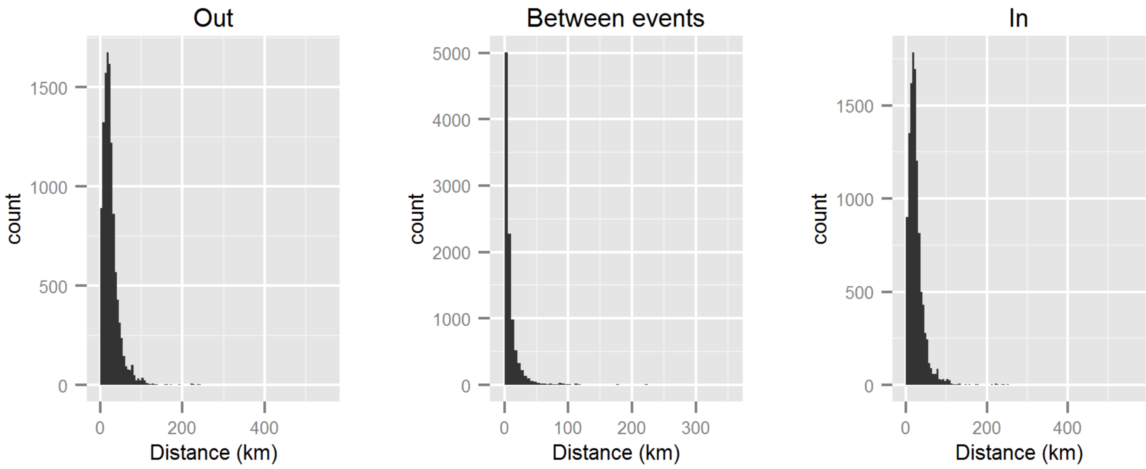

Figure 4 Distances travelled between leaving port and first fishing event (Out), between fishing events, and the last event and returning to port (In)

For day trips, records where vessels were calculated to have travelled further than physically possible in 24hrs based on their recorded steaming speed, were omitted from the dataset. On the basis of Table 2 and Figure 4 trips where vessels were calculated to have travelled more than 100km on either the inward or outward leg of a trip, or >60km between each individual fishing event within the trip, were also consequently removed. An attempt was also made to refine this process by considering what a feasible total travel distance may be at the trip level when accounting for the fact that in reality time is needed to undertake fishing events, so the vessel cannot constantly be steaming. Using a combination of the trip length (in days), the number of fishing events undertaken on the trip and the recorded service speed of the vessel and working on the assumption that to undertake a fishing event requires a vessel does not steam for a minimum of 6 hours, trips where; distance travelled (km) > [(length of trip in days*24)-(number of events*6))* Service speed in km/hr] were also omitted. In total, all of the actions described only resulted in

2.8% of trips (321) being omitted from the data set but should have captured those that were most atypical or possibly erroneous.

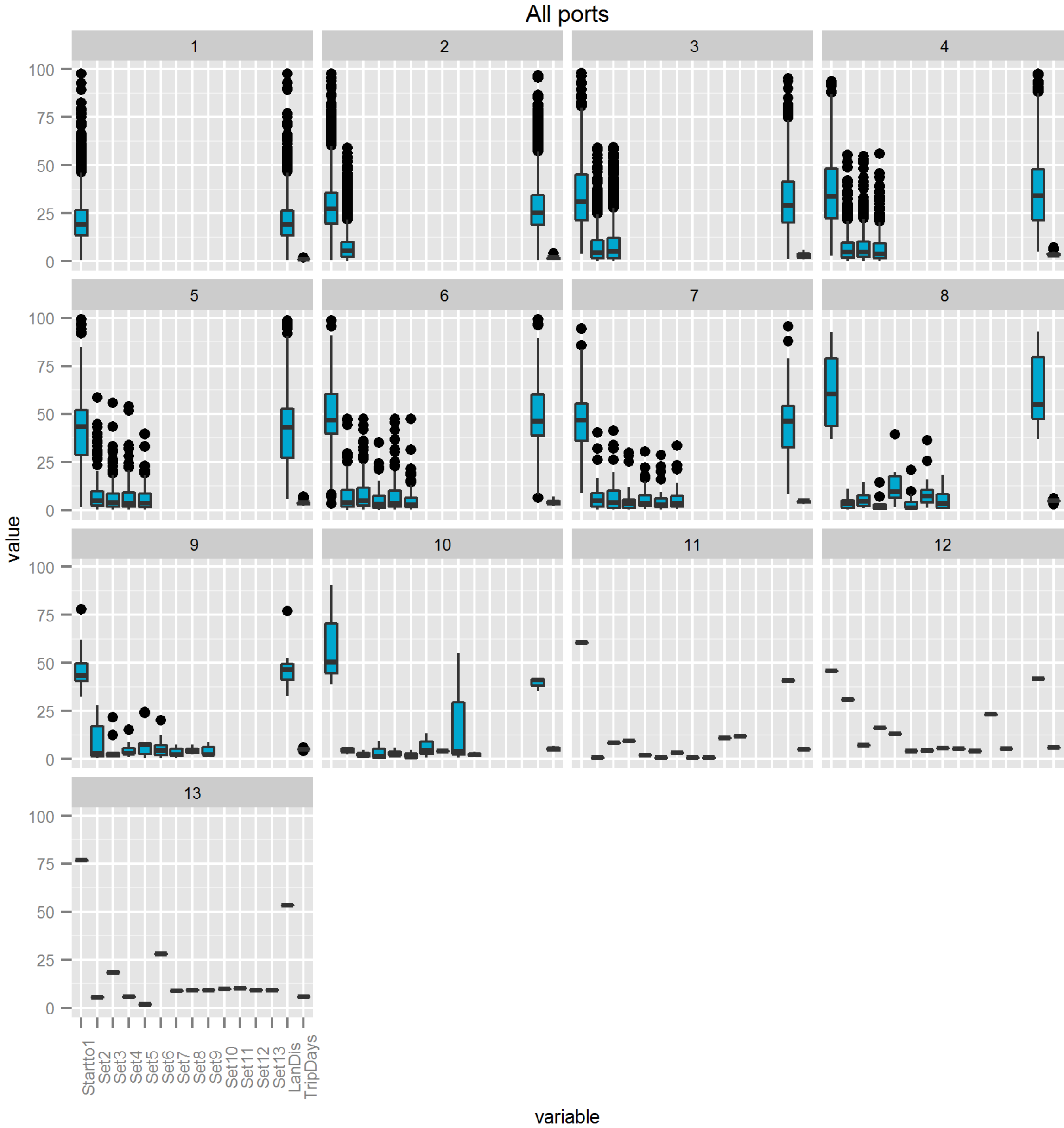

Figure 5 Distances to first fishing event, between events, and to landing for trips with differing numbers of events after cleaning (<100 start and finish, <60 between events)

The final dataset for analysis consisted of information relating to 11,033 trips, where the average trip had slightly less than two fishing events and vessels fished an average of between 75 and 87 trips per year. There is some variation around these means though; for example, in 2012-13 the maximum number of trips a vessel undertook was 201 and the greatest number of events in a single trip was 10. Such high numbers of events were exceptional though (Figure 6) and in 2012-13 only 5 trips were seen to have undertaken 7 or more events. Over the whole period observed 97% of trips carried out 4 events or less on each trip (80% with 2 or less).

Table 3 Summary of BLL vessel fishing trip data

Group			07-08	08-09	09-10	10-11	11-12	12-13
BLL		Vessels	19	22	22	23	24	25
	Trips	Mean	75	76	84	87	85	82
		Min	10	1	24	9	21	24
		Max	204	210	214	203	203	201
		Sum	1419	1667	1849	2007	2036	2055
	Events	Mean	1.7	1.8	1.9	1.9	1.9	1.9
		Min	1	1	1	1	1	1
		Max	7	8	13	10	9	10
		Sum	2402	2970	3491	3755	3865	3815
	Catch (kg)	Mean	475	532	542	564	601	639
		Min	5	12	20	21	4	5
		Max	3915	5595	4979	6382	4735	3654
		Sum	674,629	887,118	1,001,717	1,132,157	1,223,642	1,313,342

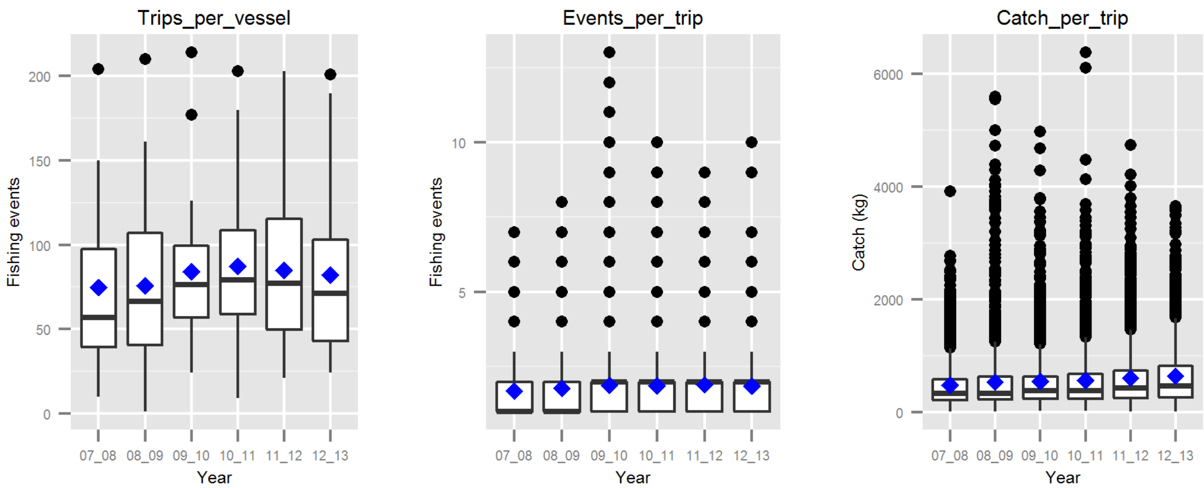

Figure 6 Trips per vessel, events per fishing trip and catch per trip at the annual level (blue diamonds denote the mean in each case)

Vessels predominantly undertook trips of 1-2 days duration, however longer trips of up to 4 or 5 days were also seen in the data (Figure 7 a). The value per-unit-of-effort of a BLL fishing event (vpue) was most commonly in the region of $0.40-1.00 per hook set (Figure 7 b). Only three trips exceeded $5 per hook and these were mainly trips with relatively low numbers of hooks being set.

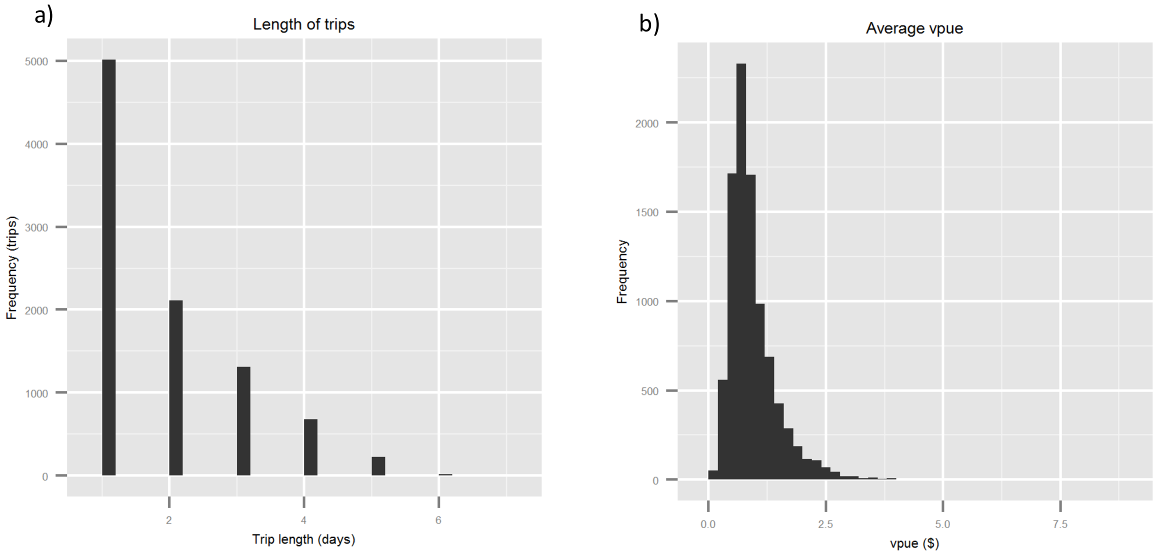

Figure 7 a) Frequency of trips of differing length and, b) average value per-unit-of-effort where effort is defined as the number of hooks set in a fishing event

4 Fishing locations

4.1 Defining fishing opportunities

The BLL vessel logbook data was also used to define a set of discrete fishing locations for the HGMP region. In the first instance, a clustering package for large datasets (clara) was used in the statistical programming language r to identify how effort was grouped in locations across the area of interest (Figure 8a). The areas identified in the clustering analysis were then used by MPI as a basis for defining polygons that approximated a set of discrete fishing areas (Figure 8b).

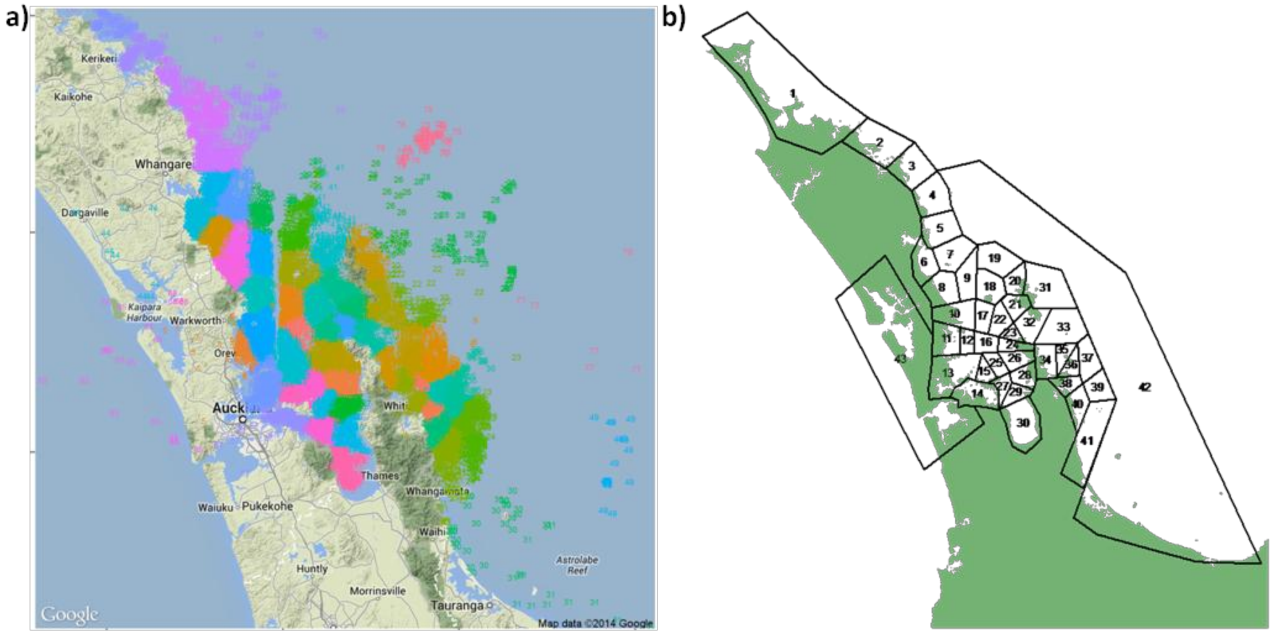

Figure 8 a) Clara derived clusters using all fishing events for the period 2007-2013, b) Locations and numbering of discrete fishing locations (1-43) for the HGMP and its surrounding waters

When defined at this level (43 areas) the fishing events undertaken within individual trips predominantly occur within a single polygon (Figure 9); 77% of trips undertook all fishing events in only one area. Given that the first event location is typically representative of the trip as a whole Individual fishing events were modelled at the trip level.

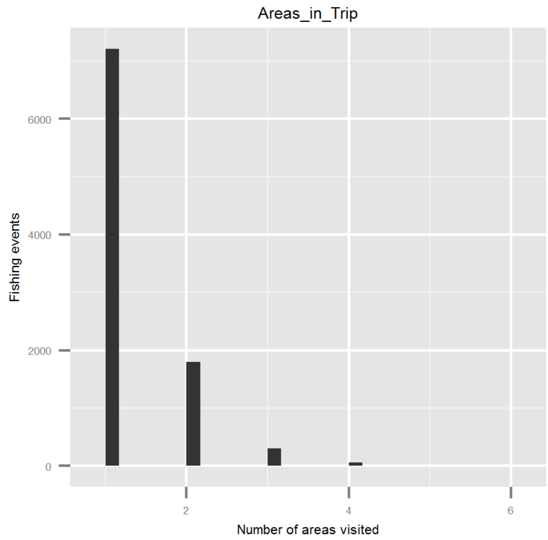

Figure 9 Number of areas visited in a trip

One further practical factor for consideration when defining fishing locations is the quantity of data that will be available. This depends at least in part on how often the areas under consideration have been fished in the past. Areas that have been fished relatively little and are thus poorly represented in the data can cause problems at the modelling stage if it results in insufficient data being available to create the choice sets. Most of the locations, as defined above, had reasonable levels of coverage when considered at the fishery level as a whole (Figure 10). Low levels of effort can be seen in some areas though (e.g. 42, 43) and resulted in them either being merged with other locations, or omitted, at the analysis stage and this is discussed in more detail at that point.

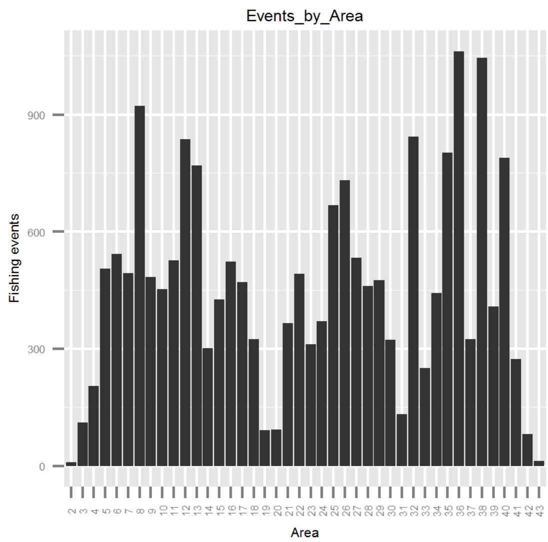

Figure 10 Frequency of trips to individual locations for the whole fishery

When considered at the port level, the level of spatial differentiation between areas fished and effort allocated by vessels fishing from different ports becomes apparent (Figure 11 and Table 4) and resulted in individual, port specific, models being estimated alongside one single HGMP level model. It is also possible to see that at the port level certain locations have relatively few trips recorded in them, e.g. areas 20-23 for Auckland, and resulted in some of these areas having to be merged at the modelling stage. Table 4 provides the numbers of events at the location level for the period 2008-09 to 2011-12 as this period was used directly when modelling the fishery. All port specific variations are discussed with the models in section 6.2.

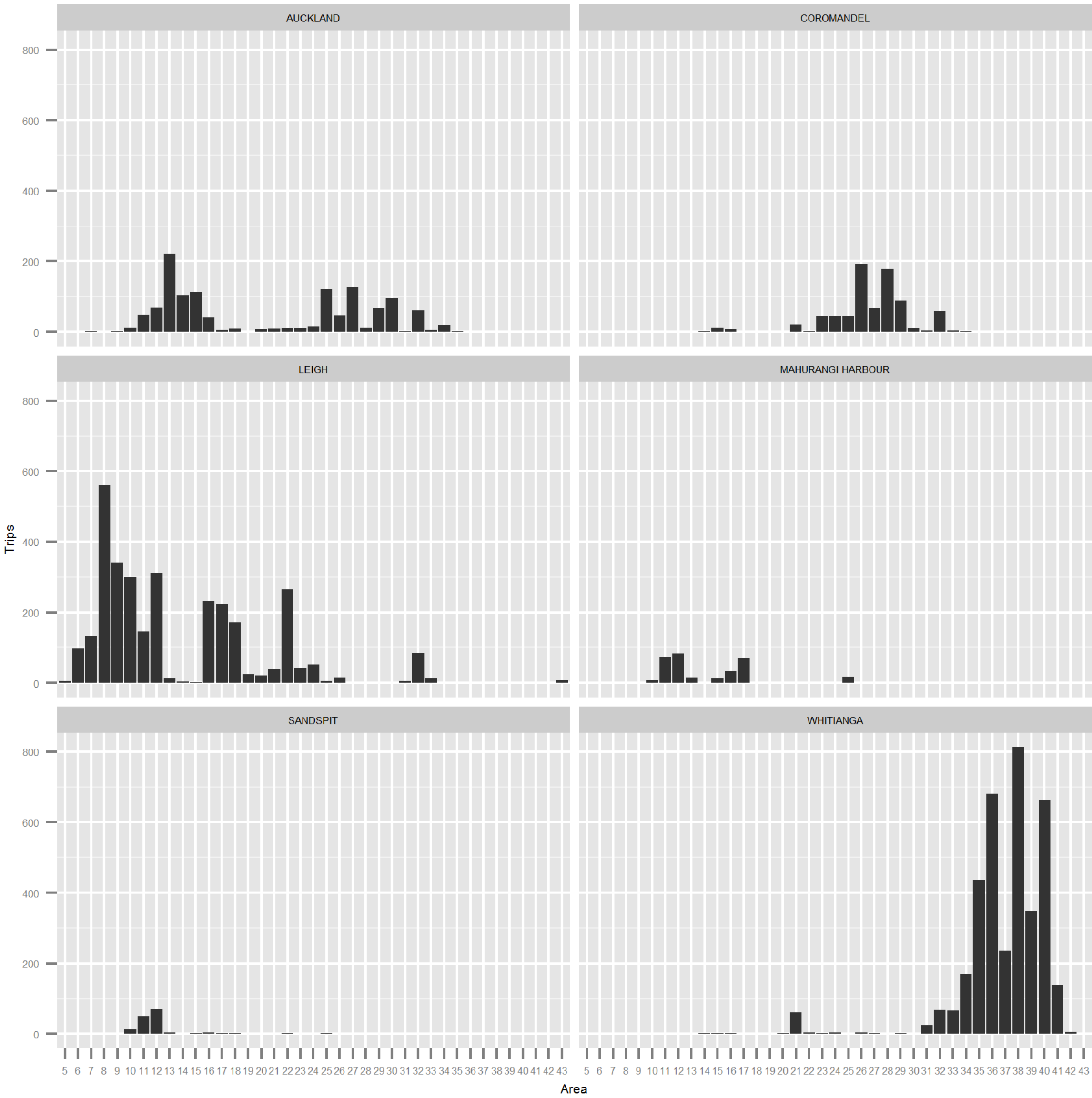

Figure 11 Frequency of trips to individual locations separated by port

Table 4 Port level trips to individual locations in the period 2008-09 to 2011-12

Location	AUCKLAND	COROMANDEL	LEIGH	MAH/SSP	WHITIANGA	MARSDEN POINT	TUTUKAKA
2							1
3						1	24
4						1	90
5			1			77	82
6			48			131	2
7	2		80			72	20
8	1		393				
9	1		222				
10	8		170	6			
11	43		68	73			
12	43		206	84			
13	146		8	17			
14	71				1		
15	75	8	2	9	2		
16	27	4	185	23	2		
17	4		128	50			
18	3		104		1		
19			14			1	3
20	4	1	16				
21	7	18	18		41		
22	7	2	122		2		
23	9	33	33		2		
24	10	35	31		1		
25	94	40	4	10	1		
26	34	143	10		1		
27	102	49					
28	11	126					
29	55	53					
30	46	8					
31	2	3			9		
32	49	4	61		44		
33	3	3	6		44		
34	15	1			122		
35	2				327		
36					492		
37					168		
38					546		
39					257		
40					470		
41					104		
42					4		22
43			5				

5 Factors influencing choice of fishing location

5.1 Fisher survey

One objective of the project was to engage with commercial fishers and characterise individual choice making behaviours by obtaining information on catch plans, operating costs and other drivers of location choice. The information that can be gained from interacting with operators is not readily available elsewhere and can be useful both as inputs in the modelling process and then later when validating models.

A survey was designed to assist with the collection of information from individuals responsible for deciding where and how vessels operate on a day-to-day basis (typically skippers). It focused primarily on decision making at the trip level and the collection of basic data relating to costs of operating as these data are not currently collected for the fishery. A wide range of factors have previously been seen to influence the decision making process and contribute to the ultimate choice of fishing location at the individual vessel level; e.g. site fidelity (Abernethy et al. 2007; Holland and Sutinen 1999), weather, expected species/value of species/abundance, distance/fuel prices, information from other fishers, and where others were going (Andersen et al. 2012; Bastardie et al. 2013a; Pascoe et al. 2013). In addition to validating input choices and modelling assumptions, the collection of economic data can be used to help estimate the financial impacts that alternative closure scenarios may have on vessels when running simulations.

The survey form and its supporting documentation (Appendix A) were developed using a combination of information sources. These included a number of previous studies where formal surveys had been used to collect data on the economics of fishing (Daurès et al. 2009; Pascoe et al. 1996; Thébaud et al. 2014) and factors influencing decision making behaviour (Abernethy et al. 2007; Andersen et al. 2012; Holland and Sutinen 1999; Salas et al. 2004; Stevenson et al. 2013). Conversations with individuals at the MPI, individuals involved in managing the fishery and a current HGMP BLL fisherman also contributed to the process of developing the survey. Finally, CSIRO human research ethics approval was obtained for the final version of the survey document, however, a combination of factors ultimately resulted in the survey component not being carried out. The tool has now been developed though and there is still the potential to utilise it at a later date.

5.2 Explanatory variables

The set of explanatory variables developed and used when modelling choice of fishing location is detailed in Table 5. They include parameters that have previously been found to significantly influence location choice in the context of commercial fishing (Abernethy et al. 2007; Bastardie et al. 2013b; Holland and Sutinen 1999; Pascoe et al. 2013; Smith 2002) and some factors identified as potentially being of importance during the discussions with individuals involved in the fishery referred to above.

Table 5 Explanatory variables derived to model location choice

parameter	Description
vpueR	Value (NZ$) per unit of effort (hook) in a location in recent history (previous 5 days)
vpueY	Value (NZ$) per unit of effort (hook) in a location for the same time period in the previous year (20 day window)
densR	Number of fishing events in a location in recent history
densY	Number of fishing events in a location for the same time period in the previous year
CvR	Coefficient of variation associated with the vpue for a location in recent history
CvY	Coefficient of variation associated with the vpue for a location in same period but previous year
PD	Cost proxy; fuel price index * distance to location
Pland	Fuel price index * distance to port of landing
PDL	Fuel price index * round trip distance
PL	PDL / vessel length
PDD	PDL / length of trip in days
LR	Dummy; 1 if vessel fished this location recently, 0 if else
LY	Dummy; 1 if vessel fished this location at the same time last year, 0 if else
NoFshR	Dummy; 1 if vessel was not fishing recently, 0 if else
NoFshY	Dummy; 1 if vessel was not fishing at the same time last year, 0 if else
Area_km2	Size of the fishing location in km2
HEwind	Dummy; 1 if wind was from the east and > 13.2 meters/second , 0 if else
HWwind	Dummy; 1 if wind was from the west and > 13.2 meters/second , 0 if else
LEwind	Dummy; 1 if wind was from the east and < 13.2 meters/second , 0 if else
LWwind	Dummy, 1 if wind was from the west and < 13.2 meters/second, 0 if else

Time series data on fuel prices was inflation adjusted to 2012 values and then converted into an index. This was then combined with location specific data relating to the distance that vessels were required to travel on trips from different ports and used as a proxy for the variable costs associated with visiting each location (PDL). Ideally fuel consumption figures would have been estimated for each vessel and location as this would have allowed a more precise calculation of fuel costs to be made, however without vessel specific fuel consumption data this is not possible.

Data relating to wind speed and direction was coded into categorical levels and then dummy variables were used to represent these in varying combinations and levels in the model. Wind strength was initially characterised in four levels (Table 6) but after testing various combination when modelling these were subsequently collapsed into two. The high wind category, denoted by an H in the parameter label, was comprised of all times when wind strength was recorded as equalling or exceeding speeds of 13.3 m/s. The low wind category, denoted by an L in the parameter label, was comprised of all times when wind strength was below 13.3 m/s. The alternative approach would have been to construct a single parameter in levels but as this would ascribe a linear relationship between wind speed/direction and choice of fishing location, something that is unlikely to be the case in reality, it was not considered appropriate in this instance.

To the extent possible the parameters for vpue and density were estimated using port specific data so as to reflect the assumption that information relating to fishing locations (e.g. catch rates etc.) is more likely to be available between vessels operating from the same port than from others. As records of fishing events did not exist for every location at every time period a complete set of data with which to parameterise the choice sets with variables such as vpueR/Y was not always available. In these instances the time period was progressively broadened backwards in time until data became available, if this period exceeded 40 days the minimum observed vpue (for that port but failing that all ports), rather than the average was applied to reflect the fact that this area was fished infrequently and knowledge or expectations with respect to its utility could reasonably be assumed to be low.

The set of locations vessels are faced with every time they go fishing, i.e. their choice set, can also be estimated at different levels. For example, one uniform choice set can be estimated for the fishery as a whole, irrespective of the port of departure, or port level choice sets can be specified that reflect the areas previously fished by vessels operating from specific ports. When making predictions about the distribution of effort the first approach results in some amount of effort from every port being assigned to every single location in the possible set (i.e. locations 3-42), whereas the latter approach limits the estimation of probabilities (and therefore effort allocation) to locations in which vessels fishing from that port have previously recorded effort. We used the latter, port level approach, in all models as it is arguably a more realistic representation of the fishery.

Various combinations of additional parameters, specified to pick up any residual seasonality in the data, were also trialled as monthly and seasonal (i.e. spring, summer etc.) dummies but none were found to significantly contribute to their performance.

Table 6 Wind speed thresholds

	cutoff%	cutoff m/s	days	Per year
Low	0.60	5.3	1258	209.8
Mod	0.85	7.7	532	88.7
High	0.99	13.2	302	50.4
extreme	0.995	14.4	22	3.7

When including multiple explanatory variables in the modelling process it is possible for correlations between them to result in multicollinearity, which has the potential to affect the significance and signs of the estimated coefficients. Whilst there are no definitive statistical tests for multicollinearity it is possible to identify any highly correlated parameters upfront and test alternative combinations of the variables of concern by re-estimating the model whilst monitoring the effect this has on overall model performance (via the AIC) and the remaining coefficients.

Correlation matrices were estimated for the full set of parameters used in each model and indicate that most had low levels of bivariate correlation (Appendix B). As expected, high levels of correlation (0.9>0.63) were seen between most of the variables interacted with fuel price (PD, Pland, PDL, PL, PDD). High levels of correlation were also observed between the alternative light wind interaction dummies.

A threshold of 0.8 has been proposed as potentially acceptable when determining whether correlation between two variables may result in problems when estimating models (Hensher et al. 2005), however, in this case all correlations observed to exceed 0.6 were investigated more closely for signs of multicollinearity when simultaneously included in a model. Furthermore, so long as the correlated variables continue to have the same influence into the future (likely to be the case in this instance) the models are still valid for the purposes of prediction, which was the ultimate objective of this work.

6 Modelling the HGMP BLL fishery

Two different approaches were taken when modelling the fishery. First, using logbook data covering the period 2008-12, a set of separate models were specified at the individual port level (section 6.2) and their ability to predict the last year of data (2012-13) tested (section 6.2.2) before using them to predict the possible consequences of a set of hypothetical area closures (section 7.1). A single HGMP level model was then estimated in the same way (section 6.3), but by incorporating data for trips from all ports simultaneously, and had the same process applied (sections 6.3.2 and 7.2, respectively).

For the individual port level models data on fishing events undertaken from Whitianga, Leigh, Auckland, Coromandel and a combination of Mahurangi Harbour and Sandspit was used to estimate five separate models. These ports had the highest numbers of trips and undertook the majority of these trips within the true bounds of the HGMP (Table 7). The remaining ports either had too few observations to model independently or fished primarily in the peripheral regions of the area defined (Marsden Point, Houhora and Tutukaka). All but one of the trips taken by vessels fishing from Houhora only occurred in area 1 so no further attempts were made to model vessels fishing from this port. Together, the five independent port level models account 86% of all the trips in the dataset (Table 7).

Table 7 Trips by port

Port	Total trips	Cumulative proportion of trips
Whitianga	3833	0.35
Leigh	3122	0.63
Auckland	1244	0.75
Coromandel	797	0.82
Marsden Point	475	0.86
Tutukaka	466	0.90
Houhora	369	0.94
Mahurangi Harbour	314	0.97
Sandspit	155	0.98
Waitangi	91	0.99
Gulf Harbour	52	0.99
Totara North	40	1.00
Mangonui	19	1.00
Tauranga	6	1.00

6.1 Modelling process and determining fit

In every case multinomial logit (MNL) models were specified in the first instance and parameterised using all but the first and last years of data (i.e. 2007-08 and 2012-13), as they were reserved for use as dummies and testing, respectively. As one of the central assumptions of the MNL specification is that all choices are independent of one another the models were then re-estimated in a nested logit (NL) form, which relaxes this assumption. The latter (NL) was then tested against the former (MNL) with respect to its relative performance and only retained if found to be preferable from a statistical perspective using LL ratio tests.

Whilst the manner in which the nests in the NL are specified may initially be guided on the basis of theoretical assumptions surrounding the attributes of the alternative sets of choices, strictly, this structure should not be interpreted as a form of decision tree. The form that nests take is really an empirically driven issue and ultimately dependent upon the underlying level of correlation in the error terms of the alternative fishing locations.

As RUMs are estimated using a maximum likelihood (MLE) approach, not ordinary least squares (OLS), standard statistical tests of model fit such as the F-statistic cannot be used. The fit and relative performance of models is instead measured using the pseudo R^2, the AIC and log-likelihood ratio tests.

The pseudo R^2 is used as a measure of overall model fit,

$$\boldsymbol{\rho^2 = 1 - \frac{LL(M_1)}{LL(M_2)}}$$

where LL(M_i) is the log-likelihood for model i, and k_i is the number of parameters used to estimate that model. When estimated directly within NLOGIT it is derived from the ratio of the LL function of the model being assessed over the LL of a base model estimated assuming equal shares across all choices. In addition to the automatically generated R^2 we estimated the ratio of LL values where the base case was estimated using the observed choice shares (as opposed to equal shares) as this is a more realistic basis from which to measure any improvement in model performance in terms of explaining variations in choice (R^2 = 1-LL estimated model / LL base model).

$$\boldsymbol{Adjusted\ R^2 = 1 - \left(\frac{\#\ observations}{\#\ observations - k_1}\right)\left(1 - \frac{LL(M_1)}{LL(M_2)}\right)}$$

It should be pointed out though that whilst the maximum value of R^2 is theoretically one, in reality its upper limit may be lower and is in fact dataset specific[1]. This makes its exact interpretation difficult if comparing between models that have been estimated using different datasets.

The AIC is also a measure of model fit,

$$\boldsymbol{AIC = -2LL + 2k}$$

Log-likelihood (LL) ratio tests are used to determine the most appropriate specification,

$$\boldsymbol{LR = -2[LL(M_1) - LL(M_2)]}$$

When the LR > $\chi^2(k_2\text{-}k_1)$ then M_2 is statistically better than M_1, where LR ≤ $\chi^2(k_2\text{-}k_1)$ the models are considered to be statistically equivalent. In the first instance, a base model is specified using only alternative specific constants to determine the current choice distribution, this is then compared to a model that contains additional explanatory variables to determine whether they contributes towards better explaining the observed distribution of choices.

Lastly, when using nested models (NL) the IV parameter values must also be tested to determine whether they are statistically different to each other, that they are bounded between zero and one, and that they are either significantly less than or equal to one. When all these cases hold the nesting is supported. If an IV parameter value exceeds one this implies that global utility maximisation assumption is no longer valid and cross-elasticities with the wrong sign will be observed. These properties are tested using t-tests,

$$\boldsymbol{t_k = \frac{\hat{\beta}_k - \hat{\beta}_l}{\sqrt{Var(\hat{\beta}_k) + (\hat{\beta}_l) - 2cov(\hat{\beta}_k, \hat{\beta}_l)}}}$$

[1] As $R^2 = 1 - [LL(M_1)/LL(M_2)]$, R^2 can only ever equal 1 when the LL of a given model= 0. In practice, this is unrealistic as it not only requires there to be no omitted variables and that the model is perfectly specified, it also requires that there is a complete lack of other error in the data to the extent that ε= 0 (this includes any idiosyncratic error). At best, LL ≠ 0 and the maximum value R^2 can attain is, in fact, dataset specific.

Where $\widehat{\beta_k}$ and $\widehat{\beta_l}$ are the coefficients of the variables being tested.

The most appropriate structural form for nests in the NL models was arrived at using the fully degenerated tree structure approach (DGNL) (Das et al. 2012; Hensher et al. 2005), where all locations are initially assigned to their own (degenerate) nest and those that display high levels of similarity are iteratively aggregated and tested until the criteria indicated above are met.

All models were specified with alternative specific constants and the whole set of explanatory variables (Table 5). Variables that were found to not be significantly different to zero were systematically removed and the impact on overall model performance tested using LL ratios and the AIC. If model performance was seen to fall in the event of removing a non-significant variable it was subsequently re-introduced on the basis that it was contributing to the model as a whole.

In an attempt to model the fishery at as high a level of detail as possible all 43 locations were incorporated in the first round of modelling, however this did not produce usable results and the models either did not solve adequately or produced poor results. This was primarily due to low numbers of observations in some locations at the individual port level (i.e. thin data with insufficient levels of variance). The requirement to omit the first year of data due to the annual lag and the last year of data so that it may be predicted as a test of model performance compounded the problem and resulted in infrequently fished areas not having any observations in some locations within the dataset used to parameterise the model.

The data was consequently reassessed and constrained to areas in the choice sets that, at the port level, had been fished at least five times or more in the period covered by the data assessed. This resulted in areas 1, 2 and 43 being omitted altogether at the HGMP level and the further loss of some infrequently fished areas at the level of individual port choice sets.

In all cases the coefficients estimated in RUMs are not standardised so the magnitude of the explanatory variable values (Tables 9 and 13) should be considered in conjunction with the magnitude of the coefficients when interpreting the results.

6.2 Port level models

6.2.1 INDIVIDUAL PORTS MODEL SPECIFICATION

The port specific models were developed by taking data for fishing events at the individual port level and modelling the choices made in regard to fishing location on this basis. As the spatial allocation of effort varies at the port level (Table 4) some of the initial definitions of fishing areas (as set out in Figure 8b) had to be amended to account for these differences. This was achieved by merging areas that had insufficient observations at the individual port level and the areas that need to be merged varied from port to port. The new port level location definitions are detailed in Table 8 below. Data relating to vessels operating from the ports of Sandspit and Mahurangi Harbour were also amalgamated due to their close proximity and the relatively small number of trips recorded as having been undertaken from these locations. The mean and SD values for the explanatory variables used in the models are provided in Table 9.

The NL specification was found to be preferable from a statistical perspective in all cases. The nests specified within each model also varied at the port level and are reported in the individual model outputs in Appendix B

Table 8 Area definitions for the port level models

Original location number	AUCKLAND	LEIGH	COROMANDEL	WHITIANGA	MAH_SSPT
5					
6		1			
7	1	2			
8	1	3			
9	1	4			
10	1	5			1
11	2	6			1
12	3	7			2
13	4	8			3
14	5			1	
15	6	8	1	1	4
16	7	9	1	1	5
17	1	10			6
18	1	11		1	
19		12			
20	8	13	2		
21	8	14	2	2	
22	8	15	3	1	
23	8	16	3	1	
24	8	17	4	1	
25	9	8	1	1	4
26	10	17	5	1	
27	11		6		
28	10		7		
29	12		8		
30	13		8		
31	14	18	9	3	
32	15	19	10	4	
33	14	18	9	5	
34	16		9	6	
35	14			7	
36				8	
37				9	
38				10	
39				11	
40				12	
41				13	

Table 9 Mean and SD values for explanatory variables used in the port level modelling process

		vpueR	vpueY	LR*	LY*	DensR	DensY	CvR	CvY	PD	PL	PDD	HWwind*
AUCKLAND	Mean	0.674	0.627	-	-	0.096	0.555	0.302	0.324	51.215	7.176	29.229	-
	SD	0.339	0.360	-	-	0.334	1.093	0.137	0.133	21.641	3.397	14.857	-
LEIGH	Mean	0.788	0.738	-	-	0.184	1.062	0.356	0.360	35.346	6.129	60.943	-
	SD	0.485	0.514	-	-	0.568	2.202	0.174	0.157	14.965	2.626	31.130	-
COROMANDEL	Mean	0.619	0.516	-	-	0.116	0.482	0.347	0.406	35.027	6.426	31.347	-
	SD	0.396	0.334	-	-	0.414	1.244	0.165	0.171	19.102	3.546	22.516	-
WHITIANGA	Mean	0.643	0.602	-	-	0.485	2.285	0.280	0.299	43.411	7.793	68.659	-
	SD	0.237	0.253	-	-	0.968	3.341	0.141	0.117	24.711	4.595	48.180	-
MAH_SPT	Mean	0.815	0.758	-	-	0.050	0.193	0.312	0.323	26.381	4.932	39.115	-
	SD	0.570	0.526	-	-	0.291	0.923	0.100	0.103	9.747	1.811	20.128	-

* Dummy variables that take the value of either 1 or 0

6.2.2 RESULTS

The estimated coefficients and measures of significance for the final set of port level models are provided in Table 10. Their adjusted pseudo R^2 values range from 0.19 to 0.35 and are consistent with values reported in the literature for other studies of this kind (Haynie and Pfeiffer 2013; Holland and Sutinen 1999; Marchal et al. 2009; Pascoe et al. 2013; Smith 2002). It is also worth stating that a pseudo R^2 value of 0.3 is considered good for a discrete choice model, being roughly equivocal to an R^2 of 0.6 in a linear regression model (Domencich and McFadden 1975).

The coefficients for vpue, in both recent time (R) and the same time in the previous year (Y), were positive and significant at the 1% level in all models indicating that the utility associated with visiting an area, and therefore the probability of going there, increased with the expected vpue of fishing in that location. The so called habit variables, LR and LY, that indicate whether a vessel has fished that location recently (LR), or at a comparable time in the previous year (LY), were also seen to be significant at the 1% level in all but two cases and again contributed positively to the probability of a vessel visiting an area.

The influence of other vessels operating in an area (DensR / DensY) varied more by port but where significant had a positive influence in all ports except Auckland and were significant at the 1% level in all ports other than Whitianga (where it was significant at the 5% level). This suggests that in all ports, other than Auckland, the probability of a vessel visiting an area increases if other vessels have been operating there recently (Leigh, Coromandel, Whitianga) or at the same time in the previous year (Mahurangi/Sandspit). The relative contribution to utility and therefore the overall probability of a vessel visiting a location, is generally relatively small though, especially when compared to factors such a revenue and habit.

Where significant, the coefficient associated with the variability of expected value per unit of effort (CvR, CvY) in an area was always seen to be negative and significant at the 1% level (Auckland, Leigh, Mahurangi/Sandspit). The magnitudes of these coefficients were also relatively large, suggesting aversion to risk in terms of vpue when choosing where to fish. This in itself is an interesting result as is contrary to what has been observed in some other fisheries (Holland and Sutinen 2000; Pascoe et al. 2013).

The cost proxy variable (PDL) was significant in all models apart from that for Mahurangi/Sandspit and PDL and the associated interaction terms (PDD and PL) were always negative in combination indicating that the cost associated with travelling to a location has a negative influence on its utility and therefore reduced the probability of going to it (all else constant). Where PL was significant it suggests that smaller vessels operating from that port derive less utility from undertaking long trips when compared to larger vessels, this effect being particularly strong for the ports of Leigh and Auckland. PDD was also significant in most models and indicates that vessels undertaking trips that are shorter in duration (in terms of days at sea) will derive less utility from travelling longer distances than vessels on longer trips.

Of all the weather proxy variables only the dummy for high westerly winds (HWWIND) was found to be having a significant influence on location choice. This was found to be a significant influence on trips from all ports other than Mahurangi/Sandspit and was always negative, which conforms to the expectation that as the westerly wind strength in an area increases the probability of a vessel visiting it decreases. Location specific coefficients, set up to account for differences in exposure as a result of proximity to land, were also trialled for the wind dummies but not found to be significant.

The inclusive values (IV) were significantly greater than zero and less than one at the 1% level in all models. They were also all significantly different to each other and along with the AIC and LL ratio tests supported the use of a NL specification over the MNL.

Whilst there was a relatively high degree of commonality between the models coefficients in terms of their significance and sign, the magnitude of their coefficients did vary and suggests some degree of port specific variation in the importance of certain factors.

Table 10 Parameter values for the individual port-level models (* sig at 1%, ** sig at 5%, * sig at 10% levels)**

Parameter	Auckland	Leigh	Coromandel	Whitianga	Mahurangi/Sandspit
VPUER	1.525***	0.766***	1.416***	1.400***	1.293***
VPUEY	0.696***	0.422***	0.585***	0.340***	0.860***
LR	1.505***	1.997***	1.067***	1.410***	1.199***
LY	1.050***	0.464***	0.295*	0.734***	-
DENSR	-	0.144***	0.437***	0.052**	-
DENSY	-0.145***	-	-	-	0.266***
CVR	-0.932***	-1.545***	-	-	-2.970***
CVY	-0.943***	-	-	-	-
PDL	0.062***	0.286***	0.036**	0.033***	-
PL	-1.270***	-2.543***	-	0.202***	-
PDD	-	-0.113***	-0.152***	-0.060***	-0.063***
HWWIND	-1.03697***	-1.271***	-1.159**	-0.522***	-
Area specific constants (not comparable across models)					
A_1	-0.37618	0.68237	-0.045	0.638	-3.089***
A_2	-1.46908	0.42683	-0.240	-2.848***	-1.875***
A_3	-0.94488	1.38904	-0.589*	-3.902***	-2.394***
A_4	-1.654	1.15814	-0.933*	-1.686***	-0.597*
A_5	-0.61724	-0.68163	-0.069	-0.618***	-0.573*
A_6	-0.53524	-0.3825	-0.496	0.588***	-
A_7	-0.93818	0.33082	-1.209	1.3773***	-
A_8	0.41178	-0.791**	-0.550	2.858***	-
A_9	0.03418	1.477**	-0.980	5.132***	-
A_10	-0.41877	0.02507	-	5.541***	-
A_11	0.07217	0.96782	-	1.728***	-
A_12	-0.14625	0.03377	-	5.906***	-
A_13	0.0364	-1.289***	-	-	-
A_14	-0.82026	-0.946***	-	-	-
A_15	0.4687	0.842*	-	-	-
A_16	-	-0.985***	-	-	-
A_17	-	-0.649**	-	-	-
A_18	-	-3.066***	-	-	-
IV parameters (also not comparable across models)					
N1	0.581***	0.656***	0.618***	0.505***	0.630***
N2	1	0.785***	1	1	1
N3	0.858***	0.536***		0.807***	-
N4	-	1	-	-	-
LL	-1818.410	-3771.200	-881.093	-4967.295	-282.272
Pseudo R^2	0.274	0.302	0.282	0.242	0.431
Adj Pseudo R2	0.191	0.335	0.205	0.136	0.348
AIC	4.237	3.938	3.330	3.717	2.180

In addition to the standard statistical tests of model fit, performance was assessed by comparing the level of correlation between predicted (i.e. model) distributions of effort and those observed in the data (i.e. logbook). Figures 12 and 13 compare the observed (logbook) allocation of effort in 2012-13 for vessels operating out of Auckland with the distribution of effort as predicted by the model at the annual and then monthly level respectively. Table 11 provides the correlation coefficients for all the ports when models were tested against data from both within (2011-12) and out (2012-13) of the sample used to parameterise them. The out of sample data is the last year of the dataset that was not included in the modelling phase. Plots comparing the observed and modelled effort allocations for all the remaining ports are provided in Appendix C .

Table 11 shows that the level of correlation between observed and modelled effort distributions when tested out of sample are reasonably high across all models (0.74-0.96) and suggests that the models perform reasonably well, especially at the annual level.

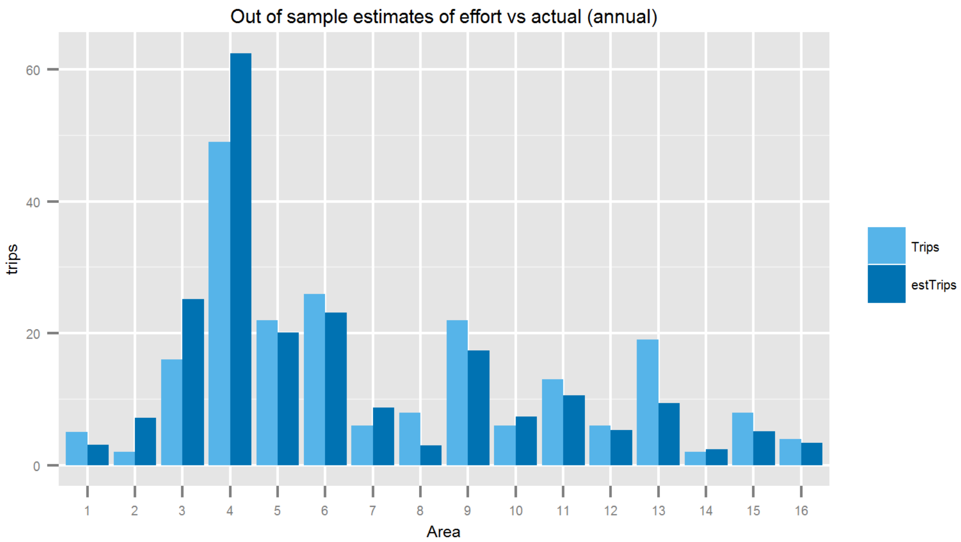

Figure 12 Out of sample fit at the annual level, observed (Trips) vs. modelled (estTrips) distributions of effort for vessels fishing from Auckland (overall correlation = 0.94)

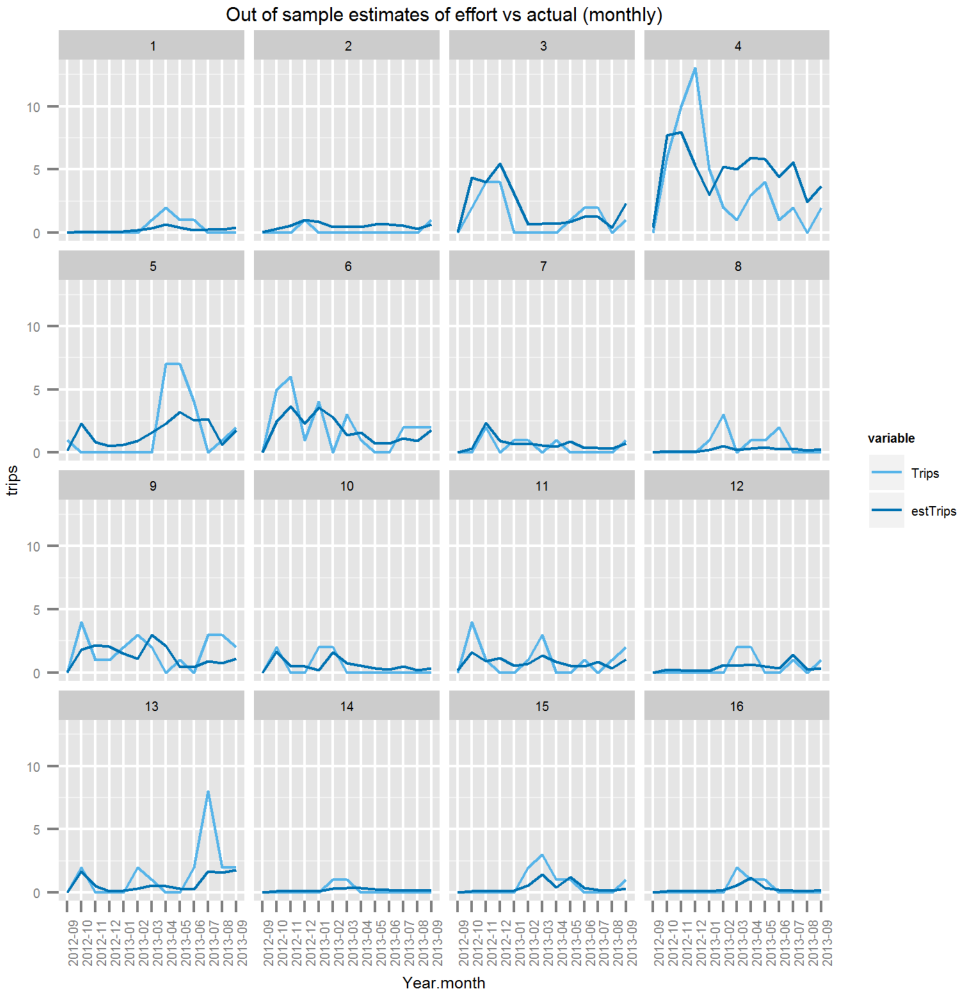

Figure 13 Out of sample fit at the monthly level, observed (Trips) vs. modelled (estTrips) distributions of effort for vessels fishing from Auckland (overall correlation = 0.67)

Table 11 Pearson correlation coefficients for modelled vs observed effort distribution when compared with the periods 2011-12 and 2012-13

Port	Comparison year	Trips in period	Annual	monthly
Auckland	2011-12	224	0.96	0.75
	2012-13	214	0.94	0.67
Leigh	2011-12	530	0.76	0.82
	2012-13	535	0.70	0.76
Coromandel	2011-12	169	0.80	0.76
	2012-13	168	0.79	0.77
Whitianga	2011-12	709	0.97	0.92
	2012-13	639	0.96	0.87
Mah_Sspt	2011-12	72	0.98	0.95
	2012-13	47	0.97	0.77

6.3 All ports model(s)

A single model that incorporated the data for all trips for vessels fishing from Whitianga, Leigh, Auckland, Coromandel, Marsden Point, Tutukaka, and a combination of Mahurangi Harbour and Sandspit was then specified and tested in the same manner as with the individual models. From the perspective of scenario testing and ease of use, having a single model is potentially desirable as once specified it requires less data handling and avoids the need for multiple runs of simulations. However, relying upon a single set of generic coefficient estimates, which is what is obtained when undertaking this approach, depends upon the relative importance of alternative factors not varying too greatly between ports. The results from the individual port level models are therefore compared with the outputs of this approach and the findings discussed.

Whilst areas were not merged in the single HGMP model the omission of areas 1, 2 and 43 resulted in the area numbers (as set out in Figure 8b) being amended to account for this. The new port level location definitions are detailed in Table 12 and the mean and SD values for the explanatory variables used in the model are provided in Table 13 below.

Table 12 Area definitions for the all ports model

Original location number	AUCKLAND	LEIGH	COROMANDEL	WHITIANGA	MAH_SSPT	MARSDEN POINT	TUTUKAKA
3	-	-	-	-	-	-	1
4	-	-	-	-	-	-	2
5	-	-	-	-	-	3	3
6	-	4	-	-	-	4	-
7	-	5	-	-	-	5	5
8	-	6	-	-	-	-	-
9	-	7	-	-	-	-	-
10	8	8	-	-	8	-	-
11	9	9	-	-	9	-	-
12	10	10	-	-	10	-	-
13	11	11	-	-	11	-	-
14	12	-	-	-	-	-	-
15	13	-	13	-	13	-	-
16	14	14	-	-	14	-	-
17	-	15	-	-	15	-	-
18	-	16	-	-	-	-	-
19	-	17	-	-	-	-	-
20	-	18	-	-	-	-	-
21	19	19	19	19	-	-	-
22	20	20	-	-	-	-	-
23	21	21	21	-	-	-	-
24	22	22	22	-	-	-	-
25	23	-	23	-	23	-	-
26	24	24	24	-	-	-	-
27	25	-	25	-	-	-	-
28	26	-	26	-	-	-	-
29	27	-	27	-	-	-	-
30	28	-	28	-	-	-	-
31	-	-	-	29	-	-	-
32	30	30	30	30	-	-	-
33	-	31	-	31	-	-	-
34	32	-	-	32	-	-	-
35	-	-	-	33	-	-	-
36	-	-	-	34	-	-	-
37	-	-	-	35	-	-	-
38	-	-	-	36	-	-	-
39	-	-	-	37	-	-	-
40	-	-	-	38	-	-	-
41	-	-	-	39	-	-	-
42	-	-	-	40	-	-	40

Table 13 Mean and SD values for explanatory variables used in the single HGMP modelling process, broken down to the port level

		vpueR	vpueY	LR*	LY*	DensR	DensY	CvR	CvY	PD	PL	PDD	HWwind*
ALL	Mean	0.707	0.682	-	-	0.257	1.290	0.340	0.356	39.505	6.706	55.096	-
	SD	0.393	0.454	-	-	0.708	2.563	0.169	0.164	19.379	3.409	37.355	-
AUCKLAND	Mean	0.661	0.638	-	-	0.080	0.459	0.341	0.372	49.526	6.974	28.299	-
	SD	0.330	0.423	-	-	0.307	1.016	0.133	0.151	17.705	2.890	12.855	-
LEIGH	Mean	0.790	0.761	-	-	0.174	1.001	0.366	0.355	35.981	6.241	62.105	-
	SD	0.484	0.529	-	-	0.554	2.158	0.189	0.156	14.897	2.615	31.159	-
COROMANDEL	Mean	0.573	0.614	-	-	0.103	0.408	0.374	0.399	30.409	5.599	27.821	-
	SD	0.394	0.411	-	-	0.389	1.164	0.150	0.144	13.609	2.548	17.576	-
WHITIANGA	Mean	0.649	0.616	-	-	0.485	2.281	0.303	0.340	42.214	7.578	66.743	-
	SD	0.247	0.337	-	-	0.968	3.347	0.158	0.176	23.025	4.291	45.387	-
MAH_SPT	Mean	0.802	0.812	-	-	0.037	0.145	0.330	0.349	26.395	4.935	39.237	-
	SD	0.504	0.540	-	-	0.252	0.784	0.107	0.149	9.797	1.821	20.219	-
MARSDEN POINT	Mean	0.783	0.704	-	-	0.036	0.490	0.253	0.347	16.398	2.903	29.672	-
	SD	0.267	0.481	-	-	0.215	1.371	0.130	0.185	4.875	0.851	11.269	-
TUTUKAKA	Mean	0.822	0.752	-	-	0.023	0.129	0.459	0.409	25.054	4.242	40.787	-
	SD	0.571	0.715	-	-	0.149	0.575	0.236	0.224	9.597	1.634	20.613	-

* Dummy variables that take the value of either 1 or 0

6.3.1 SINGLE HGMP REGION MODEL SPECIFICATION

As with the port level models, a MNL model was estimated in the first instance, again using all data except for the first and last years. The models converged quickly, generally within seven iterations, with LL ratio tests indicating they performed significantly better (1% level) as predictors of location choice when compared with base models estimated using the observed shares only (i.e. location specific constants only). The generic explanatory parameters of the estimated MNL model were all of the sign expected and all except the numbers of fishing events in a location in the previous year (densY) were statistically significant at the 1% level.

A NL was then specified and again found to be preferable to the MNL from a statistical perspective when using the LL ratio test. As before, the final structure of the individual nests was arrived at using the fully degenerated tree structure approach (DGNL) (Das et al. 2012; Hensher et al. 2005) but when plotted (Figure 14) can be seen to roughly delineate the HG fishing locations into a core HGMP area (light blue), a slightly more peripheral area (grey) and a fringe (beige).

Latent class (LC) specifications of the model, using port of departure to define the classes, was also attempted to test whether this approach could provide more information in relation to variance in location choice at the port level. Their added complexity and the relatively thin data in some cases meant that these models failed to solve adequately, even when the data was adjusted to areas that each had a minimum of 30 observations.

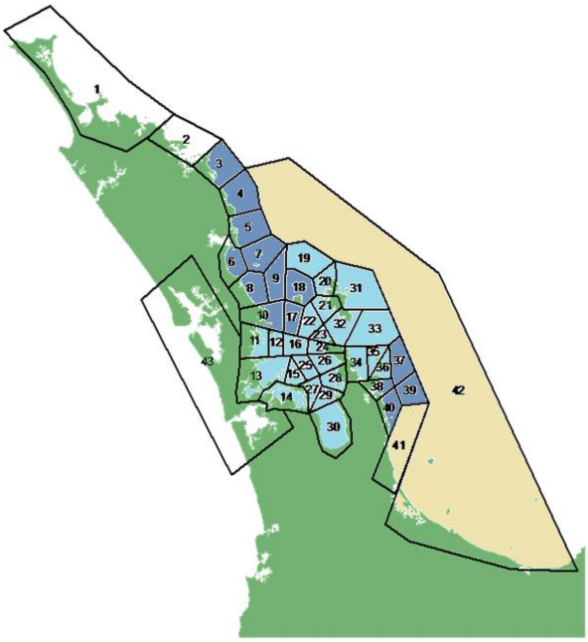

Figure 14 HGMP region NL model nest structure, individual nests denoted in light blue, beige and grey. Locations with no colour were not included in the analysis

6.3.2 RESULTS

Results for the single HGMP model are provided in Table 14. The IV parameters were all found to be significantly greater than zero and equal to or less than one (and each other) when tested, supporting use of the NL specification. The model has an adjusted pseudo R^2 of 0.18 which, again, is consistent with other fisheries based applications of RUMs reported in the literature.

As in the port level models, factors that have commonly been found to have an influence on choice of location in previous fisheries assessments were also seen to be contributing to the utility function in this case. These included; where a vessel had been fishing in the previous five days (LR), the revenue per unit of effort being obtained from a given location in the last five days (VPUER), how variable that revenue was (CVR), and the wind conditions in a given area (HWWIND). The vpue and LR parameters again had positive relationships with the utility of a given location, agreeing with the port level models by indicating that recently fished areas and those with higher expected revenues per unit of effort were more likely to be chosen in the current time period. This was also the case for the same two types of parameters when specified to account for the previous year, but in these instances whist the effect was significant and relatively strong it was weaker than for the recent past.

The coefficients for CV and wind strength/direction all contributed in a negative manner. Negative signs on the CV parameters indicate that an expectation of higher variability in the value of catch per unit of effort in a given area reduced the probability of a vessel choosing to visit it, this effect being strongest for recent time. The negative sign associated with high to extreme winds from the West, indicates that these conditions had a negative influence on choice of location when compared to all other wind conditions.

Coefficients relating to the cost of travel proxy (PDL) and the associated interaction terms relating to vessel length and length of trip were also all significant and negative in combination indicating that, all else equal, the cost of travelling to a location has a negative influence on its overall utility. Whilst these coefficients are generally amongst the smallest when considered alongside the others, the explanatory variables for PD, PL and PDD are the largest in absolute terms (Table 13) so their contribution to the utility function is still influential.

The relative magnitudes of the coefficients also reciprocate the relative importance of factors as given by a commercial fisherman in the HGMP BLL fishery; the ones of greatest importance being expected value of catch and weather. Travel cost was cited as being of lesser concern but the modelled effect of costs, i.e. when the cost coefficients are combined with the explanatory variables, suggests that these do actually play a substantive role. It should also be noted that this ranking was based on the opinion of a single fisherman so is representativeness of the fishery as a whole should be treated with the appropriate level of caution.

Whilst the LR and LY coefficients relate to habit, i.e. vessels tending to return to the same locations at the same times of year, they also pick up seasonality in the choice of locations. There are a number of factors that may be contributing to this including the seasonal locations of fish stocks and potentially even quota driven targeting behaviour based on this.

Table 14 HGMP nested logit model coefficients (* sig at 1%, ** sig at 5%, * sig at 10% levels)**

Parameter	Coefficient	SE	z	Prob
VPUER	0.99186***	0.04125	24.04	0.0000
VPUEY	0.39426***	0.03501	11.26	0.0000
LR	1.44618***	0.03551	40.73	0.0000
LY	0.52010***	0.04193	12.4	0.0000
DENSR	0.08474***	0.01587	5.34	0.0000
CVR	-1.00506***	0.09297	-10.81	0.0000
CVY	-0.32980***	0.10136	-3.25	0.0011
PDL	0.03139***	0.00375	8.38	0.0000
PL	-0.27980***	0.04806	-5.82	0.0000
PDD	-0.06981***	0.00264	-26.42	0.0000
HWWIND	-0.91420***	0.09498	-9.62	0.0000
A_1	1.66904***	0.48345	3.45	0.0006
A_2	1.26676***	0.46046	2.75	0.0059
A_3	1.55638***	0.43867	3.55	0.0004
A_4	1.33677***	0.44475	3.01	0.0026
A_5	1.76505***	0.43288	4.08	0.0000
A_6	1.62701***	0.45345	3.59	0.0003
A_7	1.22969***	0.45906	2.68	0.0074
A_8	-1.07923**	0.47809	-2.26	0.024
A_9	-0.50659**	0.23099	-2.19	0.0283
A_10	0.05277	0.22125	0.24	0.8115
A_11	0.58847**	0.23284	2.53	0.0115
A_12	0.85242***	0.2586	3.3	0.001
A_13	0.52365**	0.23776	2.2	0.0276
A_14	0.63755***	0.21847	2.92	0.0035
A_15	0.58394	0.45524	1.28	0.1996
A_16	1.08003**	0.45309	2.38	0.0171
A_17	0.25321	0.33828	0.75	0.4541
A_18	0.51807	0.32549	1.59	0.1115
A_19	0.69359***	0.2262	3.07	0.0022
A_20	0.72335***	0.22271	3.25	0.0012
A_21	0.35101	0.23408	1.5	0.1337

A_22	0.36573	0.23481	1.56	0.1193
A_23	0.79588***	0.22631	3.52	0.0004
A_24	0.76008***	0.22296	3.41	0.0007
A_25	0.91594***	0.2269	4.04	0.0001
A_26	0.33412	0.23319	1.43	0.1519
A_27	0.61257***	0.23313	2.63	0.0086
A_28	0.52287**	0.24848	2.1	0.0354
A_29	0.05829	0.38322	0.15	0.8791
A_30	1.24497***	0.21077	5.91	0
A_31	0.65180***	0.2298	2.84	0.0046
A_32	0.48182**	0.21132	2.28	0.0226
A_33	0.72871***	0.20965	3.48	0.0005
A_34	0.45932**	0.2144	2.14	0.0322
A_35	0.56929	0.43769	1.3	0.1934
A_36	-0.13955	0.46086	-0.3	0.762
A_37	0.94212**	0.43251	2.18	0.0294
A_38	0.79210*	0.44553	1.78	0.0754
A_39	-0.16931	0.2754	-0.61	0.5387
IV parameters				
N1	1	.....(Fixed Parameter).....		
N2	0.72555***	0.04955	14.64	0
N3	0.52730***	0.03245	16.25	0
LL	-12857.159			
Pseudo R^2	0.525			
Adj Pseudo R2	0.185			
AIC	3.792			

The predictive performance of the NL model was again tested against subsets of the data and the level of correlation calculated. When tested against the out of sample data (2012-13) the observed vs. modelled distributions of effort had correlation coefficients of 0.93 and 0.81 at the annual and monthly levels respectively, indicating that in general the model performs well when predicting the distribution of fishing effort at the level for the fishery as a whole. Figures15 and 16 illustrate this at the annual and monthly levels, respectively. The level of correlation was then assessed in the same way, however when broken down into individual ports within the model the ability of the single HGMP model to predict effort allocation was generally good (Table 15).

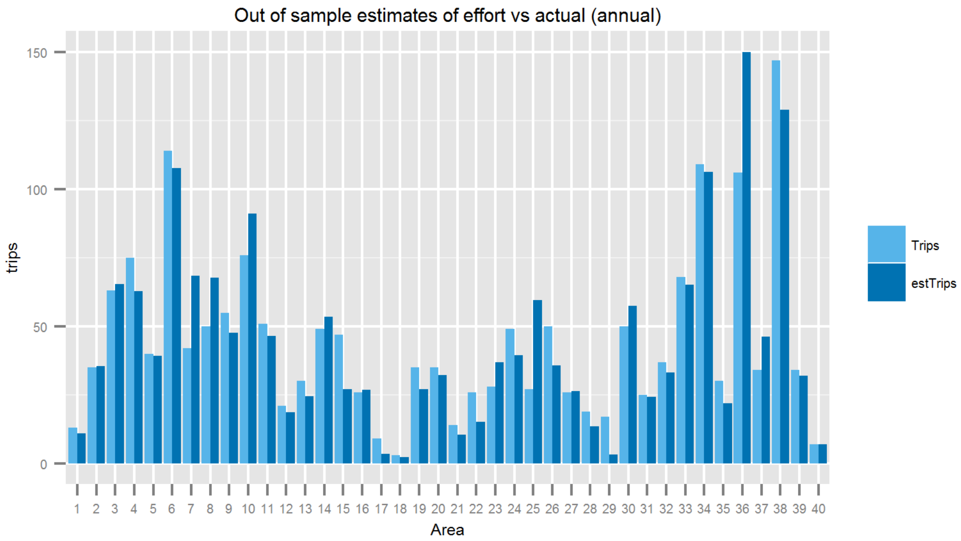

Figure 15 Out of sample fit at the annual level, observed vs. modelled distribution of effort for all vessels in the fishery (overall correlation=0.93)

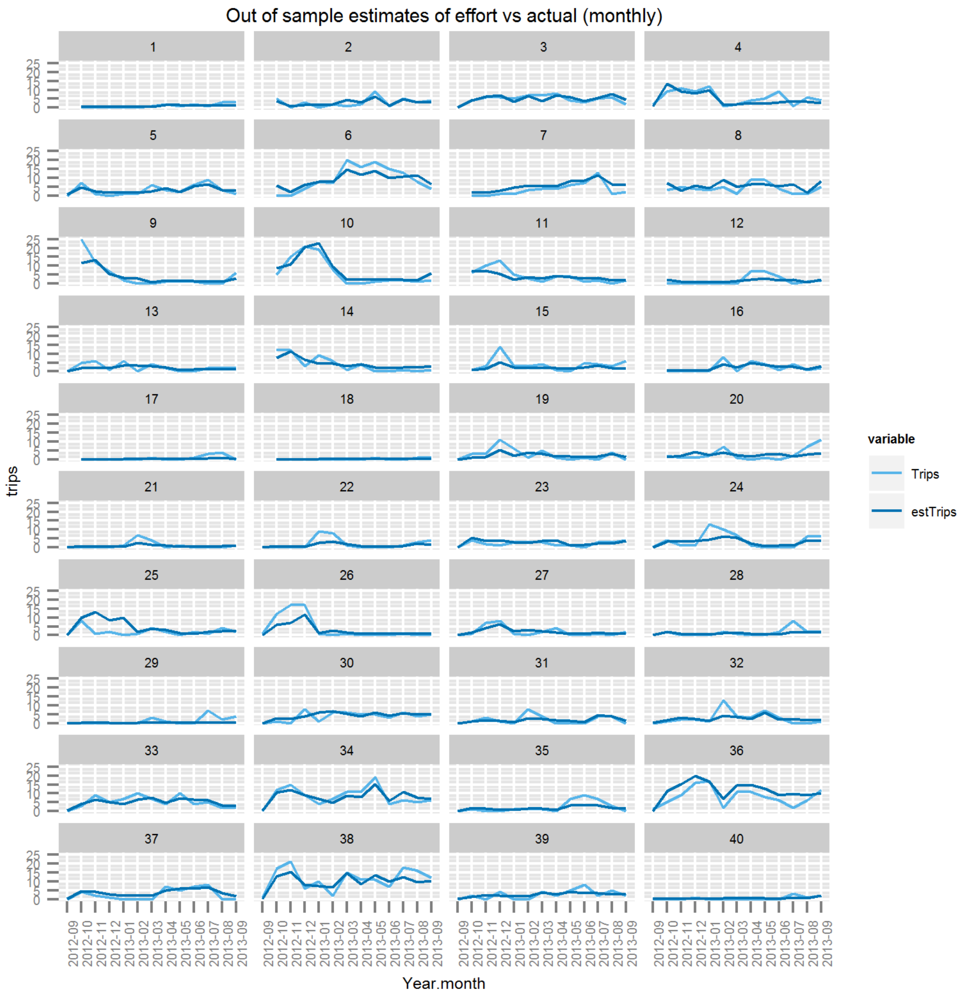

Figure 16 Out of sample fit at the monthly level, observed vs. modelled distribution of effort for all vessels in the fishery (overall correlation=0.81)

Table 15 Pearson correlation coefficients for modelled (HGMP region model) vs observed effort distribution when compared with the periods 2011-12 and 2012-13

Port	Comparison year	Trips in period	Annual
AUCKLAND	2011-12	217	0.97
	2012-13	204	0.95
LEIGH	2011-12	517	0.97
	2012-13	535	0.93
COROMANDEL	2011-12	163	0.82
	2012-13	164	0.65
WHITIANGA	2011-12	710	0.97
	2012-13	635	0.95
MAH_SPT	2011-12	70	0.95
	2012-13	47	0.81
TUTUKAKA	2011-12	30	0.81
	2012-13	100	0.99
MARSDEN POINT	2011-12	98	0.89
	2012-13	87	0.93
TOGETHER	2011-12	1805	0.96
	2012-13	1772	0.93

7 Hypothetical closure scenarios

The models estimated in section 6 were then used to assess how effort might redistribute in the event that vessels were no longer able to operate on some of their usual fishing grounds and then how this may impact the fishery from the perspective of revenues and travel costs. To do this a set of four hypothetical closure scenarios (A-D) were defined by selecting sets of fishing locations from different regions in the HGMP (Figure 17). Whilst every effort was were made to ensure that a variety of combinations were tested, the closure scenarios use locations that were arbitrarily selected by the analysts so they are purely hypothetical in nature and have been developed for the sole purpose of testing this modelling approach.

Scenarios A to C close a total of four fishing locations each and, respectively, account for 11%, 12% and 4% of the total area modelled. Scenario D was more restrictive and closed eleven locations which combined equated to 32% of the area modelled (Table 17). These proportions omit area 42 when calculating the total due to its disproportionately large size (22,583km^2) and very low levels of effort which distorts the reported magnitude of the closures. When area 42 is included the closed proportions fall to 5%, 5%, 2% and 15% for areas A-D. For the port level models the relative proportions of their fishing areas closed varied under different scenarios as the areas closed did not always all fall within the fishery's fishing areas. In addition to this the definitions of locations also varied by port and more details on how this was handled are provided in the next section.

As cost and earnings data is not available for HGMP BLL vessels, the effects of the alternative closure scenarios were quantified by estimating the changes in total fishery revenue and fuel costs at the annual level. The revenue effects were estimated by first modelling the spread of effort (in terms of numbers of hooks set) in a selected base year (e.g. 2011-12) and combining this with the observed vpues of a location to calculate total revenue in a 'business as usual', i.e. no closure, situation. Boxplots illustrating these 'actual vpue' values are provided after the simulation results for each model in Appendix C .These figures were then compared with the revenue that vessels would have obtained (calculated in the same way) if their effort had been spread as predicted by the model when the closure scenarios were imposed.

Changes in the variable costs vessels faced were assessed using a proxy cost variable, derived by combining the distance a vessel must travel to fish within a given location with the inflation adjusted data on fuel prices. As with the revenue estimates, changes in fuel consumption were thus derived by first modelling expected fishery level fuel costs under the conditions in a given base year and then comparing these figures with those derived when certain areas were no longer available and effort was displaced into alternative locations. This fishery level estimate is a proxy that obviously cannot account for the inevitable variations in fuel consumption that will occur at the individual vessel level in reality. This estimate could be improved if data relating to vessel level fuel consumption could be included.

The closure scenarios were tested using the separate port level models and the single fishery level model and the respective results are discussed below in sections 7.1 and 7.2.

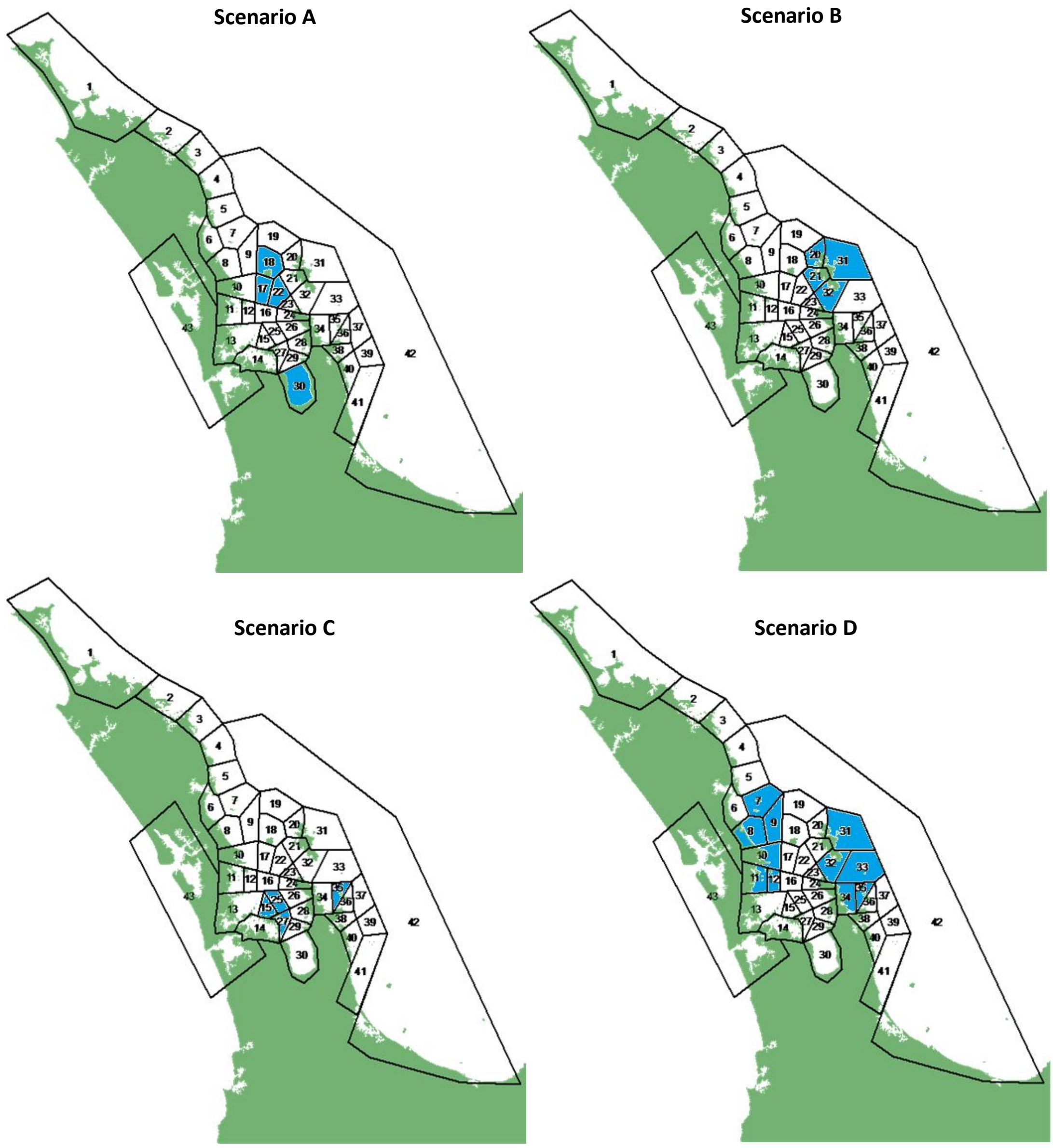

Figure 17 Hypothetical closure scenarios with closed areas denoted in blue for each case (A-D)

7.1 Port level simulations

Wherever possible exactly the same closures were applied to all models. However, as low levels of effort resulted in some of the fishing locations in the port level models having to be merged these area definitions did not always match up exactly with the closures, which were designed using the original set of locations (Figure 17). The areas amalgamated in each port level model are set out in Table 8 and the redefined closure areas, as used in the simulations, are listed in Table 16 below. When one of the original areas planned for closure fell inside what was part of a new (larger) port level location it was assumed that unless the original area accounted for more than 50% of the observed trips in the new location that the whole area effectively remained open to vessels from that port. In reality the impact of these slight differences on the overall outcome is likely to be minor as the fact they required merging indicates they represent areas fished very infrequently by vessels from the port under consideration.

In addition to information on the characteristics of each closure scenario, Table 16 also provides a summary of the predicted changes in revenue and the fuel proxy for each port and each closure scenario. The redistribution of effort, in terms of both trip numbers and hooks set in different locations, for vessels fishing from Auckland under scenarios A and D and Leigh for scenario D are illustrated in Figure 18, Figure 19 and Figure 20, respectively. These plots provide an example of a scenario in which closures are predicted to have little impact (A) and a second scenario (D) where revenues are predicted to fall by approximately 5%. Plots for the remaining port/scenario combinations are provided with all other model specific information in Appendix C .

Table 16 Predicted proportional changes in revenues and fuel proxy under alternative scenarios for port level models

Port	Scenario	Locations closed (port specific location numbers)	Total km^2	% of area modelled	ΔRevenue	ΔFuel proxy
Auckland	A	13	954	7%	-0.5%	-1.2%
	B	15	493	4%	+0.6%	-1.3%
	C	6,9	637	5%	+3.7%	+2.0%
	D	1,2,3,14,15,16	6,222	49%	-5.3%	-9.1%
Leigh	A	10,11,15	1,156	11%	+0.2%	-0.6%
	B	13,14,19	1,127	10%	-1.7%	-3.6%
	C	NA	0	0	NA	NA
	D	2,3,4,5,6,7,18,19	5,546	51%	-5.0%	+22.9%
Coromandel	A	NA	0	0	NA	NA
	B	2,10	1,127	16%	+1.5%	-7.6%
	C	1,6	914	13%	-5.5%	-3.8%
	D	9,10	2,929	42%	+1.3%	-8.9%
Whitianga	A	NA	0	0	NA	NA
	B	2,3,4	1,917	20%	-1.4%	-7.2%
	C	7	224	2%	+0.9%	-0.7%
	D	3,4,5,6,7	3,153	33%	-0.4%	-8.5%
Mah/Sspit	A	6	322	9%	+0.8%	-4.0%
	B	NA	0	0	NA	NA
	C	4	427	13%	+1.0%	-1.7%
	D	1,2	1,351	40%	-48%	+75%

The predicted impacts of each scenario varied by port, with the proximity and magnitude of closures relative to each port's usual fishing grounds obviously contributing to this variation. Scenario A was predicted to have the least effect on revenues across all ports and was similarly predicted to have little impact on costs. It did not close any locations for vessels operating from Coromandel or Whitianga and only prevented fishing in locations that had previously not been of great importance to the other ports (e.g. Figure 18 area 13). On the other hand, scenario D was predicted to have the greatest revenue impact on vessels fishing from Auckland (-5.3%), Leigh (-5.0%) and Mahurangi/Sandspit (-48.0%) and reflects the relatively large number of fishing areas it renders unavailable. The proximity to Leigh and Mahurangi/Sandspit of a number of the areas closed under scenario D resulted in this being the scenario predicted as having the greatest adverse impact on costs for vessels fishing from these ports. The fuel proxy variable was predicted to increase by 22.9% and 75% for Leigh and Mahurangi/Sandspit, respectively, as they D effectively closes all areas in their immediate vicinity. As a consequence, these vessels are forced to travel further and utilise the more peripheral areas of their usual grounds. For example, a large proportion of the displaced effort from vessels fishing out of Leigh went into locations 16, 17 and 22 which are located further from port towards the centre of the Hauraki Gulf (these translate into port specific locations 9, 10 and 15 in Figure 20).

Changes in port level effort allocation

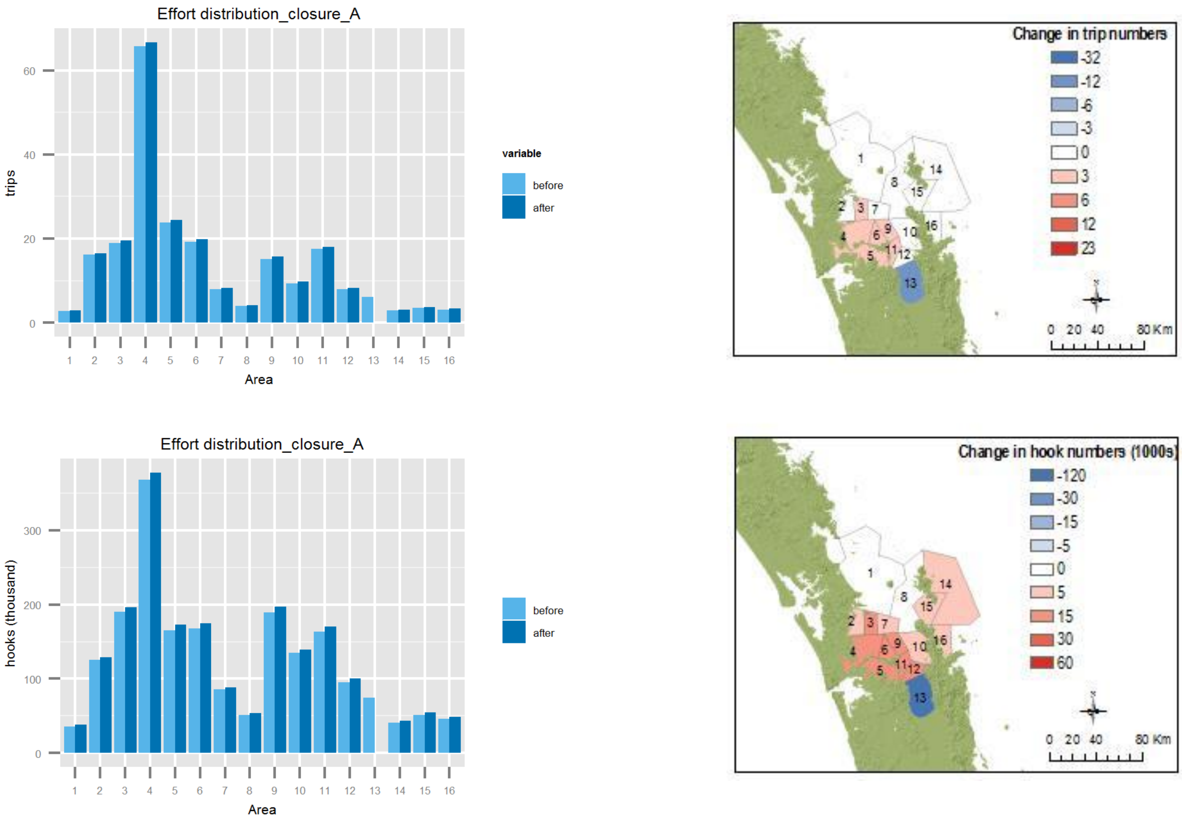

Figure 18 Predicted effort redistributions for the Auckland model under scenario A, trips to locations and numbers of hooks set

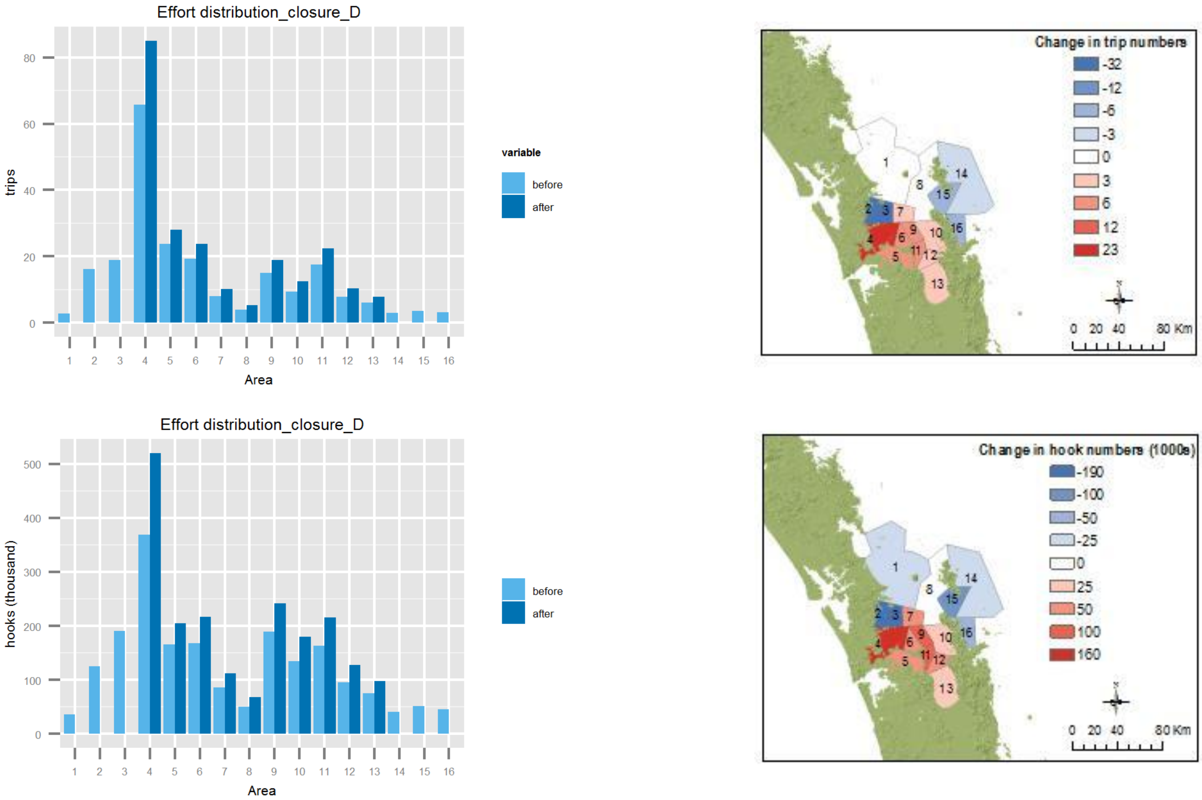

Figure 19 Predicted effort redistributions for the Auckland model under scenario D, trips to locations and numbers of hooks set

Figure 20 Predicted effort redistributions for the Leigh model under scenario D, trips to locations and numbers of hooks set

7.2 Single HGMP region model simulations

Total predicted changes in revenues and the fuel proxy for each closure scenario when assessed using the single HGMP region model are provided in Table 17. As the sizes and locations of areas selected in the scenarios directly matched the areas modelled there was no need for any size related adjustments in this case. However, as locations 1, 2 and 43 were not included in the model the area labels no longer align, i.e. area 1 in the model is in fact area 3 in Figure 8 and so on. The overall redistribution of effort (trips and hooks) by fishing area is illustrated for scenario A (Figure 21) and plots of the other scenarios are again provided in the appendix (Appendix C).

Table 17 Anticipated proportional changes in revenues and fuel proxy under alternative scenarios

Scenario	Model locations closed	Total km^2	% of area modelled*	ΔRevenue	ΔFuel proxy
Closure A	15,16,20,28	2,110	11%	+0.25%	-0.82%
Closure B	18,19,29,30	2,237	12%	-0.25%	-1%
Closure C	13,23,25,33	861	4%	-0%	-2.54%
Closure D	5,6,7,8,9,10,29,30,31,32,33	6,222	32%	+0.83%	+24.90%

*The % of area modelled does not include locations 1,2 or 43 as they were not modelled but it also excludes area 42 as it is exceptionally large (22,583km^2), had low effort and distorts the figures with respect to the realistic proportion of the area closed.

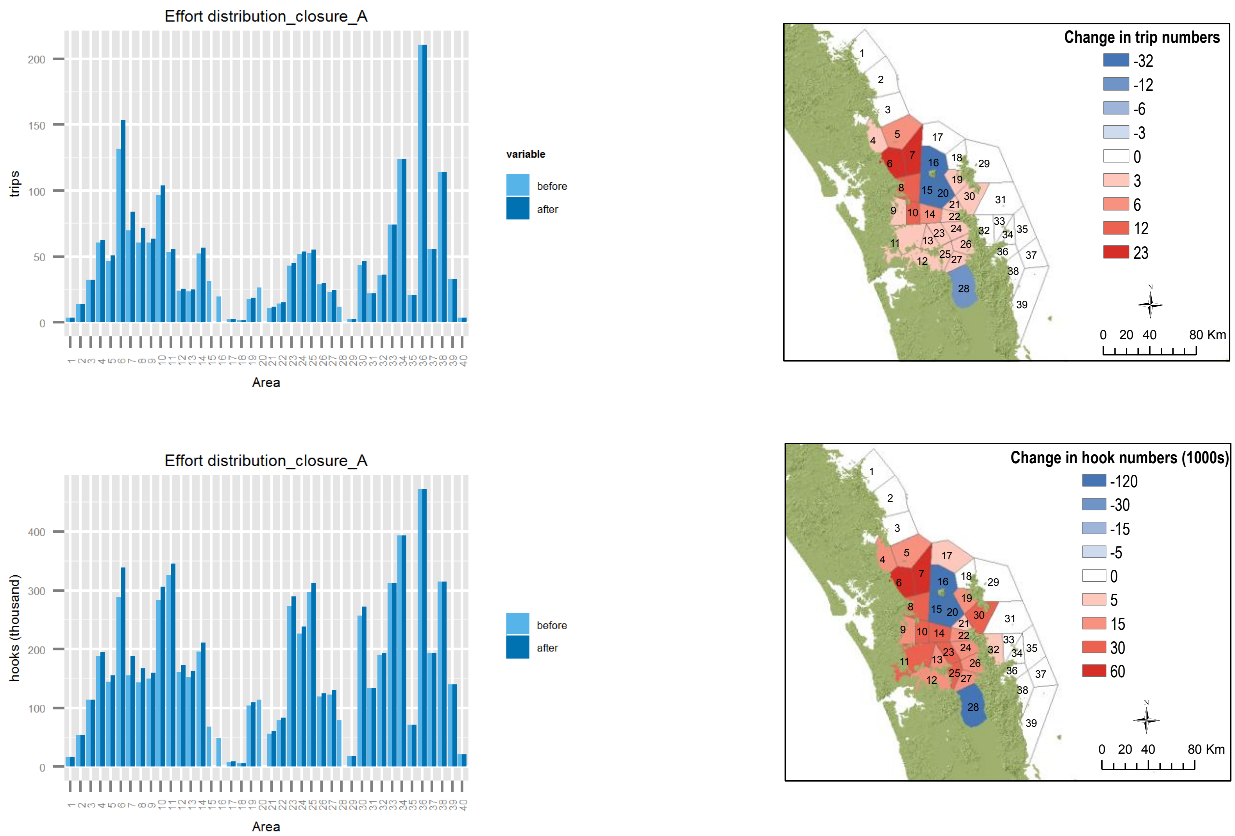

Figure 21 Predicted effort redistributions for the single HGMP region model under scenario A, trips to locations and numbers of hooks set

The modelled redistribution of effort and its associated effects on revenues and costs (assessed via the fuel proxy), were also calculated at the individual port level from this model so that these predictions could be directly compared with those from the set of single port models. A summary of these results are presented in Table 18 and the change in effort by location under scenario A (trips and hooks set) are illustrated at the port level in Figures 22 and 23. As before plots for all the remaining closure/port combinations are provided in the appendix (Appendix C).

Table 18 Predicted proportional changes in revenues and fuel proxy under alternative scenarios using the single HGMP region model

Port	Scenario	Total km^2 of port range	% of fishery range*	ΔRevenue	ΔFuel proxy
Auckland	A	1,276	17%	+0.7%	-2.6%
	B	807	10%	-0.5%	-5.5%
	C	637	8%	+2.2%	+2.9%
	D	2,296	30%	-2.6%	-7.0%
Leigh	A	1,156	12%	-0.5%	-1.4%
	B	1,127	12%	-0.3%	-3.0%
	C	0	0	NA	NA
	D	4,436	47%	+1.8%	+19.5%
Coromandel	A	954	26%	+0.4%	-0.5%
	B	807	22%	-0.3%	-7.0%
	C	637	18%	-3.9%	-3.5%
	D	493	14%	-0.7%	-5.1%
Whitianga	A	0	0	NA	NA
	B	1,917	29%	-2.9%	-5.5%
	C	224	3%	+1.5%	-1.2%
	D	3,153	48%	-1.1%	-10.7%
Mah/Sspit	A	322	9%	-0.0%	-1.9%
	B	0	0	NA	NA
	C	427	13%	+1.3%	-3.5%
	D	1,351	40%	-27.6%	+92.0%
Marsden Point	A	0	0	NA	NA
	B	0	0	NA	NA
	C	0	0	NA	NA
	D	612	34%	+1.1%	-9.3%
Tutukaka	A	0	0	NA	NA
	B	0	0	NA	NA
	C	0	0	NA	NA
	D	612	22%	-0.4%	-2.5%

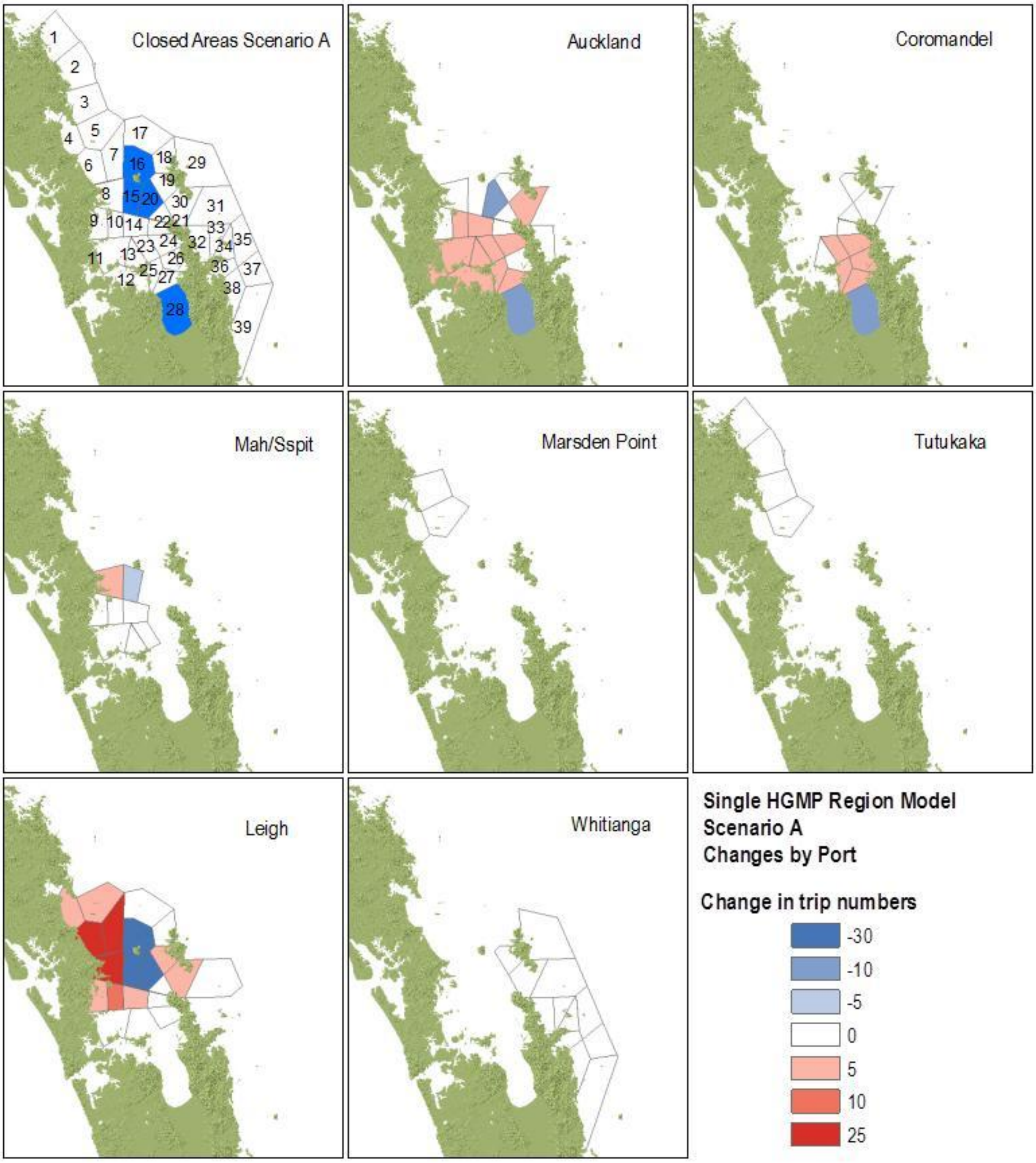

Figure 22 Predicted redistribution of trips at the port level when using the single HGMP region model under scenario A

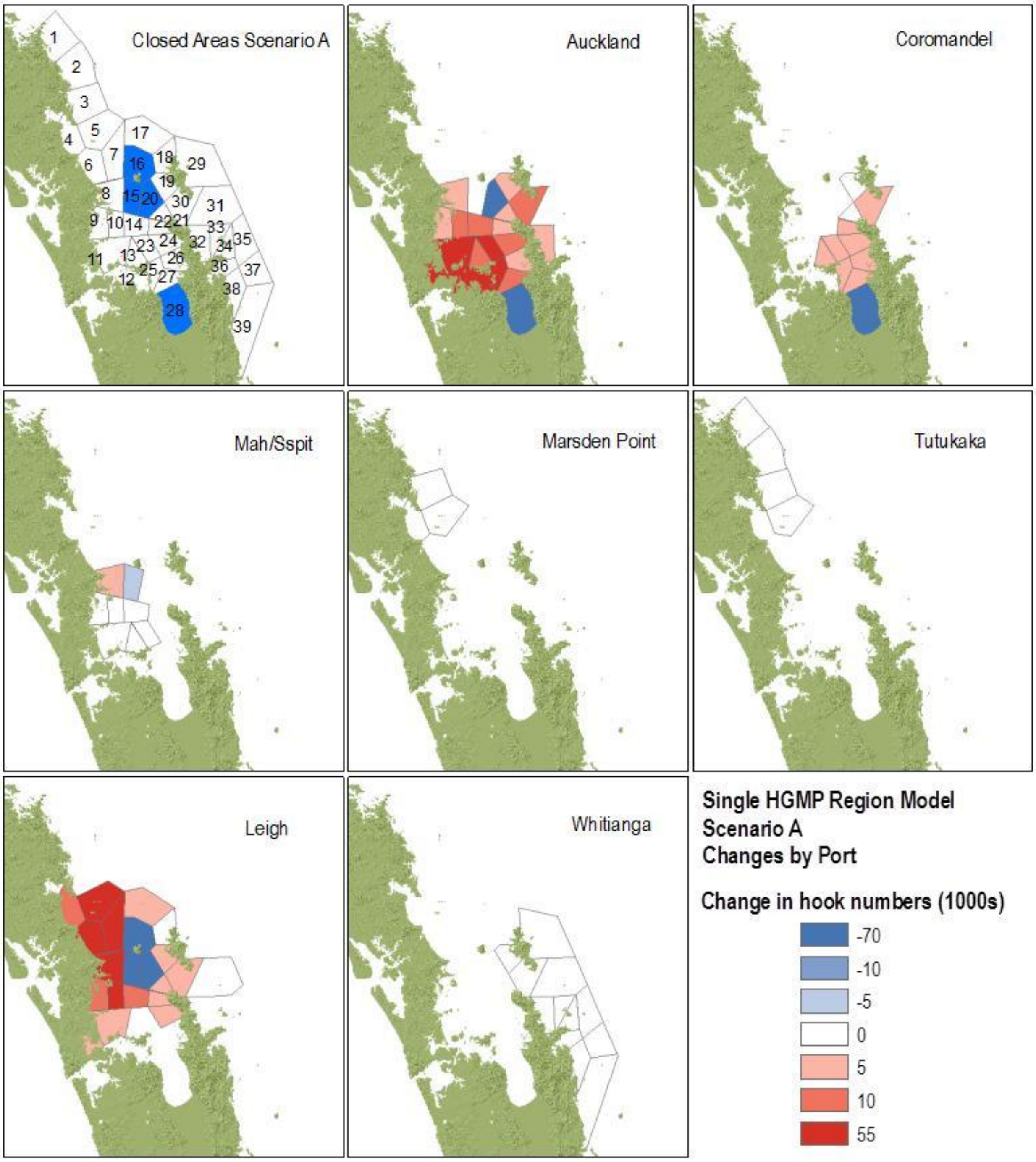

Figure 23 Predicted redistributions of hooks set at the port level when using the single HGMP region model under scenario A

8 Discussion and conclusions

MODELS

Random utility models were estimated for vessels that operate using primarily bottom longline gear in the Hauraki Gulf Marine Park region. Logbook data was used in combination with additional data relating to the weather and factors such as fuel costs to estimate a set of five separate port specific nested logit models for the ports of Auckland, Leigh, Whitianga, Coromandel and then Mahurangi Harbour and Sandspit combined. An additional model was then developed that incorporated data for the ports of Marsden Point, Tutukaka and all the ports that had previously been modelled individually. The ability of these models to predict known effort distributions was then tested before using them to simulate the effects of four sets of hypothetical closure scenarios. The redistributions of effort predicted to occur as a result of the closures were then used as a basis for estimating the impacts of alternative scenarios on revenues and a proxy cost variable.

The abilities of different models to predict the overall distribution of effort from an out of sample logbook data subset were good and broadly comparable. Correlation coefficients comparing predictions of effort by location to that observed in the logbook data were seen to range between 0.70 and 0.97, with the majority being in excess of 0.90.

Whilst some variability was observed in the magnitudes of coefficients and even in the mix of significant parameters between the separate models, there was also a substantial amount of similarity. The factors found to have the strongest positive contribution to the utility of a fishing location were in all cases those associated with either the recent value per unit of effort in a location (vpueR), or the location that a vessel had been fishing in recently (LR). In both instances recent was defined as the last 5 days wherever possible. Seasonal influences were also seen to be significant in many of the models, with the vpue of a location at the same time in the previous year (vpueY), or the location a vessel was fishing at that time last year (LY) contributing positively to the utility function. The magnitude of the annual effect (Y) was invariably smaller than that seen for recent (R) conditions though. The influence of so called 'habit' variables (i.e. LR, LY) is a commonly observed result when modelling fisher location choice (e.g. Holland and Sutinen 1999; Marchal et al. 2009; Pascoe et al. 2013).

The number of vessels that had been operating in a location (densR/Y) was also seen to have a positive influence, indicating that the greater the number of vessels in an area, either recently or in the previous year, the higher the utility of visiting the same area now. The strength of this was relatively minor though in all models when compared to the other coefficients and, amongst other things, could be a stock induced effect. Most BLL vessels primarily target snapper when possible and if the stock is not uniformly distributed over the entire range of the fishery then if vessels are catching fish in an area it may be an incentive to also try and operate in the vicinity of that region.

Adverse weather in the form of strong westerly winds, travel cost variables, and the level of variability in value per unit of effort all had negative signs in all models and, all else equal, reduced the utility of a location as the associated explanatory variable increased in size. The negative contribution of these factors have previously been seen to be significant in other fisheries (Kahui and Alexander 2008; Marchal et al. 2009)

The level of similarity across models is a positive sign as even when the data is parsed into subsets of varying sizes the coefficient estimates appear to be relatively stable (a condition also observed when estimating earlier iterations of all the models). Of the two modelling approaches undertaken, the separate port level models are expected to provide better predictions of what will happen at the individual port level though, as the ability for their coefficients to vary and reflect port level effects ultimately gives greater flexibility despite them being estimated with fewer observations.

CLOSURES

When the impacts of the alternative closure scenarios were estimated, the single HGMP region model tended towards predicting a lower level of impact when compared to the individual models, but this is not always the case. Some of the variation in predicted impacts will also be due to the differences in how the areas are defined in some cases. However, when ranking which scenarios were predicted to have the greatest negative impact on revenues at the port level and then the greatest impact on costs they both select the same scenarios on all but one occasion.

For many ports the closure scenarios are predicted to result in relatively small (either +/-) percentage changes in revenues and fuel costs. The largest proportional changes, accounting for both revenue and costs, were predicted to occur under scenario D for the ports of Leigh and Mahurangi/Sandspit. Vessels operating from Mahurangi/Sandspit fish fewer areas than any of the other ports and scenario D closes the locations closest them. Even under these relatively large closures though, with up to 11 locations closed across the gulf as a whole and a large number of these close to Whitianga, vessels operating from the ports of Coromandel and Whitianga were predicted to be no worse off at the annual level under scenario D. The potential for such disparity in the effects of different closure scenarios demonstrates that distributional impacts are a possibility, i.e. that the impact will not be felt evenly by all ports. It also demonstrates that empirical analyses such as this are useful tools for identifying the implicit tradeoffs associated with alternative strategies and allows them to be formally incorporated into the planning process.

As a significant proportion of the value in BLL vessel landings comes from snapper, which they reportedly have the ability to target reasonably efficiently, it can result in the level of variance between the vpues obtained in alternative fishing areas being relatively low (actual vpue variances are provided at the end of Appendix C). Consequently even when closures are implemented the modelled impact of vessels being displaced to an alternative location/s can be relatively small in terms of revenue, unless it happens to be a particularly marginal area. The largest closure induced proportional changes are often seen in the cost proxy as opposed to the revenue variable and is at least in part an artefact of their relative absolute sizes. Variable costs should in reality be a fraction of total revenues so a small percentage change in revenues would have a greater impact on a vessels financial viability than an equivocal percentage change in their fuel and oil costs. This being said, in many commercial fisheries the margin between revenues and total costs (both fixed and variable) is often small so any decrease in revenue or increase in costs (even if it is only the variable component) is likely to be detrimental. More detailed economic data is required for the implications to be quantified though. It is also worth reiterating that the projected revenue impacts do not factor in the potential for location specific vpues to fall in the longer run if excessive effort ends up being displaced to areas.

In addition to some relatively small movements in revenues and costs there are also a number of instances where closure scenarios are predicted to result in a reduction in costs, an increase in revenues, or both, but most often the first of these. Whilst typically small, predictions of improvements in fishery performance may appear counterintuitive so are now discussed in more detail. RUMs are not optimisation models and work on the basis that the probability of a vessel visiting a given location is dependent on the attributes of that vessel and the attributes of the location. When closures are imposed vessels will, in some instances, be forced to fish in areas that they otherwise would not have on that trip and in some cases this results in them actually performing better than they would have otherwise. This can be because the location is closer to port (i.e. reduced costs), because the area has a larger vpue (increased revenue), or both. Because the initial ‘status quo’ prediction of effort distribution is not an optimisation, and more than just vpue and cost drive the expected utility of visiting an area, it is not necessarily an optimal distribution to begin with. Rather, it is how fishers are expected to behave under a given set of circumstances, based on how they are observed to have behaved in the past. A direct consequence of this is the potential for latent improvements in performance and in some cases these become apparent when vessels are forced to operate in alternative locations.

It is also the case that cost minimising behaviour picked up through the negative PDD, PDL and PL coefficients reduces the probability of a vessel travelling to distant locations unless there is something else about the area that compensates for the impact of distance. This effect is reinforced by the positive densR/Y coefficients that do not increase the probability of travelling further if areas that are close are also frequently fished. In reality though it is likely that for fixed demersal gears like BLL there may also be some level of pre-existing territorial understanding between fishers with regards to who tends to fish where and when, which would prevent vessels from grouping up so much and being able to reduce their costs and this would not be picked up by the models.

Closure induced displacement of effort is explicitly accounted for in the modelling process, however, if vessels are displaced to areas with lower vpues and their revenues fall as a result, they may respond by applying more effort to compensate for these losses and to facilitate the landing of their full ACE. Should this be the case, areas that remain open to fishing after any closures are imposed may face not only displaced effort but also the secondary influence of any compensatory increase in effort that may arise if vessels attempt to offset revenue impacts. It is not possible to account for the latter effect in the models but given that some level of fixed costs will have already been incurred when undertaking a trip, applying additional effort in the form of extra fishing events or fishing with more gear is a plausible response as the marginal cost of doing so may be relatively small. However, the likelihood or the extent to which this would happen is dependent upon how large any increase in variable costs would be relative to the additional revenues obtained (i.e. the marginal benefits) from doing so, and any additional practical or operational constraints vessels face. In reality there are likely to be a number of potential constraints, for example, attempting to increase the number of hooks shot in an event or increasing the number of shots in a trip may result in conflict with other vessels that operate in the same area. It is believed that the ability to land fish soon after capture, ensuring maximum freshness and therefore value for the snapper export market may reduce the marginal benefit, and therefore willingness, of vessels to extend the length of trips.

Increasing the number of trips a vessel undertakes in a year is an alternative way that effort may be increased, however, whether this is likely to occur again depends upon the associated costs and benefits of doing so. Without additional economic data on the operating costs of vessels and information on how vpue may change it is not possible to make reliable predictions around what influence this could have. However, given the relatively small impact on revenue predicted under most scenarios it is unlikely that compensatory increases in effort are a great risk in most cases and are certainly of less concern than the possible long run influence of displaced fishing effort on vpue in areas. Post-simulation analysis of the results could be undertaken to provide some insight into the level of additional effort that would be required to offset any revenue losses vessels are predicted to face. However, this would be based on the underlying assumption that any additional effort would be distributed in the same manner as predicted under the closures (i.e. all effort would simply proportionally increase in the areas displaced to) which has the potential to be overly simplistic as it fails to account for the issues associated with costs and constraints discussed above.

LIMITATIONS

A number of simplifying assumptions were necessary in the process of modelling the fishery and are detailed at various stages throughout the report. One such assumption was that the location of the first fishing event in a trip provides an accurate representation of all areas fished in the entire trip. The fact that 77% of the trips assessed did not fish in more than one location on a trip supports the assumption but it is also still a potential area for refinement in the modelling process that could begin by looking more closely into the sequential distribution of effort within trips. If adjoining locations are frequently fished in sequence redefining the polygons or merging them could be considered.

An alternative approach would be to specify multiple models, one to estimate the probability of where a vessel will choose to fish after leaving port, typically the longest leg (along with the last one), as demonstrated earlier in the report. A second model could then be set up to predict the trip movements which occur over a far smaller spatial range and are also not likely to be influenced by exactly the same factors as the initial trip from port to the area first fished. Information on what influences trip and intra-trip decision making is the type of data that could be collected from vessel skippers as part of the survey tool developed in this project.

It should also be noted that random utility models cannot explicitly account for any stock effects that the displacement of effort might have over time. As a result the estimated revenue (and cost) effects are likely to be most appropriately considered as short run measures of the impacts of closures. Over the longer term, effort may again shift if what was displaced in the first instance was sufficient to impact catch rates in the new location. It is also a possibility that if closure scenarios have a great enough impact on vessels with respect to the locations they have historically fished it may result in behavioural shifts not previously observed in the logbook data and that could be difficult to anticipate as a consequence. If factors altering the cost of visiting a location could be estimated and then factored into the analysis (e.g. reduced catch rates due to increased crowding) it may be possible to iteratively estimate longer run redistributions. Further analysis of observed catch rates against the sequence and timing of visits to any one location may provide an indication of crowding effects.

The way that port level choice sets are currently set up in the single HGMP region model reflects the areas that they have historically fished and are assumed to have knowledge about. If trips from all ports were specified with a single generic choice set this assumption could be relaxed to allow for the assumption that if faced with significant changes vessels may expand the area that they operate in. This approach was not undertaken in this round of modelling as assessing all ports across one single choice set also results in probabilities being estimated for every single location considered in the choice set, regardless of whether vessels from the port in question have ever fished there. This has a distortionary influence on predictions of effort allocation for both the base cases and scenario simulations, the magnitude of this effect will vary with the relative difference in the size of the ports 'real' and 'potential' fishing locations and may impose unrealistic assumptions about the ability of vessels to operate in certain locations. The habit variables LR and LY could likewise be suppressed in any simulation to prevent them from inhibiting movement into locations previously unfished by vessels operating out of that port.

A further limitation of the current setup is that as the level of total effort applied in a scenario is currently defined by whatever reference year is used, vessels will always exert that amount of effort even if given the choices they face, the ultimate economic consequences would likely have caused them to stop fishing or exit the fishery. For example, scenario D is predicted to reduce revenues by 48% for vessels in the Marsden Point/Sanspit model and increase costs by 75%. This could be tested by building in the ability for vessels to actively choose to not fish as an additional choice in the model, rather than displacing to an area that may be unattractive to fish from an economic perspective. If this approach was to be undertaken it would be beneficial to also incorporate some form of data that represents the opportunity cost of remaining in the fishery.

Incorporating quota data is another potential extension of the model that could not be achieved at this stage. Discussions with individuals involved in this fishery indicate that may be worth attempting, or the incorporation of data relating to possible catch plans that vessels may be attempting to adhere to. The latter of these two would be likely to have an influence on fishing behaviour, especially if attempting to avoid over-catching certain species. Again, information on catch plans would most likely need to be obtained directly from the industry itself and could be done as part of a broader face-to-face survey collecting decision making and economic information.

This case study is based on a relatively simple fishery for a single species with minimal bycatch of other species and relatively uniform catch rates across the locations of the fishery. By contrast the trawl fishery is more spatially complex with regard to target species and bycatch composition and in that case catch plans may be a strong determinant of location choice and would need to be factored in the models.

CONCLUSIONS

The models developed in this analysis provide insights into the relative importance specific factors have for HGMP BLL vessels when deciding on where to fish and thus where effort is likely to eventuate under given sets of conditions for vessels from different ports. The outputs of this assessment, in the form of RUM models and r code, may also be utilised and extended by resource managers to test more targeted questions surrounding the potential impacts of more alternative spatial management questions. For the scenarios that were tested the models generally predict that the short run effects from all of the closure scenarios tested would be relatively limited at the overall fishery level in terms of their impacts on gross revenues. However, the largest of the closure scenarios is predicted to result in a 24.9% increase in fuel costs as a consequence of some vessels having to travel further in order to operate. Even in the absence of detailed economic costs and earnings data, it is likely that such a substantial increase would represent a significant threat to the economic viability of vessels in this fishery.

When considered at the port level, both modelling approaches suggest that impacts are likely to vary by port and depend on the exact characteristics of any areas closed. It is only when the alternative scenarios are considered at this level that the potential disparity of impacts on individual ports can really be observed. This is driven at least in part by the fact that, whilst there is some overlap in terms of the areas exploited by vessels fishing from different ports, the data demonstrates that there is also a relatively high degree of delineation in the areas that vessels from specific ports fish most. The aggregate impact of losing one such location can therefore be misleading and is unlikely to be felt evenly across all the ports. This was clear in scenario D where the aggregate impact was predicted to result in just under a 25% increase in fuel cost, but at the individual port level most were not anticipated to have any increase in fuel costs whilst a few had substantial increases.

In addition to the anticipated changes in vessel revenues and costs, the models developed in this assessment provide estimates of how effort will redistribute across the HGMP region. Any measure that results in persistently higher levels of effort being applied to areas also has the potential to result in localised depletion in the longer term and reductions in cpue, which is an additional cost that is not picked up in this modelling approach. Whilst determining the point at which this will occur is a biological question the information that this assessment provides in terms of predicted changes in effort could be used in combination with any such analysis to assess whether predicted levels of effort displacement could be detrimental to the fishery (or biodiversity values in areas that receive higher effort) in the longer term.

Despite the limitations discussed above, the RUMs developed in this analysis perform well when predicting fishing effort distribution in the HGMP, both within and out of sample, and provide useful insights into how effort is likely to redistribute in the event of area closures. To summarise, effort allocation models were developed for BLL vessels identified as being dependent upon fishing in the HGMP. The anticipated value per unit of effort and where vessels had been operating recently generally had positive influences on the probability of a vessel operating in an area, whist strong winds from the west, high variability in the value per unit of effort of an area and cost factors had negative influences. The distribution of fishing effort was modelled and effort redistribution under hypothetical closure scenarios was then tested at the HGMP level and for individual ports. The effects of these hypothetical management changes were generally seen to be relatively minor in most cases at the HGMP level but more mixed at the port level, demonstrating a need to consider impacts at the port level.

Appendix A Survey documents

Participant information sheet

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PARTICIPANT INFORMATION SHEET

Survey of Fishing Location Choice – Hauraki Gulf Longline Fleet

The Hauraki Gulf Marine Park is rightly recognised as a national taonga. Between now and September 2015, a partnership led by mana whenua and central and local government will be creating Sea Change – Tai Timu Tai Pari, a marine spatial plan designed to safeguard this treasure.

Fishing is a key topic of interest in the Park and the spatial planning process involves reviewing the location of fishing activities with respect to other uses and values. MPI aims to protect access to, and productivity of, economically important fishing grounds and achieve broad stakeholder acceptance of the final Marine Spatial Plan for the Park.

To do this MPI have asked CSIRO to help them value fishing grounds and understand how they are used and what the consequences would be if any access was lost.

What is involved?

As a member of the longline fleet that operates in the Hauraki Gulf Marine Park area we have identified you as a potential respondent to this survey. MPI will have already been in contact and sought consent for us to now invite you to participate in a face-to-face interview with a member of the project team. We expect the survey to take approximately 20 to 25 minutes, but may take longer if you wish to discuss components of the survey in greater detail.

Participation and withdrawal

Participation in this study is completely voluntary and you are free to withdraw from this study at any time without prejudice. If you wish to withdraw, simply notify a member of the project team, the details of whom are provided at the end of this form. If you withdraw from the study, and if you do so before we produce the aggregated results for the survey, the questionnaire information you have provided will be deleted and will not be used in the analysis.

Risks

Participation in this study should involve no physical or mental discomfort, and no risks beyond those of everyday living. If, however, you should find any question or procedure to be invasive or offensive, you are free to omit answering that question. If you have any concerns about any aspects of the study, please contact one of the team members (see below for contact details).

Confidentiality

The data will only be seen by members of our research team and will be stored by MPI in a secure area that is not accessible to any individuals other than the research team. The collected data will become the property of MPI and be used by MPI for the purposes outlined in this document and meeting any other statutory requirements of the Fisheries Act. Other than to CSIRO, and only for the purposes of this study, no private information will be released by MPI to any third party.

Will I receive any payment for taking part in the study?

No, participation is voluntary, although if you wish we will acknowledge your involvement in the reports and publications which are produced based on the results of this survey. Please contact one of the members of the research team if you would like this to occur.

How will my information be used?

With this questionnaire MPI and CSIRO aim to:

- get a better understanding of the factors that influence choice of fishing location for vessels in the Hauraki Gulf longline fleet,
- gather data on the costs and characteristics of their fishing operations,
- use the data to develop an economic model for this fleet.

How can I find out more about the study?

Please feel free to contact us at any time during the study. This study is being funded by the MPI.

Ethical clearance and contacts

This study has been cleared in accordance with the ethical review processes of CSIRO and the MPI, within the guidelines of the Australian National Statement on Ethical Conduct in Human Research. If you have any questions concerning your participation in the study feel free to contact the researchers involved. Alternatively any concerns or complaints about the study can be raised with CSIRO's Social Science Human Research Ethics Committee by email at csshrec@csiro.au or by contacting the CSIRO Manager of Social Responsibility and Ethics on +61 7 3833 5693.

Thank you for your help with this important research.

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Ministry for Primary Industries
Manatū Ahu Matua

Participant consent form

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CSIRO

RESEARCH PARTICIPANT CONSENT FORM
Survey of Fishing Location Choice – Hauraki Gulf Longline Fleet

Dear Participant

Please review the information below and sign where required if you agree to participate in this research project

---

I acknowledge that:

- I have agreed to participate in the above project being conducted by the Ministry of Primary Industries and CSIRO.
- I have been provided with information about the project and had any questions regarding my participation and any associated risks and benefits answered to my satisfaction. I understand my participation in the research will involve the following activities: *interview by a member of the project team*.
- I have been provided with contact details of the investigating officers and understand that I can contact them at any point during the study. I have also been provided with the contact details of an independent ethics officer at CSIRO should I wish to raise any concerns or complaints about the conduct of the research.
- I understand that my participation in the project is entirely voluntary and that I am free to withdraw from the study at any time and without having to provide a reason for my withdrawal.
- I understand that I may ask for part of all of the information provided by me to be removed from the study without penalty or explanation.
- I understand that the information I provide for this research will be used for the following purposes: *get a better understanding of the factors that influence choice of fishing location for vessels in the Hauraki Gulf longline fleet, gather data on the costs and characteristics of their fishing operations, develop an economic model for this fleet* and will be treated confidentially.
- Neither me, nor the information I provide, will be identified in any publications resulting from the study except where I have given my written permission for this to occur.
- Information provided by me will become the property of MPI and be used by MPI for the purposes outlined above and meeting any other statutory requirements of the Fisheries Act. No private information will be released by MPI to any third party and it will be stored securely by the MPI.

Name:______________________________________

Signature: ___________________________________

Date: ______________________________________

We thank you for your agreement to participant in this research.

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Ministry for Primary Industries
Manatū Ahu Matua

Australian Science, Australia's Future www.csiro.au

Survey document

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CSIRO

Survey Fishing Location Choice - Hauraki Gulf Longline Fleet

The Hauraki Gulf Marine Park is rightly recognised as a national taonga. Between now and September 2015, a partnership led by mana whenua and central and local government will be creating Sea Change – Tai Timu Tai Pari, a marine spatial plan designed to safeguard this treasure.

Fishing is a key topic of interest in the Park and the spatial planning process involves reviewing the location of fishing activities with respect to other uses and values. MPI aims to protect access to, and productivity of, economically important fishing grounds and achieve broad stakeholder acceptance of the final Marine Spatial Plan for the Park.

To do this we must be able to value fishing grounds and understand how they are used and what the consequences would be if any access was lost. With this questionnaire CSIRO aim to

- get a better understanding of the factors that influence choice of fishing location for vessels in the Hauraki Gulf longline fleet and
- gather data on the costs and characteristics of their fishing operations.
- use the data for an economic model for this fleet to be developed by fisheries economists at CSIRO Australia.

The collected data will become the property of MPI and be used by MPI for the stated purpose and meeting any other statutory requirements of the Fisheries Act. Other than to CSIRO, and only for the purposes of this study, no private information will be released by MPI to any third party.

All participation is on a voluntary basis and may be withdrawn at any time

For further information please contact, either:

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Laura Furneaux, Tel: 09 820 7762, Email: Laura.Furneaux@mpi.govt.nz
James Innes, Tel: +61 7 3833 5939, Email: James.Innes@csiro.au

1. Vessel and fishing characteristics

Vessel name: ________________________ Is this vessel: Independent ☐, Company owned/run ☐

You are the: Owner operator ☐, Employed skipper ☐, Other:______________________

Vessel length ________(m), Engine power ________(kW), Crew size ________(inc. skipper),

Beam ________(m), Hull construction ________ Base port ________________________

Steaming speed ________(knots), Fuel consumption when steaming ________(litres/hr)

When using BLL, average number of hooks in a set ________, Bait costs ________(per trip day/or X hooks)

Approximate proportion of fishing events undertaken using BLL ________(%)

How many **other** types of gear do you fish with **this vessel?** ________

Please circle (or add if missing) BT, CP, CRP, DI, DL, DPN, DS, FP, HL, OCP, PL, PS, RLP, RN, SLL, SN, T, TL,

others:____

Are crew paid on a share basis?

skipper________% engineer________% crew________% crew________%

Is this after costs have been taken out? Yes ☐ No ☐,

if yes, please circle which cost/s: fuel, food, quota, other:______________________________

2. Please can you describe a typical fishing trip on this vessel

Gear/s used ________ ________ ________, Primary target species ________ ________ ________

Trip length ________(days/hours) (min ________, max ________)

Average number of sets? ________ (min ________, max ________)

Average distance to first set________ (nm or km) (min ________, max ________)

likelihood of, or reason for moving a substantial distance after that? ______________________

Do you ever switch methods mid trip, and how often does this happen? ______________________ (%)

if yes, what might cause you to do this ____?

What determines when you end a trip____?

Port /s land to: ________________(%), ________________(%), ________________(%)

3. General decision making and choice of fishing location

a) Please can you describe a how you **plan** a typical fishing trip (assuming this is a BLL trip)?

a. What influences your decision on whether to go fishing/start a trip?

b. What then influences the location you chose to fish in?

b) What level of importance do the following factors have when choosing when and where to fish? Please assign a score of 100 to the most important factor(s) in each case. Then give the remaining factors scores of between 0 and 99 to indicate their importance *relative* to the most important factor(s), a high score indicating that they are important.

When to start a trip	Score
Price of target species	
Price of fuel	
Time of year	
Quantity of ACE remaining at that point in the season	
% of overall TAC remaining	
Weather forecast (wind strength/ direction?)	

Choice of fishing location	Score
Price of target species	
Price of fuel	
Time of year	
Quantity of ACE remaining at that point in the season	
% of target species TAC remaining	
Weather forecast (wind strength/ direction?)	
You did well in that location previously (trip/year)	
Other vessels catch rates	
Distance to location	
Uncrowded	
Fishing to a catch plan	
Low risk of bycatch	

4. Interactions with other fishers/vessels in the fleet

a) How often do you tend to speak with other fishers and share information relating to fishing locations? (this includes you receiving information from them)

Frequently (once a week or more) ☐, Occasionally (every 2-4 weeks) ☐,

Infrequently (less than once a month) ☐

b) If you do speak with other skippers/vessels, is this because they are from the same:

Port ☐, Fishing company ☐, Other: ____

c) If you are become aware that the fishing is currently good in a specific location/s how long would you generally expect this information remain useful for?

___________________________________ days/weeks

5. If your five most valued fishing grounds were no longer available:

a) What action would you take? (e.g. fish the remaining grounds you know harder, search for new grounds, etc.)

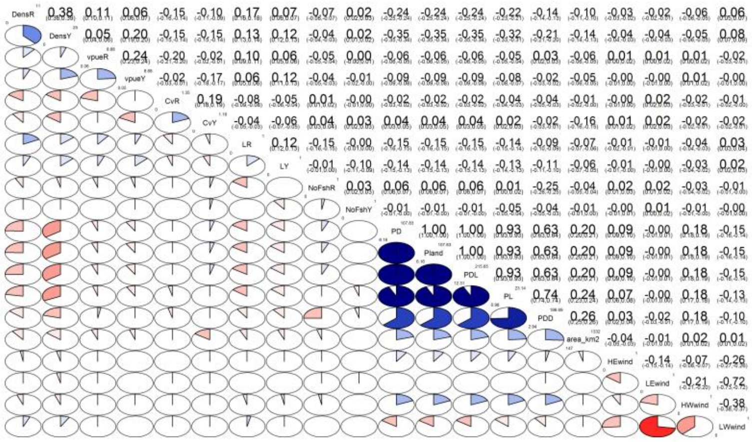
b) By what process would you make this decision?

Are there any additional factors that influence your decisions about where and when to fish that we have not discussed?

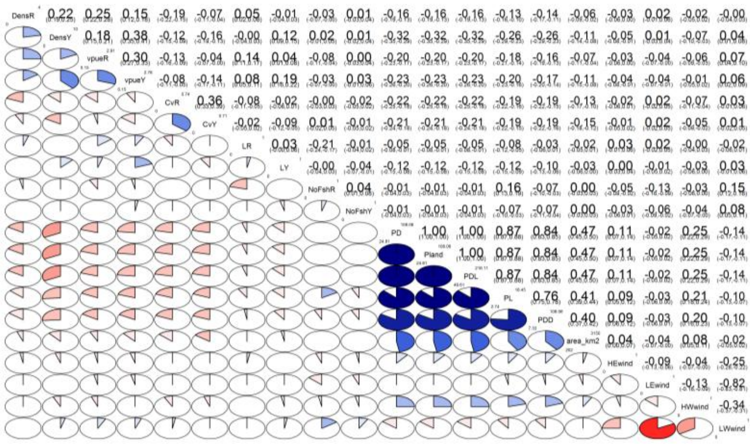
Thank you for your time.

Appendix B Correlation matrices

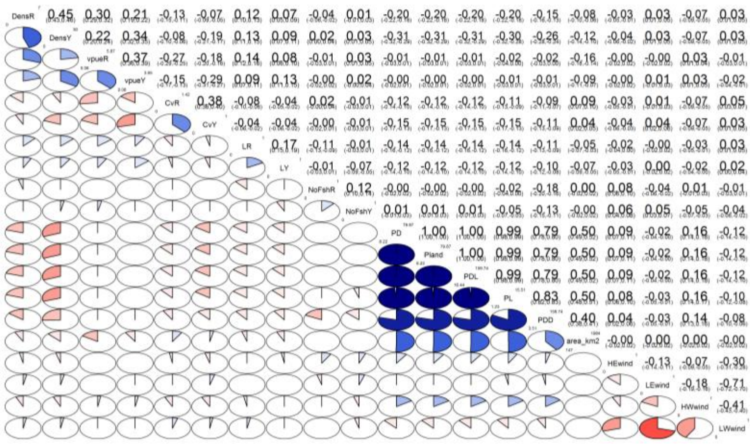
Figures B.1-6 provide pairwise measures of correlation between all explanatory variables (labelled on the diagonal) for the datasets used.



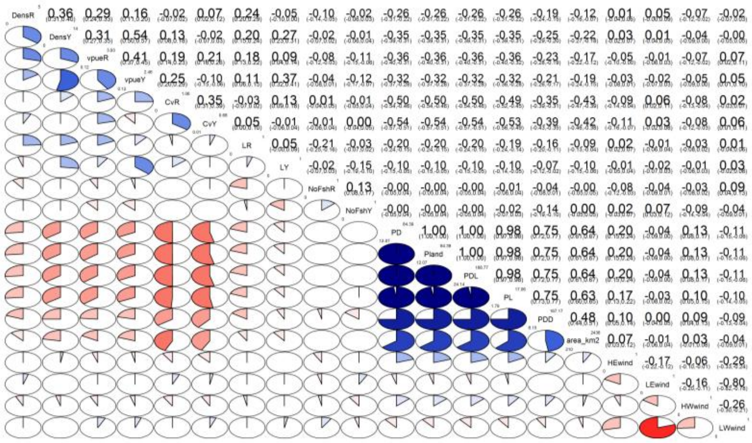
Apx Figure B.1 Correlation matrix for all ports dataset (pearson correlations)



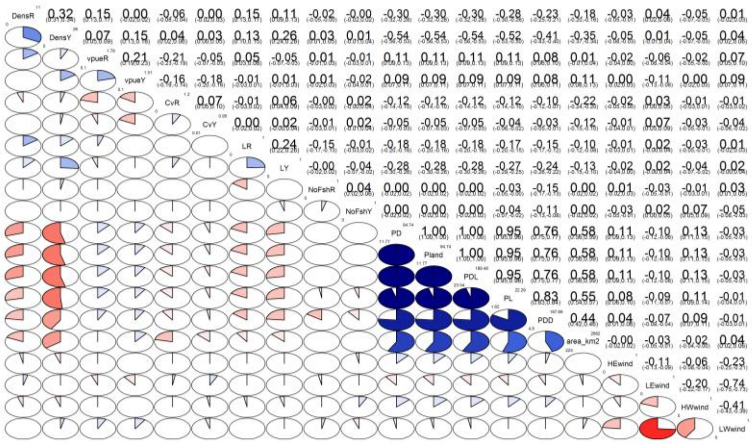
Apx Figure B.2 Correlation matrix for Auckland dataset (pearson correlations)



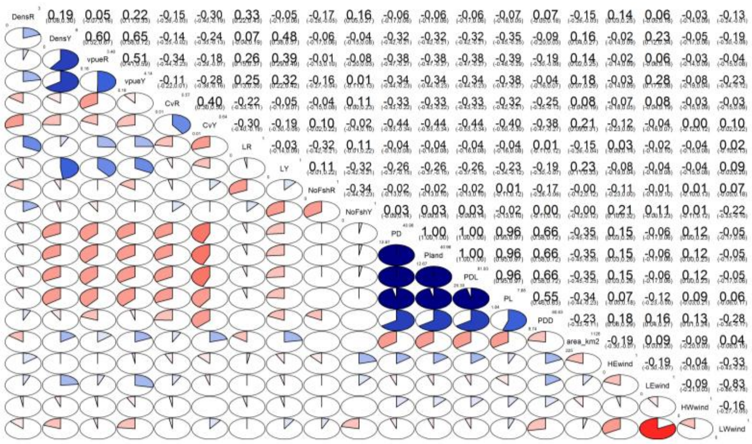
Apx Figure B.3 Correlation matrix for Leigh dataset (pearson correlations)



Apx Figure B.4 Correlation matrix for Coromandel dataset (pearson correlations)



Apx Figure B.5 Correlation matrix for Whitianga dataset (pearson correlations)



Apx Figure B.6 Correlation matrix for Mahurangi and Sandspit dataset (pearson correlations)

Appendix C Model outputs and associated information

C.1 Port level models

C.1.1 AUCKLAND

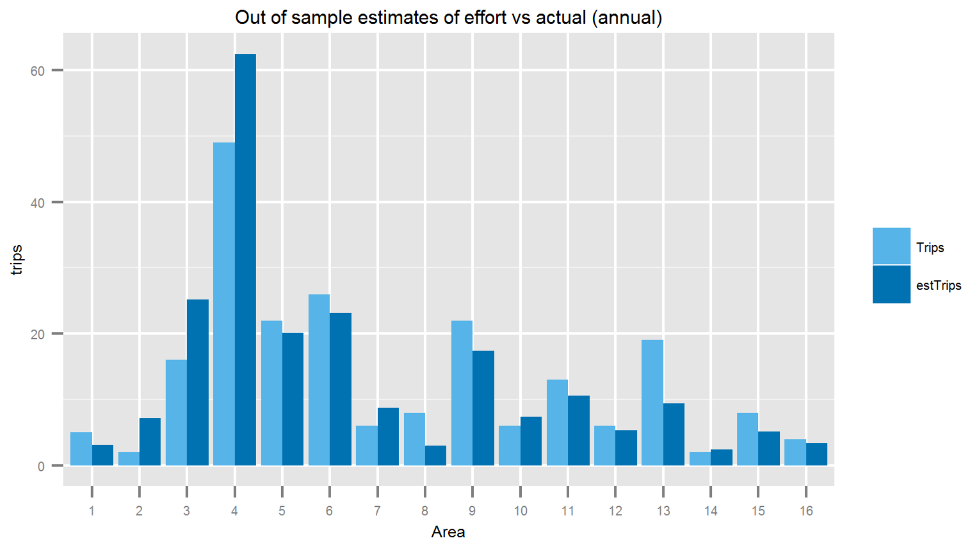
Apx Table C.1 Auckland area definitions and application of closure scenarios

Initial location	port specific location	obs	scenario A	scenario B	scenario C	scenario D
7	1	2				1
8	1	1				1
9	1	1				1
10	1	8				1
11	2	43				2
12	3	43				3
13	4	146				
14	5	71				
15	6	75			6	
16	7	27				
17	1	4	NA			
18	1	3	NA			
20	8	4		NA		
21	8	7		NA		
22	8	7	NA			
23	8	9				
24	8	10				
25	9	94	9		9	
26	10	34				
27	11	102			11	
28	10	11				
29	12	55				
30	13	46	13			
31	14	2		NA		14
32	15	49		15		15
33	14	3				14
34	16	16				16
35	14	2			NA	14

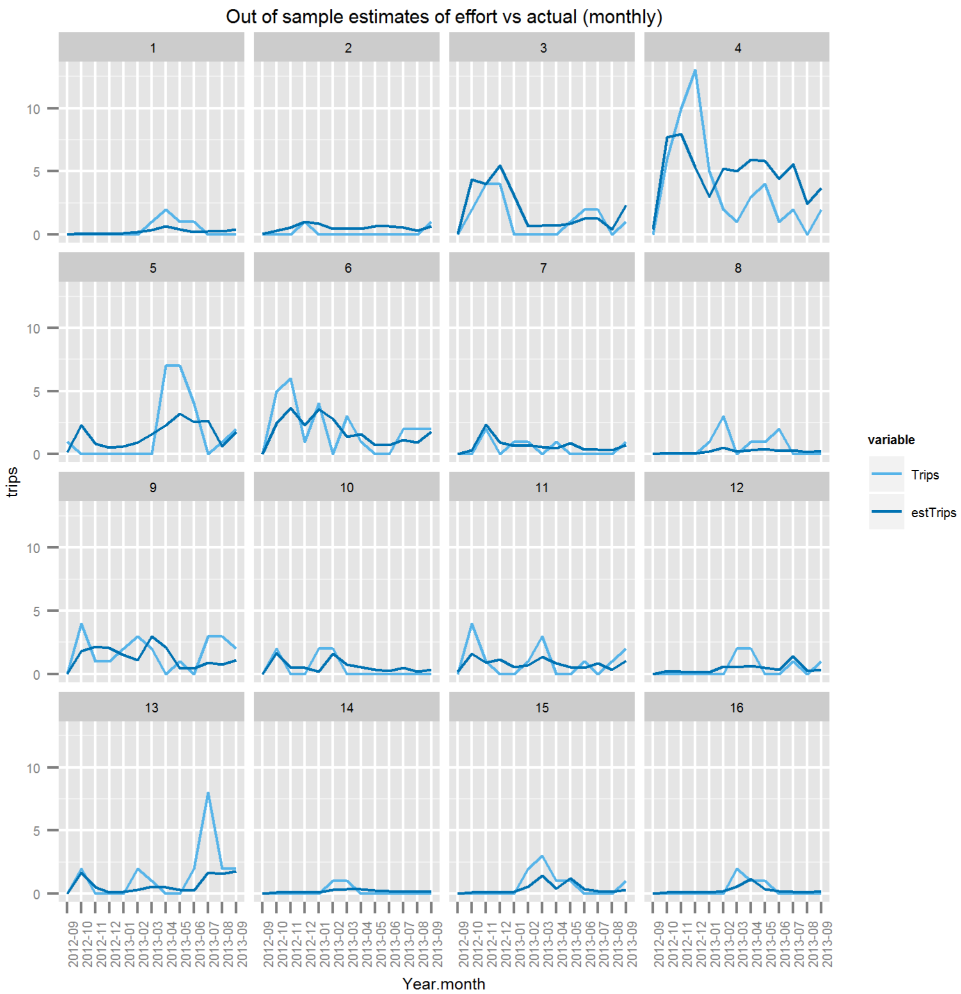
MODEL OUTPUT

```
|-> NLOGIT
    ;Lhs=CHOICE,CSET,ALTIJ;Choices=1,2,3,4,5,6,7,8,
    9,10,11,12,13,14,15,16
    ;Rhs=vpueR,vpueY,LR,LY,DensY,CvR,CvY,PDL,
    PL,HWwind
    ;rh2= one
    ;TREE= n1(1,2,4),n2(3,5,16,6,9,15,10,12,13),n3(7,11,8,14)
    ;ivset: (n2)=[1.0]
    ;maxit=100
    ;checkdata$
+-----------------------------------------------------------+
| Inspecting the data set before estimation.                |
| These errors mark observations which will be skipped.     |
| Row Individual = 1st row then group number of data block |
+-----------------------------------------------------------+
No bad observations were found in the sample
Normal exit:   6 iterations. Status=0, F=    1835.522
-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -1835.52249
Estimation based on N =     871, K =  25
Inf.Cr.AIC  =    3721.0 AIC/N =    4.272
Model estimated: Sep 03, 2014, 17:00:43
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only must be computed directly
               Use NLOGIT ;...;RHS=ONE$
Chi-squared[10]            =     822.24415
Prob [ chi squared > value ] =    .00000
Response data are given as ind. choices
Number of obs.=     871, skipped     0 obs
--------+--------------------------------------------------------------------
        |                Standard             Prob.       95% Confidence
  CHOICE|  Coefficient       Error        z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
   VPUER|    1.40680***      .12272     11.46  .0000     1.16628    1.64732
   VPUEY|     .68812***      .12294      5.60  .0000      .44715     .92908
      LR|    1.49275***      .12781     11.68  .0000     1.24225    1.74325
      LY|    1.01704***      .10433      9.75  .0000      .81256    1.22152
   DENSY|    -.17028***      .03880     -4.39  .0000     -.24634    -.09423
     CVR|    -.91171***      .29064     -3.14  .0017    -1.48136    -.34206
     CVY|    -.78962**       .32539     -2.43  .0152    -1.42737    -.15186
     PDL|     .05210***      .01091      4.77  .0000      .03071     .07350
      PL|   -1.20470***      .12259     -9.83  .0000    -1.44497    -.96444
  HWWIND|    -.97976***      .32610     -3.00  .0027    -1.61890    -.34063
     A_1|    -.70364         .53228     -1.32  .1862    -1.74689     .33961
     A_2|   -1.83773*        .96173     -1.91  .0560    -3.72269     .04723
     A_3|   -1.64230*        .97427     -1.69  .0919    -3.55183     .26723
     A_4|   -2.04001        1.24446     -1.64  .1012    -4.47911     .39908
     A_5|   -1.58366        1.22429     -1.29  .1958    -3.98322     .81590
     A_6|   -1.36292        1.12078     -1.22  .2240    -3.55960     .83377
     A_7|   -1.56650*        .91143     -1.72  .0857    -3.35288     .21988
     A_8|    -.01989         .53320      -.04  .9702    -1.06495    1.02517
     A_9|    -.62106         .93351      -.67  .5059    -2.45070    1.20858
    A_10|    -.90865         .74693     -1.22  .2238    -2.37262     .55531
    A_11|    -.55926         .90094      -.62  .5348    -2.32507    1.20655
    A_12|    -.68868         .80595      -.85  .3928    -2.26830     .89095
    A_13|    -.39036         .63828      -.61  .5408    -1.64137     .86065
    A_14|    -.83575*        .47949     -1.74  .0813    -1.77553     .10403
    A_15|     .30213         .38901       .78  .4374     -.46031    1.06457
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-----------------------------------------------------------------------------
Normal exit:  37 iterations. Status=0, F=    1818.410
-----------------------------------------------------------------------------
FIML Nested Multinomial Logit Model
Dependent variable               CHOICE
Log likelihood function     -1818.40983
Restricted log likelihood   -2503.78117
Chi squared [  27 d.f.]      1370.74267
Significance level               .00000
McFadden Pseudo R-squared      .2737345
Estimation based on N =     871, K =  27
Inf.Cr.AIC  =    3690.8 AIC/N =    4.237
Model estimated: Sep 03, 2014, 17:00:46
Constants only must be computed directly
               Use NLOGIT ;...;RHS=ONE$
```

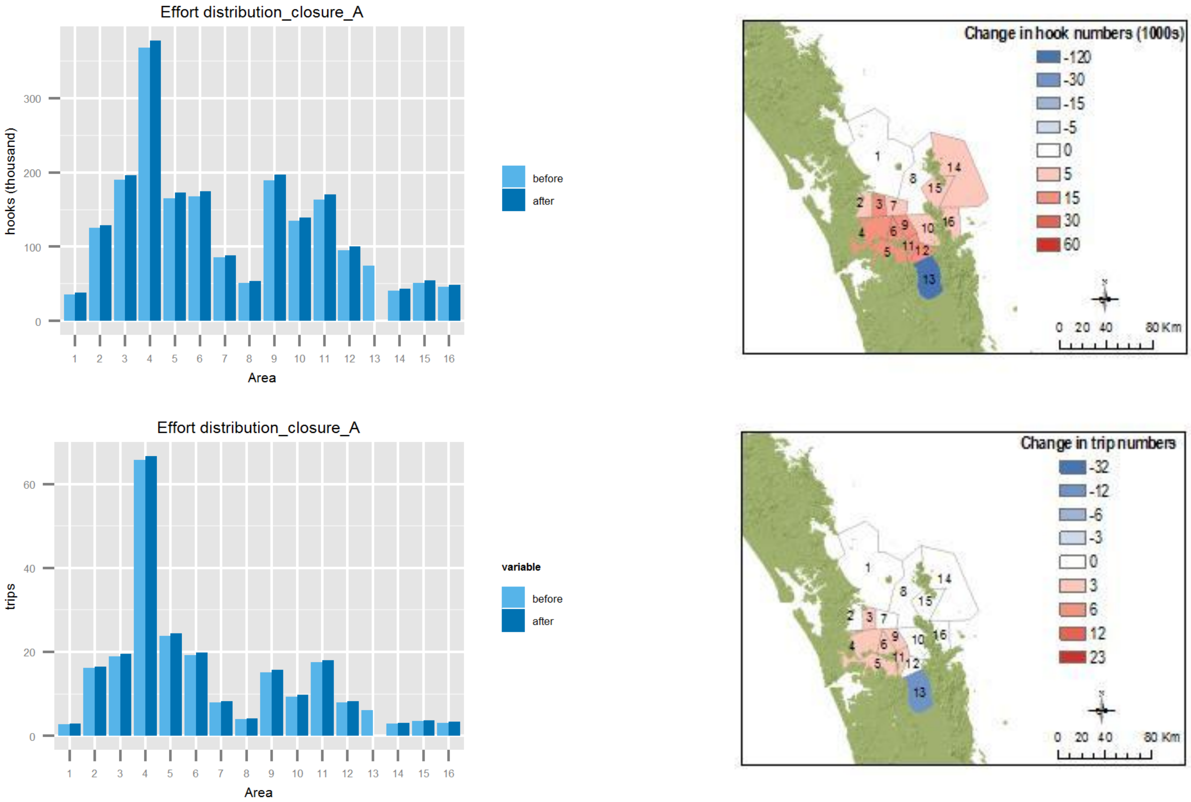
```
At start values -1835.5225  .0093******
Response data are given as ind. choices
The model has 2 levels.
Nested Logit form:IVparms=Taub|l,r,Sl|r
& Fr.No normalizations imposed a priori
Number of obs.=    871, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*          Interval
--------+--------------------------------------------------------------------
        |Attributes in the Utility Functions (beta)
   VPUER|    1.52458***     .13051     11.68  .0000     1.26878    1.78038
   VPUEY|     .69594***     .13219      5.26  .0000      .43686     .95502
      LR|    1.50524***     .13707     10.98  .0000     1.23658    1.77389
      LY|    1.04961***     .11346      9.25  .0000      .82723    1.27199
   DENSY|    -.14490***     .04186     -3.46  .0005     -.22694    -.06286
     CVR|    -.93226***     .30880     -3.02  .0025    -1.53749    -.32702
     CVY|    -.94279***     .34701     -2.72  .0066    -1.62292    -.26266
     PDL|     .06232***     .01006      6.19  .0000      .04260     .08204
      PL|   -1.26967***     .11579    -10.97  .0000    -1.49662   -1.04272
  HWWIND|   -1.03697***     .33428     -3.10  .0019    -1.69216    -.38179
     A_1|    -.37618       1.54204      -.24  .8073    -3.39853    2.64617
     A_2|   -1.46908       1.97288      -.74  .4565    -5.33585    2.39768
     A_3|    -.94488        .89732     -1.05  .2923    -2.70360     .81384
     A_4|   -1.65400       2.23641      -.74  .4596    -6.03729    2.72930
     A_5|    -.61724       1.11705      -.55  .5806    -2.80663    1.57215
     A_6|    -.53524       1.02547      -.52  .6017    -2.54512    1.47463
     A_7|    -.93818       1.08453      -.87  .3870    -3.06382    1.18745
     A_8|     .41178        .73117       .56  .5733    -1.02128    1.84485
     A_9|     .03418        .85951       .04  .9683    -1.65043    1.71879
    A_10|    -.41877        .69666      -.60  .5478    -1.78420     .94667
    A_11|     .07217       1.07744       .07  .9466    -2.03958    2.18391
    A_12|    -.14625        .74711      -.20  .8448    -1.61056    1.31805
    A_13|     .03640        .60060       .06  .9517    -1.14076    1.21356
    A_14|    -.82026        .50914     -1.61  .1072    -1.81816     .17763
    A_15|     .46870        .37815      1.24  .2152     -.27246    1.20986
        |IV parameters, tau(b|l,r),sigma(l|r),phi(r)
      N1|     .58078***     .07296      7.96  .0000      .43777     .72378
      N2|        1.0     .....(Fixed Parameter).....
      N3|     .85832***     .05422     15.83  .0000      .75204     .96459
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
Fixed parameter ... is constrained to equal the value or
had a nonpositive st.error because of an earlier problem.
-----------------------------------------------------------------------------
```



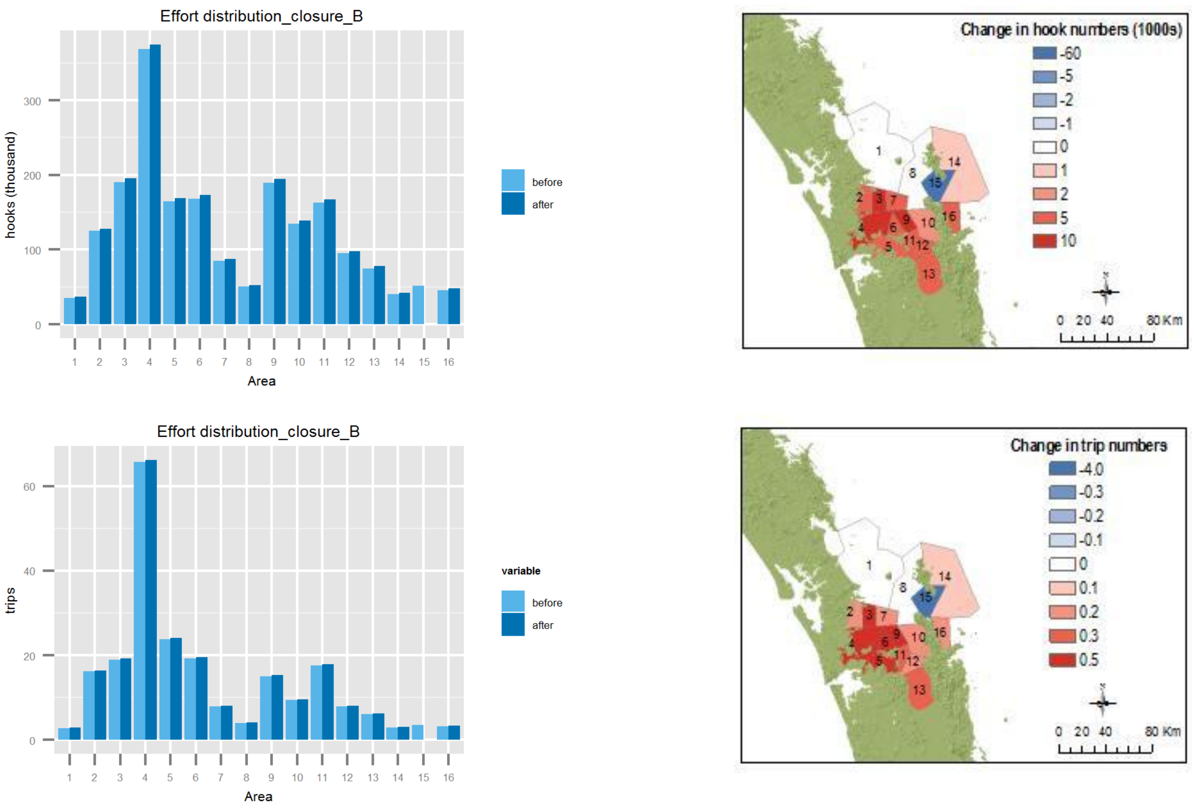
Apx Figure C.1 Out of sample fit at the annual level, observed vs. modelled distribution of effort for vessels fishing from Auckland



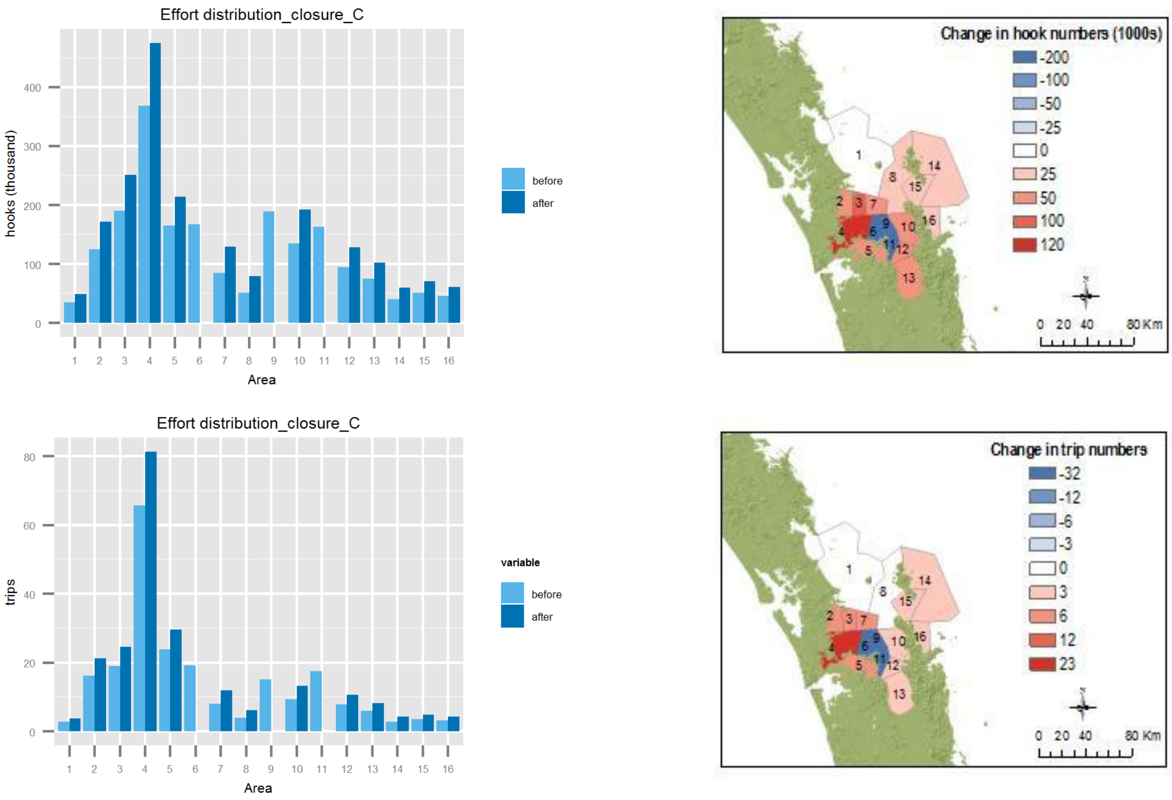
Apx Figure C.2 Out of sample fit at the monthly level, observed vs. modelled distribution of effort for vessels fishing from Auckland



Apx Figure C.3 Predicted effort redistributions for the Auckland model under scenario A, trips to locations and numbers of hooks set

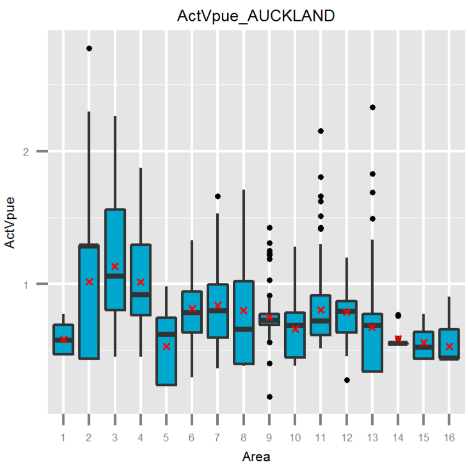


Apx Figure C.4 Predicted effort redistributions for the Auckland model under scenario B, trips to locations and numbers of hooks set



Apx Figure C.5 Predicted effort redistributions for the Auckland model under scenario C, trips to locations and numbers of hooks set

Apx Figure C.6 Predicted effort redistributions for the Auckland model under scenario D, trips to locations and numbers of hooks set



Apx Figure C.7 Actual VPUE values by location in 2011-12, red x indicates the mean

C.1.2 LEIGH

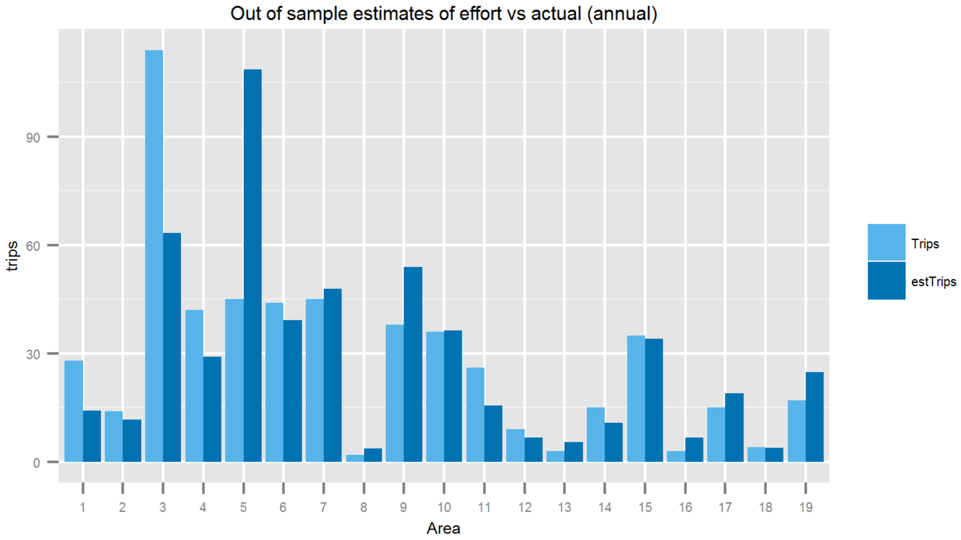
Apx Table C.2 Leigh area definitions and application of closure scenarios

Initial location	port specific location	obs	scenario A	scenario B	scenario C	scenario D
6	1	48				
7	2	80				2
8	3	393				3
9	4	222				4
10	5	170				5
11	6	68				6
12	7	206				7
13	8	8				
15	8	2			NA	
16	9	185				
17	10	128	10			
18	11	104	11			
19	12	14				
20	13	16		13		
21	14	18		14		
22	15	122	15			
23	16	33				
24	17	31				
25	8	4			NA	
26	17	10				
31	18	2		NA		18
32	19	61		19		19
33	18	6				18

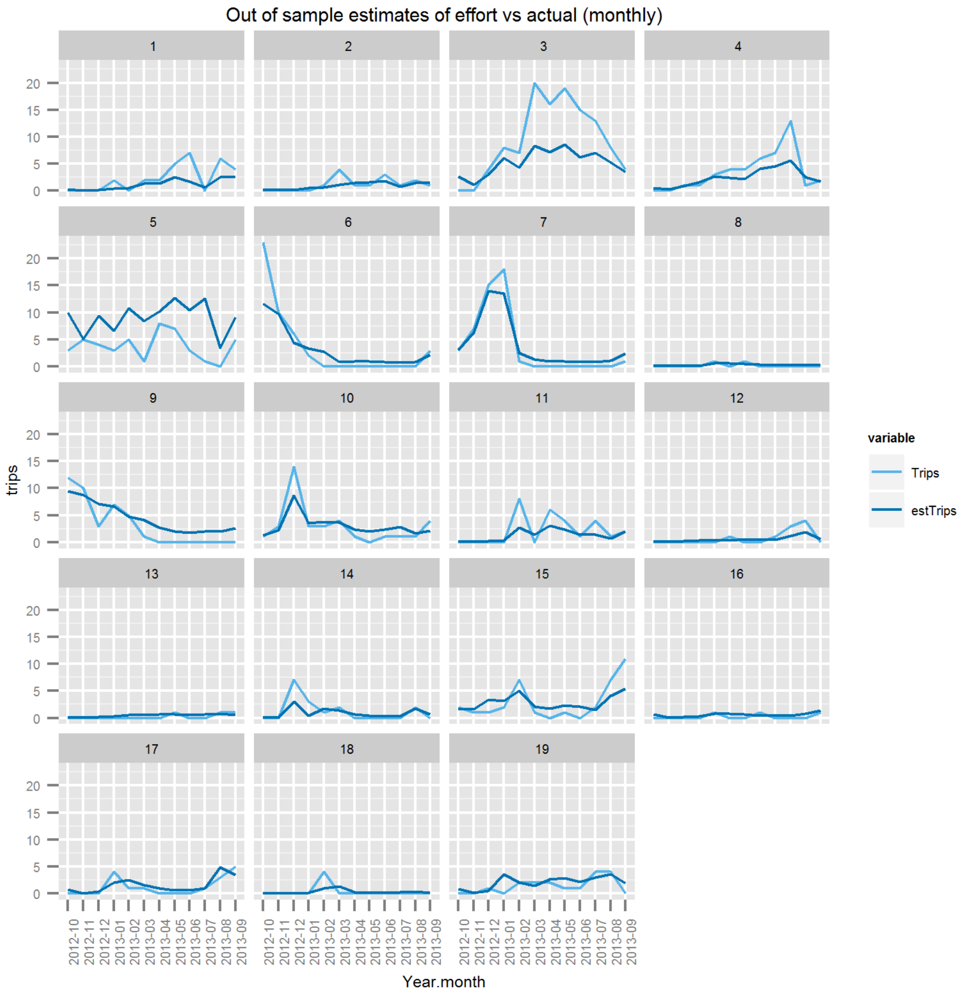
MODEL OUTPUT

```
|-> NLOGIT; M3
    Lhs=CHOICE,CSET,ALTIJ;Choices=1,2,3,4,5,6,7,8,
    9,10,11,12,13,14,15,16,17,18,19
    ;Rhs=vpueR,vpueY,LR,LY,DensR,CvR,PDL,
    PL,PDD,HWwind
    ;Rh2=one
    ;RU1
    ;TREE= n1(1,9,12,4,11),n2(2,10,15,19),n3(3),n4(6,5,7,8,13,14,16,17,18)
    ;ivset: (n4)=[1.0]
    ;maxit=100
    ;checkdata$
+-----------------------------------------------------------+
| Inspecting the data set before estimation.                |
| These errors mark observations which will be skipped.     |
| Row Individual = 1st row then group number of data block |
+-----------------------------------------------------------+
No bad observations were found in the sample
Normal exit:   7 iterations. Status=0, F=    3837.570
-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -3837.56995
Estimation based on N =    1931, K =  28
Inf.Cr.AIC  =   7731.1 AIC/N =    4.004
Model estimated: Sep 03, 2014, 17:02:12
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only must be computed directly
               Use NLOGIT ;...;RHS=ONE$
Chi-squared[10]            =   2139.37222
Prob [ chi squared > value ] =   .00000
Response data are given as ind. choices
Number of obs.=  1931, skipped    0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.      95% Confidence
  CHOICE|  Coefficient     Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
   VPUER|     .67891***     .04413    15.38  .0000       .59241     .76540
   VPUEY|     .39468***     .04287     9.21  .0000       .31065     .47871
      LR|    1.68219***     .06027    27.91  .0000      1.56406    1.80031
      LY|     .47183***     .08985     5.25  .0000       .29572     .64793
   DENSR|     .09432***     .03035     3.11  .0019       .03484     .15381
     CVR|   -1.47999***     .15777    -9.38  .0000     -1.78921   -1.17078
     PDL|     .22638***     .02704     8.37  .0000       .17337     .27938
      PL|   -1.81526***     .30280    -5.99  .0000     -2.40873   -1.22178
     PDD|    -.10456***     .00687   -15.22  .0000      -.11802    -.09109
  HWWIND|   -1.21238***     .15005    -8.08  .0000     -1.50647    -.91829
     A_1|     .31689        .31958      .99  .3214      -.30947     .94325
     A_2|     .55079*       .31294     1.76  .0784      -.06257    1.16414
     A_3|    1.55914***     .59986     2.60  .0093       .38345    2.73484
     A_4|    1.32272**      .62912     2.10  .0355       .08967    2.55577
     A_5|     .11790        .90967      .13  .8969     -1.66503    1.90082
     A_6|     .21933        .60419      .36  .7166      -.96487    1.40353
     A_7|     .97424        .63290     1.54  .1237      -.26621    2.21470
     A_8|    -.14481        .37632     -.38  .7004      -.88239     .59277
     A_9|    1.39427***     .51298     2.72  .0066       .38884    2.39970
    A_10|     .47653        .63363      .75  .4520      -.76536    1.71843
    A_11|     .84417*       .50714     1.66  .0960      -.14980    1.83814
    A_12|    -.56032*       .32411    -1.73  .0838     -1.19557     .07493
    A_13|    -.54005*       .29654    -1.82  .0686     -1.12126     .04115
    A_14|    -.25391        .35583     -.71  .4755      -.95132     .44349
    A_15|    1.06156**      .45619     2.33  .0200       .16743    1.95568
    A_16|    -.20707        .27887     -.74  .4578      -.75364     .33949
    A_17|     .10032        .23740      .42  .6726      -.36497     .56561
    A_18|   -2.27292***     .55385    -4.10  .0000     -3.35846   -1.18739
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-----------------------------------------------------------------------------
Normal exit:  42 iterations. Status=0, F=    3771.200
-----------------------------------------------------------------------------
FIML Nested Multinomial Logit Model
Dependent variable               CHOICE
Log likelihood function     -3771.19952
Restricted log likelihood   -5402.39034
```

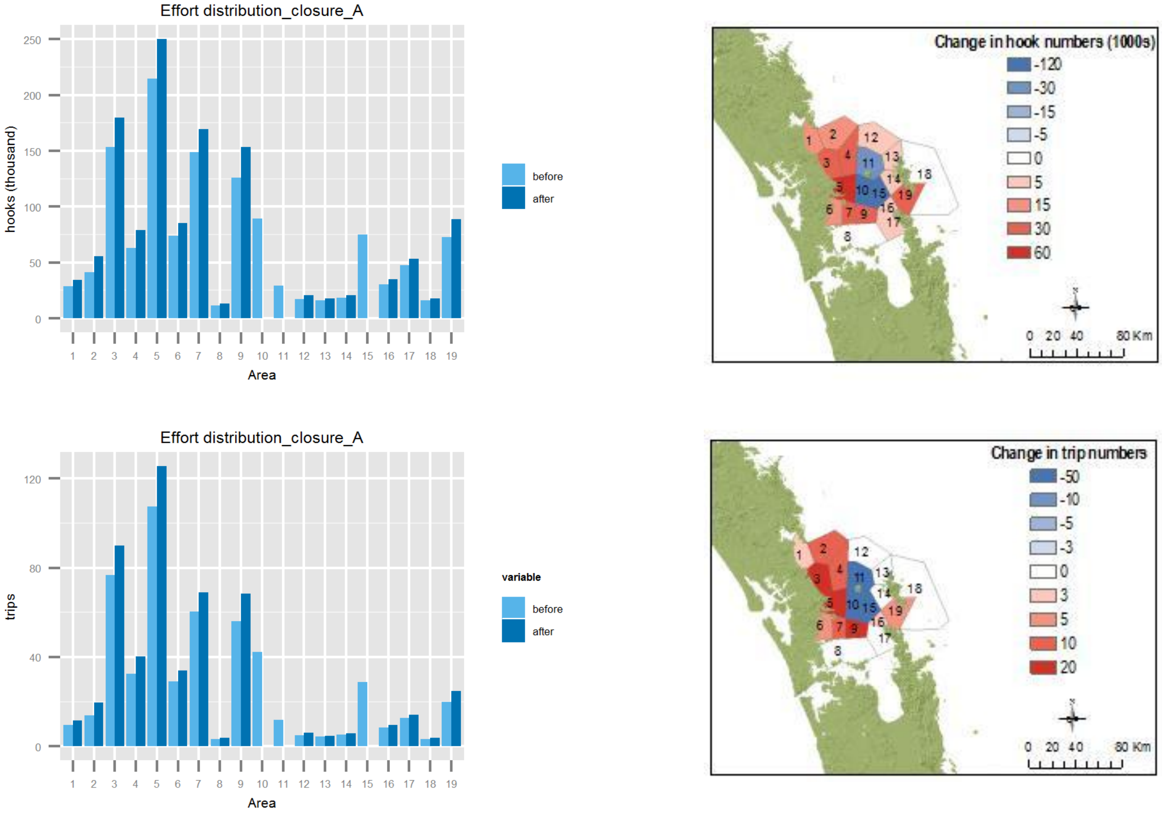
```
Chi squared [  31 d.f.]       3262.38163
Significance level                .00000
McFadden Pseudo R-squared       .3019387
Estimation based on N =    1931, K =  31
Inf.Cr.AIC  =    7604.4 AIC/N =    3.938
Model estimated: Sep 03, 2014, 17:02:20
Constants only must be computed directly
               Use NLOGIT ;...;RHS=ONE$
At start values -3837.5700  .0173******
Response data are given as ind. choices
The model has 2 levels.
Random Utility Form 1:IVparms = LMDAb|l
Number of obs.=  1931, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
        |Attributes in the Utility Functions (beta)
   VPUER|     .76638***      .05333     14.37  .0000      .66185    .87090
   VPUEY|     .42245***      .05029      8.40  .0000      .32389    .52101
      LR|    1.99740***      .07736     25.82  .0000     1.84577   2.14903
      LY|     .46357***      .10639      4.36  .0000      .25505    .67209
   DENSR|     .14408***      .03560      4.05  .0001      .07430    .21385
     CVR|   -1.54544***      .17872     -8.65  .0000    -1.89573  -1.19516
     PDL|     .28555***      .02973      9.60  .0000      .22728    .34382
      PL|   -2.54344***      .33799     -7.53  .0000    -3.20590  -1.88098
     PDD|    -.11307***      .00737    -15.34  .0000     -.12752   -.09863
  HWWIND|   -1.27093***      .16381     -7.76  .0000    -1.59199   -.94987
     A_1|     .68237         .54067      1.26  .2069     -.37732   1.74206
     A_2|     .42683         .32061      1.33  .1831     -.20156   1.05522
     A_3|    1.38904        1.13481      1.22  .2209     -.83516   3.61323
     A_4|    1.15814         .87269      1.33  .1845     -.55230   2.86858
     A_5|    -.68163         .70796      -.96  .3356    -2.06920    .70595
     A_6|    -.38250         .40679      -.94  .3471    -1.17979    .41479
     A_7|     .33082         .43028       .77  .4420     -.51250   1.17415
     A_8|    -.79109**       .32076     -2.47  .0137    -1.41978   -.16241
     A_9|    1.47721**       .74932      1.97  .0487      .00857   2.94586
    A_10|     .02507         .65525       .04  .9695    -1.25919   1.30932
    A_11|     .96782         .74140      1.31  .1918     -.48530   2.42094
    A_12|     .03377         .49761       .07  .9459     -.94153   1.00907
    A_13|   -1.28919***      .34332     -3.76  .0002    -1.96209   -.61630
    A_14|    -.94555***      .29064     -3.25  .0011    -1.51521   -.37590
    A_15|     .84167*        .46993      1.79  .0733     -.07937   1.76271
    A_16|    -.98515***      .25285     -3.90  .0001    -1.48072   -.48957
    A_17|    -.64868**       .26600     -2.44  .0147    -1.17003   -.12732
    A_18|   -3.06582***      .77602     -3.95  .0001    -4.58680  -1.54485
        |IV parameters, lambda(b|l),gamma(l)
      N1|     .65648***      .03548     18.50  .0000      .58694    .72601
      N2|     .78511***      .03486     22.52  .0000      .71678    .85344
      N3|     .53619***      .04457     12.03  .0000      .44883    .62355
      N4|        1.0      .....(Fixed Parameter).....
        |Underlying standard deviation = pi/(IVparm*sqr(6))
      N1|    1.95369***      .10559     18.50  .0000     1.74674   2.16064
      N2|    1.63359***      .07254     22.52  .0000     1.49142   1.77576
      N3|    2.39197***      .19885     12.03  .0000     2.00224   2.78170
      N4|    1.28255      .....(Fixed Parameter).....
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
Fixed parameter ... is constrained to equal the value or
had a nonpositive st.error because of an earlier problem.
-----------------------------------------------------------------------------
```



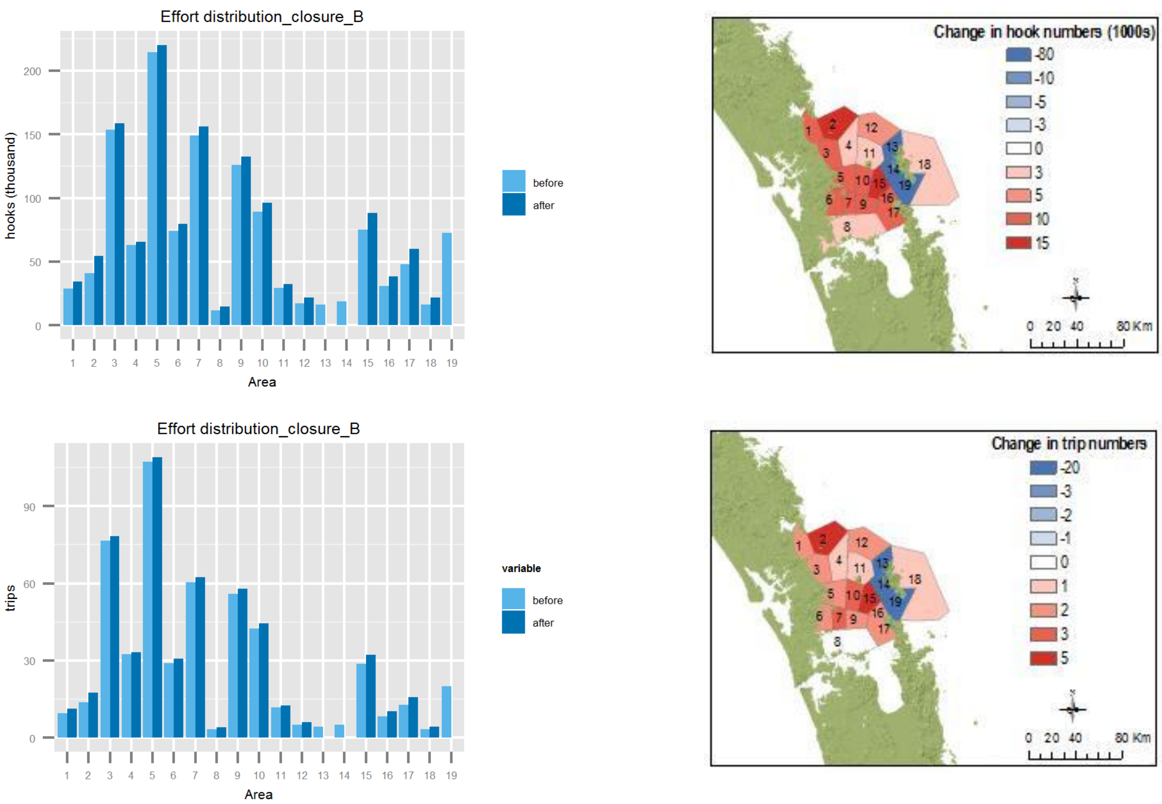
Apx Figure C.8 Out of sample fit at the annual level, observed vs. modelled distribution of effort for vessels fishing from Leigh



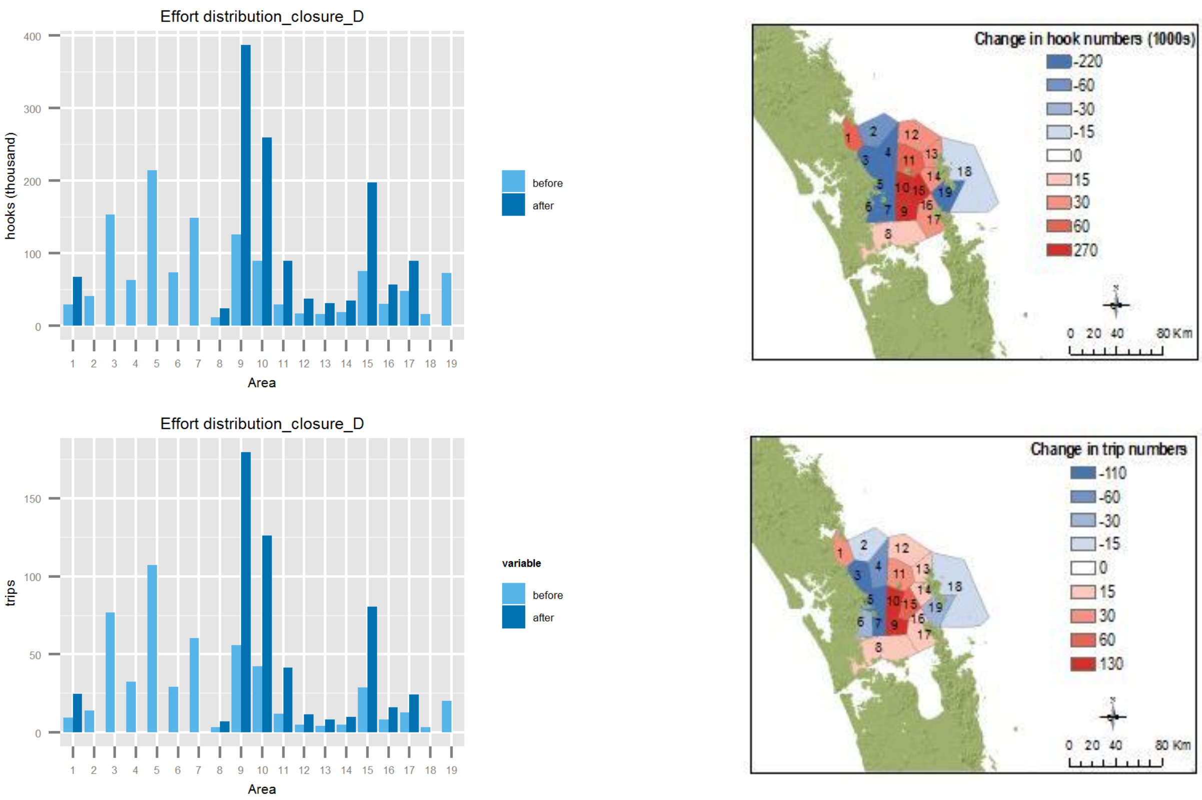
Apx Figure C.9 Out of sample fit at the monthly level, observed vs. modelled distribution of effort for vessels fishing from Leigh



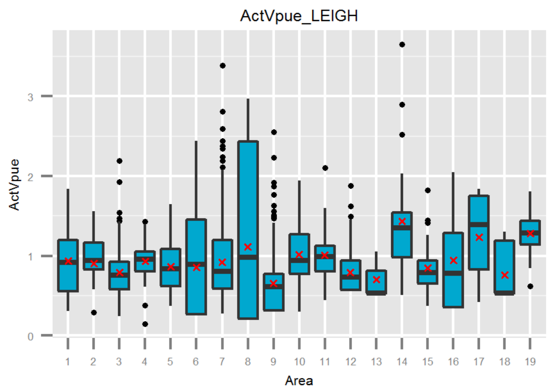
Apx Figure C.10 Predicted effort redistributions for the Leigh model under scenario A, trips to locations and numbers of hooks set



Apx Figure C.11 Predicted effort redistributions for the Leigh model under scenario B, trips to locations and numbers of hooks set



Apx Figure C.12 Predicted effort redistributions for the Leigh model under scenario D, trips to locations and numbers of hooks set



Apx Figure C.13 Actual VPUE values by location in 2011-12, red x indicates the mean

C.1.3 COROMANDEL

Apx Table C.3 Coromandel area definitions and application of closure scenarios

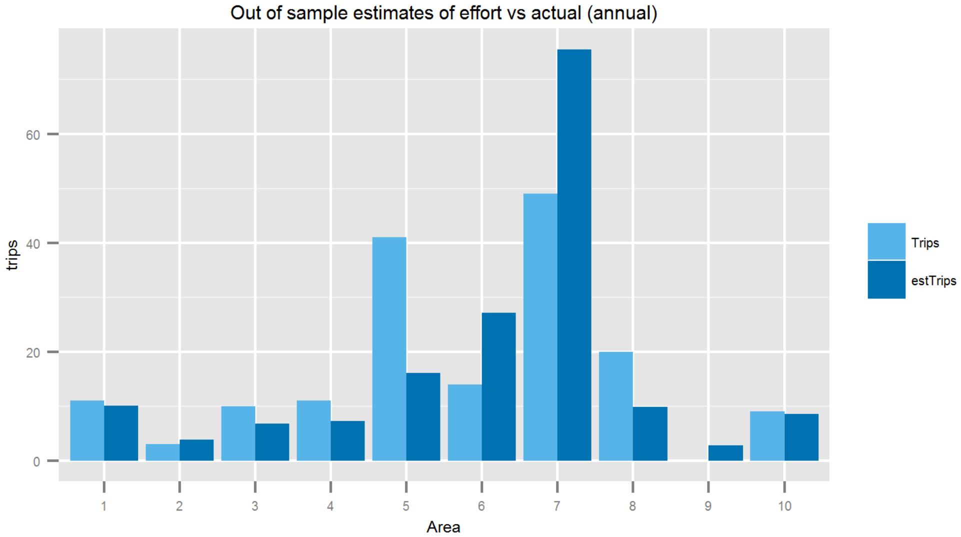
Initial location	port specific location	obs	scenario A	scenario B	scenario C	scenario D
15	1	8			1	
16	1	4			1	

20	2	1			2		
21	2	18			2		
22	3	2	NA				
23	3	33					
24	4	35					
25	1	40				1	
26	5	143					
27	6	49				6	
28	7	126					
29	8	54					
30	8	8	NA				
31	9	3		NA			9
32	10	47			10		10
33	9	3					9
34	9	1					9

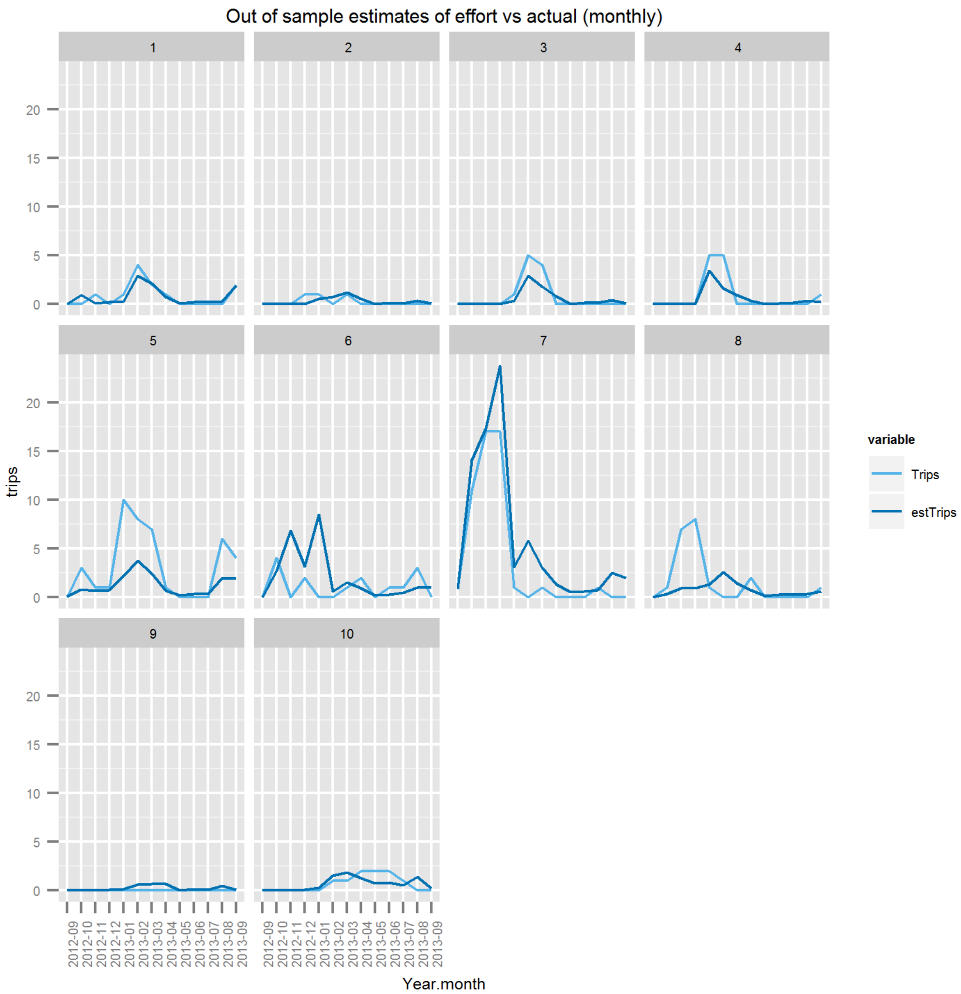
MODEL OUTPUT

```
|-> NLOGIT;  M5
    Lhs=CHOICE,CSET,ALTIJ;Choices=1,2,3,4,5,6,7,8,
    9,10
    ;Rhs=vpueR,vpueY,LR,LY,DensR,PDL,PDD,HWwind
    ;Rh2=one
    ;RU1
    ;TREE= n1(1,5,6,8),n2(2,3,4,7,9,10)
    ;ivset: (n2)=[1.0]
    ;maxit=100
    ;checkdata$
+--------------------------------------------------------+
| Inspecting the data set before estimation.             |
| These errors mark observations which will be skipped.  |
| Row Individual = 1st row then group number of data block |
+--------------------------------------------------------+
No bad observations were found in the sample
Normal exit:   6 iterations. Status=0, F=    890.4075
-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function      -890.40749
Estimation based on N =     540, K =  17
Inf.Cr.AIC  =   1814.8 AIC/N =    3.361
Model estimated: Sep 03, 2014, 14:22:28
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only must be computed directly
               Use NLOGIT ;...;RHS=ONE$
Chi-squared[ 8]           =    436.90045
Prob [ chi squared > value ] =   .00000
Response data are given as ind. choices
Number of obs.=    540, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.       95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*          Interval
--------+--------------------------------------------------------------------
   VPUER|   1.35163***      .14085     9.60  .0000      1.07556   1.62770
   VPUEY|    .56939***      .17354     3.28  .0010       .22926    .90953
      LR|   1.00145***      .13344     7.50  .0000       .73992   1.26299
      LY|    .28202*        .15478     1.82  .0685     -.02135    .58539
   DENSR|    .35826***      .08974     3.99  .0001       .18237    .53415
     PDL|    .02402         .01553     1.55  .1219     -.00642    .05445
     PDD|   -.13190***      .02043    -6.46  .0000     -.17193   -.09187
  HWWIND|  -1.18967**       .50374    -2.36  .0182    -2.17698   -.20236
     A_1|   -.89608         .55660    -1.61  .1074    -1.98699    .19484
     A_2|   -.17304         .35511     -.49  .6260     -.86904    .52295
```

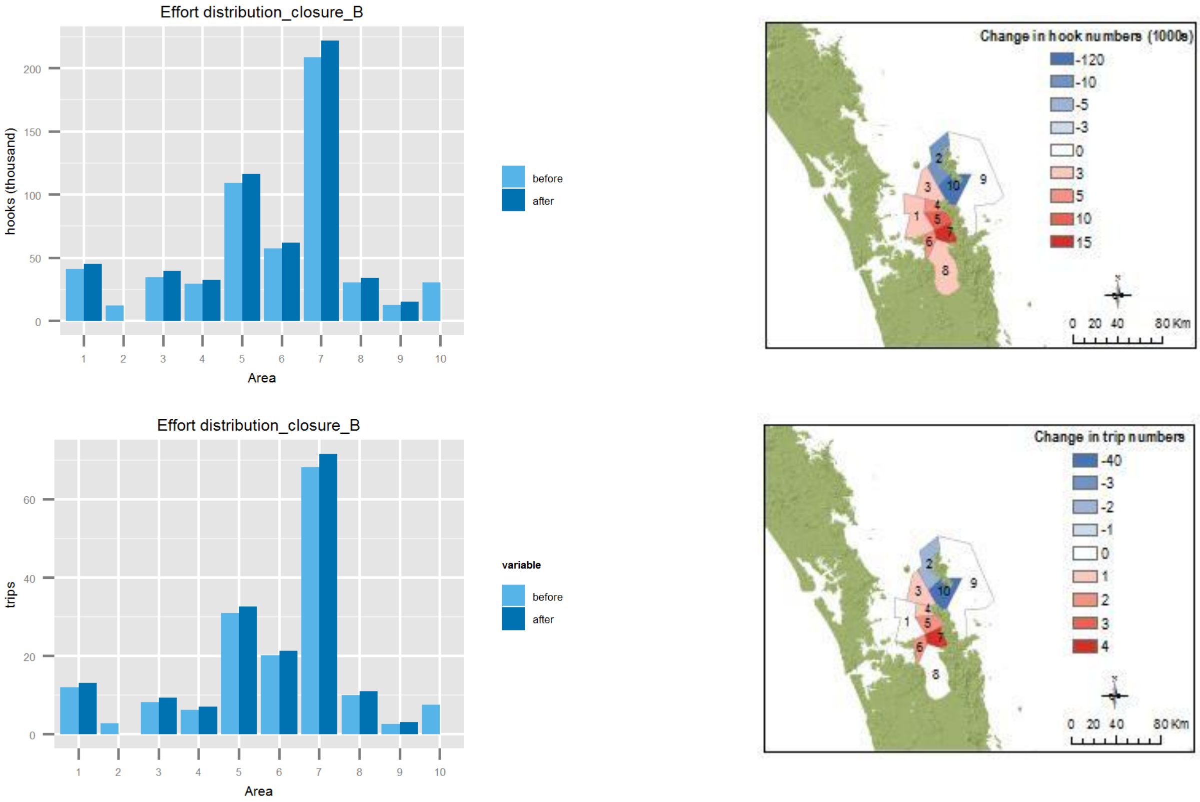
```
     A_3|    -.69040**       .33043     -2.09  .0367    -1.33803    -.04277
     A_4|   -1.12689**       .55834     -2.02  .0436    -2.22122    -.03256
     A_5|    -.98084         .81862     -1.20  .2309    -2.58532     .62363
     A_6|   -1.39608*        .78900     -1.77  .0768    -2.94250     .15034
     A_7|   -1.61040        1.08770     -1.48  .1387    -3.74225     .52145
     A_8|   -1.41870         .87824     -1.62  .1062    -3.14001     .30261
     A_9|    -.69350         .78531      -.88  .3772    -2.23268     .84568
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-----------------------------------------------------------------------------
Normal exit:  26 iterations. Status=0, F=    881.0931
-----------------------------------------------------------------------------
FIML Nested Multinomial Logit Model
Dependent variable               CHOICE
Log likelihood function      -881.09312
Restricted log likelihood   -1227.50843
Chi squared [  18 d.f.]       692.83063
Significance level               .00000
McFadden Pseudo R-squared      .2822101
Estimation based on N =     540, K =  18
Inf.Cr.AIC  =   1798.2 AIC/N =    3.330
Model estimated: Sep 03, 2014, 14:22:28
Constants only must be computed directly
               Use NLOGIT ;...;RHS=ONE$
At start values  -890.4075  .0105******
Response data are given as ind. choices
The model has 2 levels.
Random Utility Form 1:IVparms = LMDAb|l
Number of obs.=   540, skipped    0 obs


--------+--------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z     |z|>Z*        Interval
--------+--------------------------------------------------------------------
        |Attributes in the Utility Functions (beta)
   VPUER|    1.41623***      .15340      9.23  .0000     1.11558    1.71688
   VPUEY|     .58540***      .18033      3.25  .0012      .23195     .93885
      LR|    1.06714***      .14716      7.25  .0000      .77871    1.35556
      LY|     .29484*        .16424      1.80  .0726     -.02707     .61675
   DENSR|     .43722***      .09959      4.39  .0000      .24203     .63241
     PDL|     .03582**       .01422      2.52  .0118      .00794     .06369
     PDD|    -.15210***      .02395     -6.35  .0000     -.19905    -.10516
  HWWIND|   -1.15909**       .50985     -2.27  .0230    -2.15838    -.15980
     A_1|    -.04461        1.28989      -.03  .9724    -2.57274    2.48353
     A_2|    -.24047         .33767      -.71  .4764     -.90229     .42135
     A_3|    -.58923*        .31066     -1.90  .0579    -1.19811     .01964
     A_4|    -.93314*        .50147     -1.86  .0628    -1.91600     .04973
     A_5|    -.06897        1.52356      -.05  .9639    -3.05510    2.91716
     A_6|    -.49640        1.49663      -.33  .7401    -3.42974    2.43694
     A_7|   -1.20859         .95257     -1.27  .2045    -3.07560     .65842
     A_8|    -.54973        1.57318      -.35  .7268    -3.63310    2.53364
     A_9|    -.97984         .71812     -1.36  .1724    -2.38734     .42766
        |IV parameters, lambda(b|l),gamma(l)
      N1|     .61746***      .08665      7.13  .0000      .44762     .78730
      N2|        1.0      .....(Fixed Parameter).....
        |Underlying standard deviation = pi/(IVparm*sqr(6))
      N1|    2.07715***      .29151      7.13  .0000     1.50580    2.64850
      N2|    1.28255      .....(Fixed Parameter).....
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
Fixed parameter ... is constrained to equal the value or
had a nonpositive st.error because of an earlier problem.
-----------------------------------------------------------------------------
```



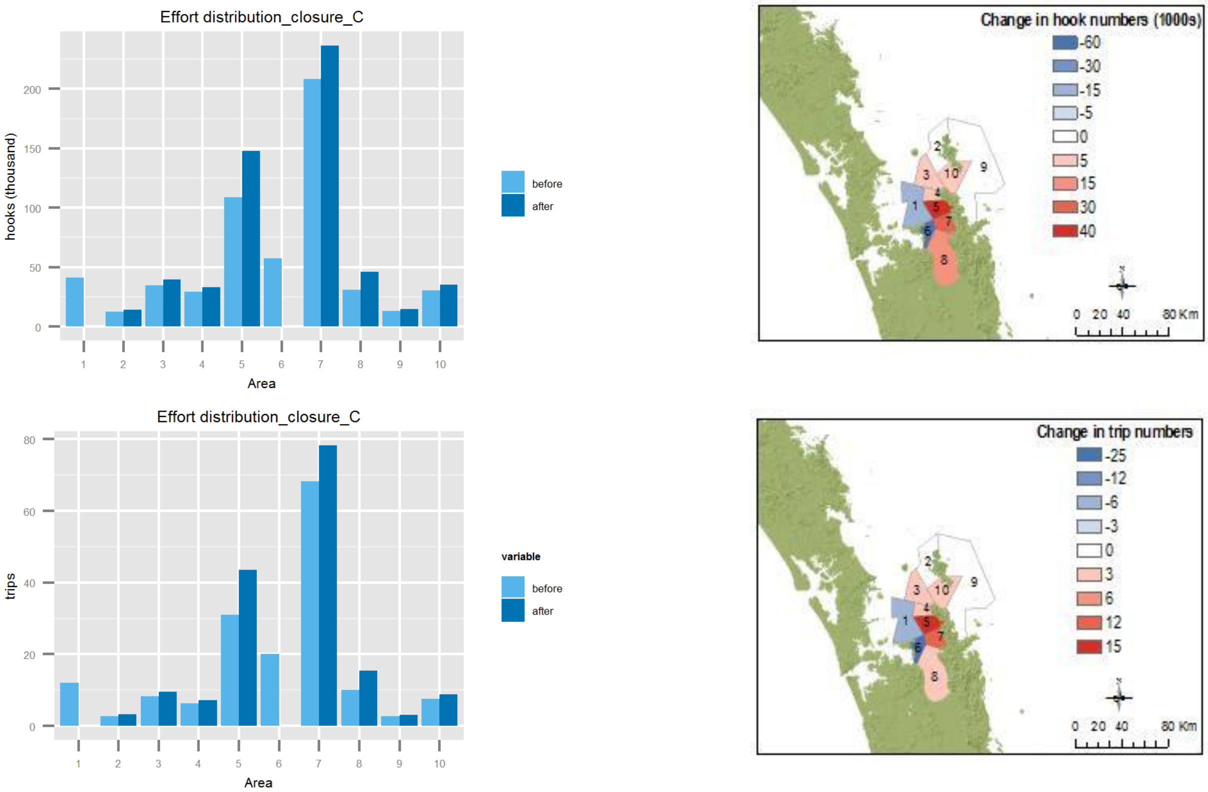
Apx Figure C.14 Out of sample fit at the annual level, observed vs. modelled distribution of effort for vessels fishing from Coromandel



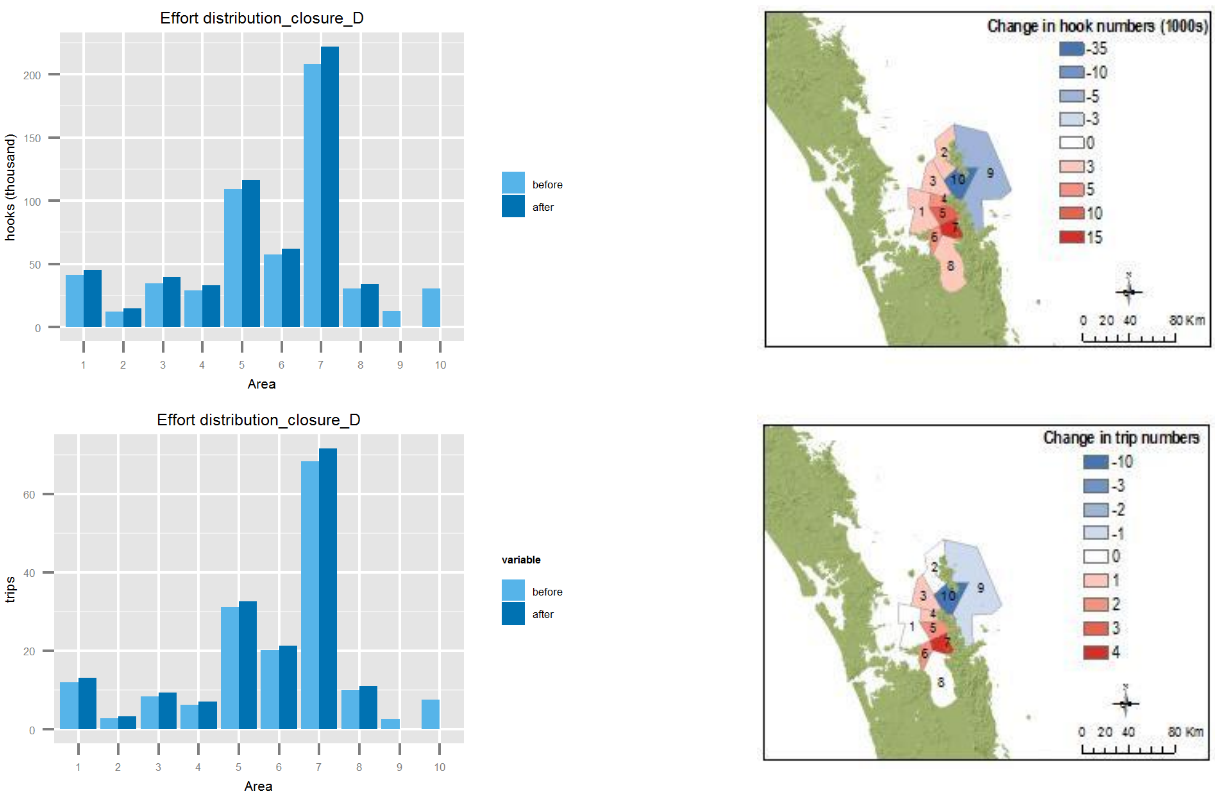
Apx Figure C.15 Out of sample fit at the monthly level, observed vs. modelled distribution of effort for vessels fishing from Coromandel



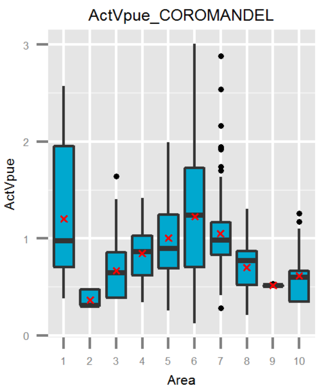
Apx Figure C.16 Predicted effort redistributions for the Coromandel model under scenario B, trips to locations and numbers of hooks set



Apx Figure C.17 Predicted effort redistributions for the Coromandel model under scenario C, trips to locations and numbers of hooks set



Apx Figure C.18 Predicted effort redistributions for the Coromandel model under scenario D, trips to locations and numbers of hooks set



Apx Figure C.19 Actual VPUE values by location in 2011-12, red x indicates the mean

C.1.4 WHITIANGA

Apx Table C.4 Whitianga area definitions and application of closure scenarios

Initial location	port specific location	obs	scenario A	scenario B	scenario C	scenario D
6	1	48				
7	2	80				2

8	3	393				3
9	4	222				4
10	5	170				5
11	6	68				6
12	7	206	7			7
13	8	8	NA			
15	8	2			NA	
16	9	185				
17	10	128	10			
18	11	104				
19	12	14				
20	13	16		13		
21	14	18		14		
22	15	122				
23	16	33				
24	17	31				
25	8	4	NA		NA	
26	17	10				
31	18	2		NA		18

MODEL OUTPUT

```
|-> NLOGIT M5
    ;Lhs=CHOICE,CSET,ALTIJ;Choices=1,2,3,4,5,6,7,8,
    9,10,11,12,13
    ;Rhs=vpueR,vpueY,LR,LY,DensR,PDL,
    PL,PDD,HWwind
    ;rh2= one
    ;TREE= n1(1,9,10,12),n2(2,3,4,5,6,7,13),n3(8,11)
    ;ivset: (n2)=[1.0]
    ;maxit=100
    ;checkdata$
+-----------------------------------------------------------+
| Inspecting the data set before estimation.                |
| These errors mark observations which will be skipped.     |
| Row Individual = 1st row then group number of data block |
+-----------------------------------------------------------+
No bad observations were found in the sample
Normal exit:   6 iterations. Status=0, F=    4993.271
-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable                 Choice
Log likelihood function     -4993.27084
Estimation based on N =    2685, K =  21
Inf.Cr.AIC  =  10028.5 AIC/N =    3.735
Model estimated: Sep 03, 2014, 17:03:53
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only must be computed directly
               Use NLOGIT ;...;RHS=ONE$
Chi-squared[ 9]          =   1518.20075
Prob [ chi squared > value ] =    .00000
Response data are given as ind. choices
Number of obs.=  2685, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
   VPUER|    1.37753***      .11569    11.91  .0000     1.15078   1.60428
   VPUEY|     .30324***      .10861     2.79  .0052      .09038    .51610
```

LR	1.27446***	.05087	25.06	.0000	1.17476	1.37415
LY	.65853***	.06571	10.02	.0000	.52974	.78731
DENSR	.04010**	.01858	2.16	.0309	.00369	.07650
PDL	.03656***	.00881	4.15	.0000	.01930	.05382
PL	.17467**	.08231	2.12	.0338	.01335	.33599
PDD	-.06757***	.00442	-15.30	.0000	-.07622	-.05891
HWWIND	-.41740***	.15063	-2.77	.0056	-.71263	-.12217
A_1	-3.76149***	.71100	-5.29	.0000	-5.15503	-2.36796
A_2	-2.62777***	.62098	-4.23	.0000	-3.84487	-1.41067
A_3	-3.69278***	.68229	-5.41	.0000	-5.03005	-2.35552
A_4	-1.52159***	.42730	-3.56	.0004	-2.35908	-.68411
A_5	-.54619**	.22188	-2.46	.0138	-.98108	-.11131
A_6	.53403***	.14535	3.67	.0002	.24915	.81892
A_7	1.28529***	.15470	8.31	.0000	.98208	1.58849
A_8	1.72027***	.23834	7.22	.0000	1.25313	2.18742
A_9	.81962***	.18630	4.40	.0000	.45448	1.18475
A_10	1.17746***	.38148	3.09	.0020	.42977	1.92515
A_11	.69929***	.15921	4.39	.0000	.38725	1.01132
A_12	1.56458***	.25867	6.05	.0000	1.05760	2.07156

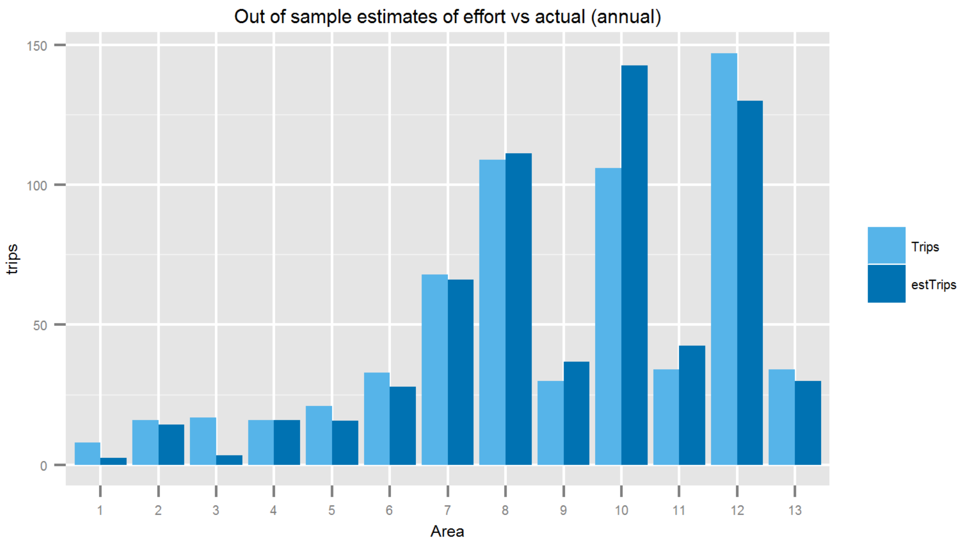
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

Normal exit: 46 iterations. Status=0, F= 4967.295

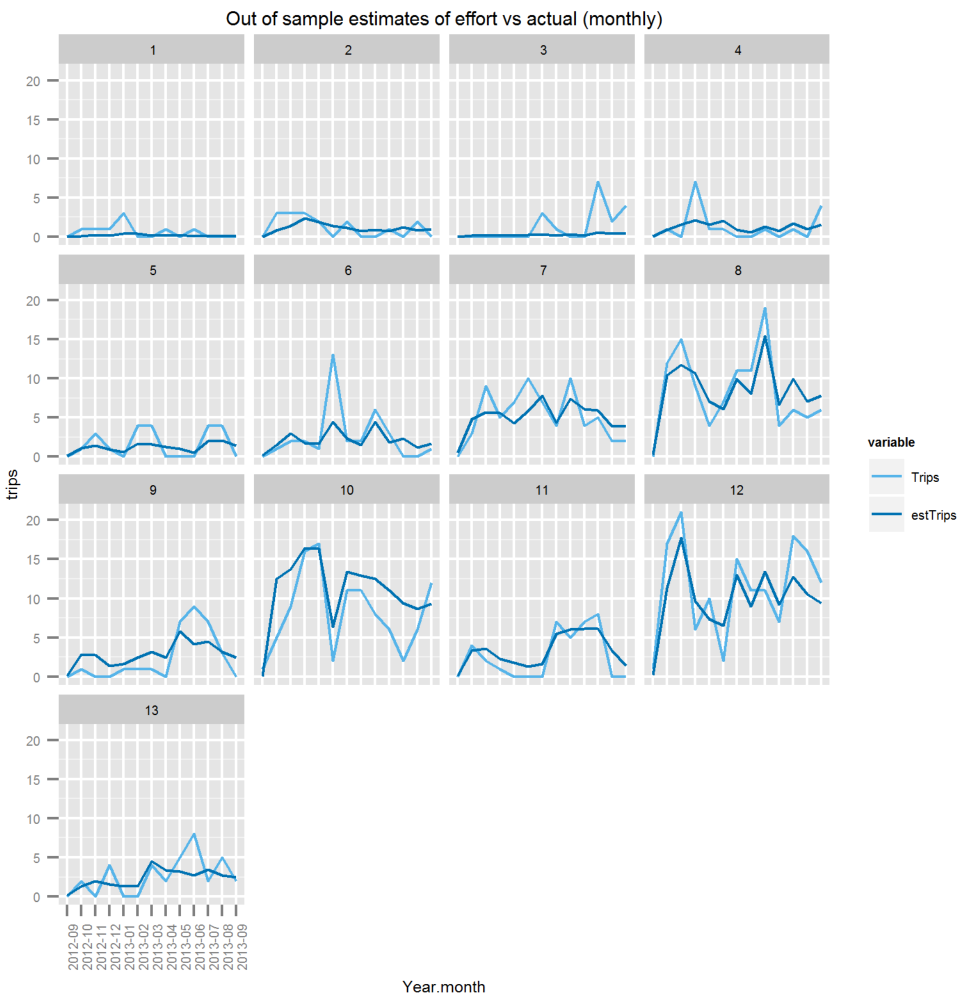
FIML Nested Multinomial Logit Model
Dependent variable CHOICE
Log likelihood function -4967.29504
Restricted log likelihood -6556.31559
Chi squared [23 d.f.] 3178.04110
Significance level .00000
McFadden Pseudo R-squared .2423649
Estimation based on N = 2685, K = 23
Inf.Cr.AIC = 9980.6 AIC/N = 3.717
Model estimated: Sep 03, 2014, 17:04:01
Constants only must be computed directly
Use NLOGIT ;...;RHS=ONE$
At start values -4993.2708 .0052******
Response data are given as ind. choices
The model has 2 levels.
Nested Logit form:IVparms=Taub|l,r,Sl|r
& Fr.No normalizations imposed a priori
Number of obs.= 2685, skipped 0 obs

CHOICE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
	Attributes in the Utility Functions (beta)					
VPUER	1.40012***	.12541	11.16	.0000	1.15432	1.64592
VPUEY	.33982***	.11346	2.99	.0027	.11744	.56221
LR	1.40973***	.06111	23.07	.0000	1.28996	1.52949
LY	.73409***	.07423	9.89	.0000	.58859	.87959
DENSR	.05178**	.02104	2.46	.0138	.01054	.09301
PDL	.03348***	.00725	4.62	.0000	.01928	.04768
PL	.20227***	.06733	3.00	.0027	.07032	.33423
PDD	-.06048***	.00361	-16.74	.0000	-.06756	-.05340
HWWIND	-.52159***	.15231	-3.42	.0006	-.82011	-.22307
A_1	.63807	1.30293	.49	.6243	-1.91562	3.19177
A_2	-2.84776***	.53366	-5.34	.0000	-3.89372	-1.80180
A_3	-3.90171***	.60510	-6.45	.0000	-5.08768	-2.71573
A_4	-1.68555***	.37304	-4.52	.0000	-2.41668	-.95441
A_5	-.61794***	.20770	-2.98	.0029	-1.02503	-.21085
A_6	.58770***	.14430	4.07	.0000	.30488	.87052
A_7	1.37726***	.14535	9.48	.0000	1.09238	1.66214
A_8	2.85777***	.44991	6.35	.0000	1.97596	3.73959
A_9	5.13154***	1.34792	3.81	.0001	2.48968	7.77341
A_10	5.54090***	1.43668	3.86	.0001	2.72505	8.35675
A_11	1.72787***	.40081	4.31	.0000	.94231	2.51343
A_12	5.90572***	1.38365	4.27	.0000	3.19381	8.61763
	IV parameters, tau(b|l,r),sigma(l|r),phi(r)					
N1	.50534***	.06985	7.23	.0000	.36843	.64224
N2	1.0	.....(Fixed Parameter).....				
N3	.80689***	.05409	14.92	.0000	.70088	.91290

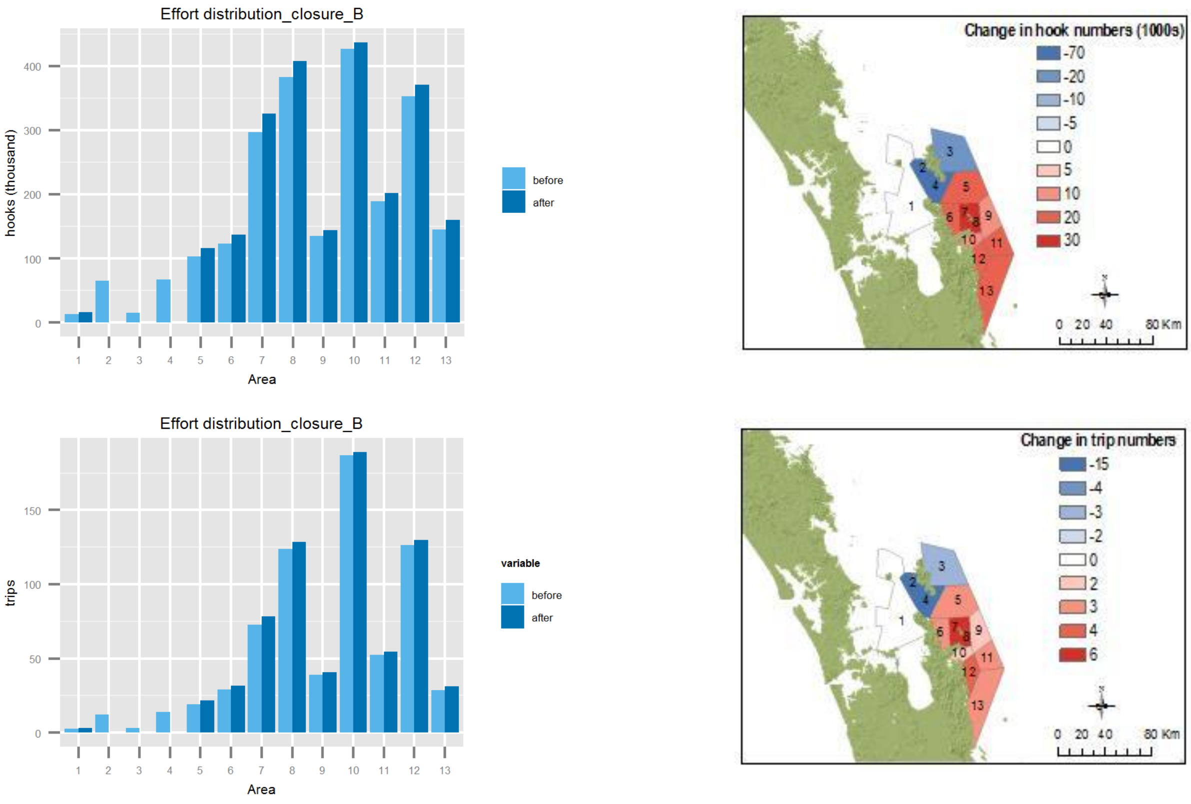
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
Fixed parameter ... is constrained to equal the value or
had a nonpositive st.error because of an earlier problem.



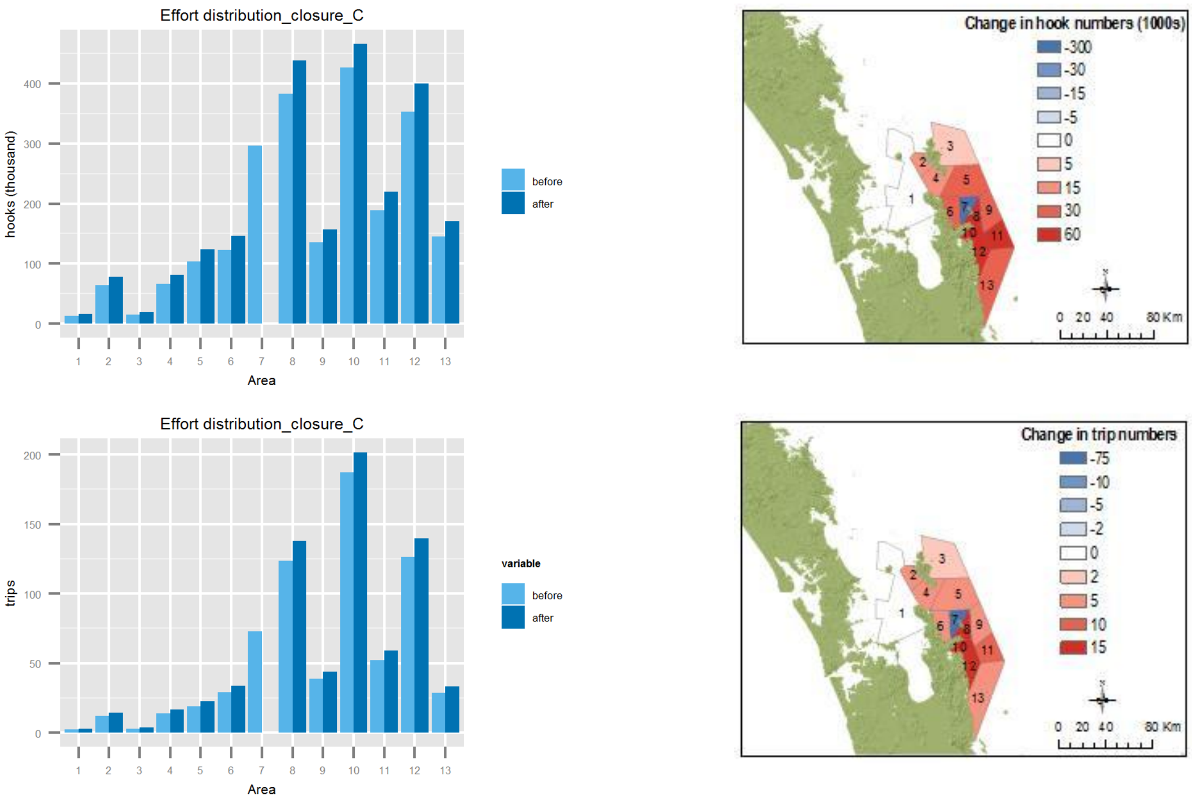
Apx Figure C.20 Out of sample fit at the annual level, observed vs. modelled distribution of effort for vessels fishing from Whitianga



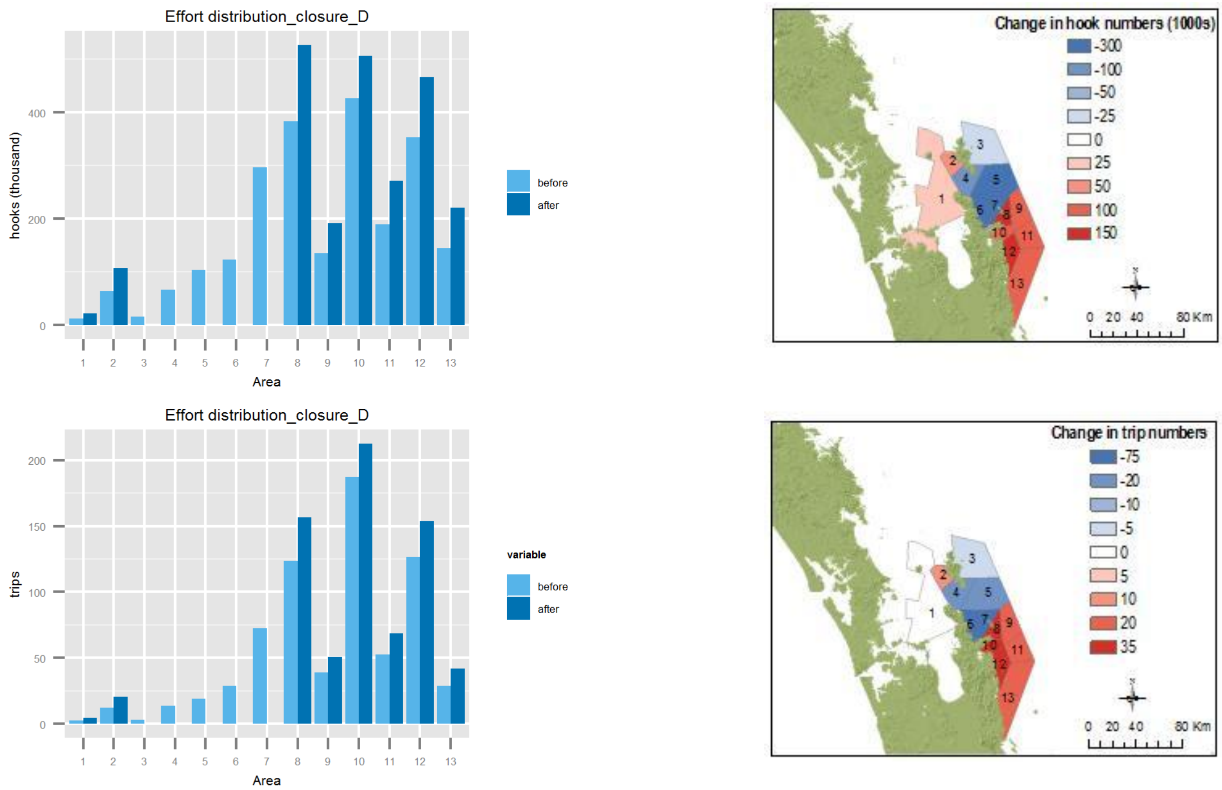
Apx Figure C.21 Out of sample fit at the monthly level, observed vs. modelled distribution of effort for vessels fishing from Whitianga



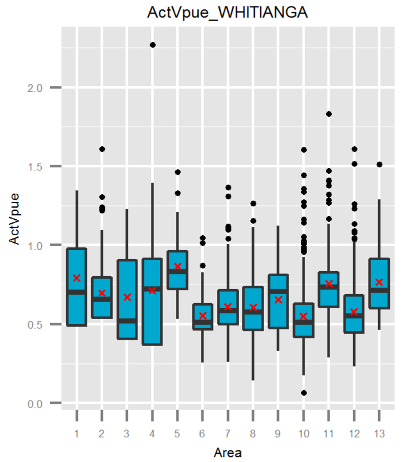
Apx Figure C.22 Predicted effort redistributions for the Whitianga model under scenario B, trips to locations and numbers of hooks set



Apx Figure C.23 Predicted effort redistributions for the Whitianga model under scenario C, trips to locations and numbers of hooks set



Apx Figure C.24 Predicted effort redistributions for the Whitianga model under scenario D, trips to locations and numbers of hooks set



Apx Figure C.25 Actual VPUE values by location in 2011-12, red x indicates the mean

C.1.5 MAHURANGI _SANDSPIT

Apx Table C.5 Mahurangi and Sandspit area definitions and application of closure scenarios

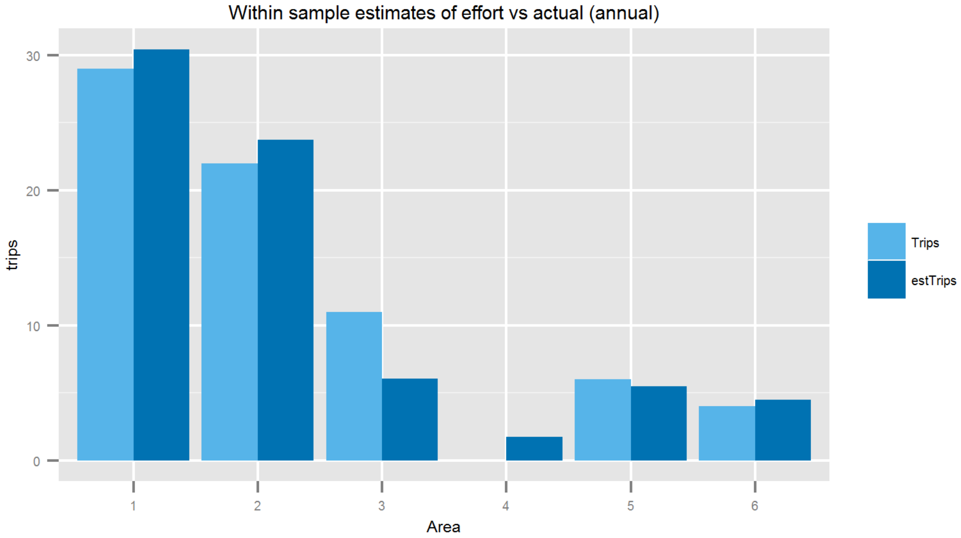
Initial location	port specific location	obs	scenario A	scenario B	scenario C	scenario D

10	1	6			1
11	1	73			1
12	2	84			2
13	3	17	3		
15	4	9		4	
16	5	23			
17	6	50	6		
25	4	10	NA	4	

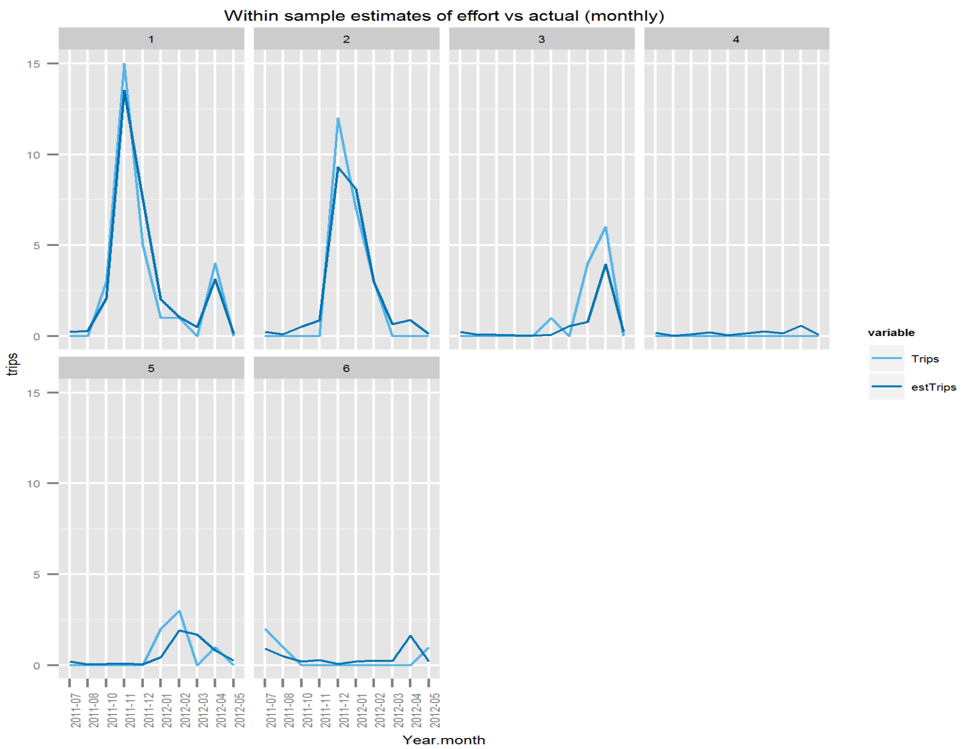
MODEL OUTPUT

```
|-> NLOGIT; M5
    Lhs=CHOICE,CSET,ALTIJ;Choices=1,2,3,4,5,6
    ;Rhs=vpueR,vpueY,LR,DensY,CvR,PDD
    ;Rh2=one
    ;RU1
    ;TREE= n1(1,3),n2(2,4,5,6)
    ;ivset: (n2)=[1.0]
    ;maxit=100
    ;checkdata$
+-------------------------------------------------------------+
| Inspecting the data set before estimation.                  |
| These errors mark observations which will be skipped.       |
| Row Individual = 1st row then group number of data block |
+-------------------------------------------------------------+
No bad observations were found in the sample
Normal exit:   6 iterations. Status=0, F=    286.1192
-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable                Choice
Log likelihood function      -286.11917
Estimation based on N =     270, K =  11
Inf.Cr.AIC  =    594.2 AIC/N =    2.201
Model estimated: Sep 03, 2014, 17:05:03
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only must be computed directly
               Use NLOGIT ;...;RHS=ONE$
Chi-squared[ 6]           =    293.93330
Prob [ chi squared > value ] =    .00000
Response data are given as ind. choices
Number of obs.=   270, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
   VPUER|   1.15237***      .19075     6.04  .0000      .77852   1.52623
   VPUEY|    .71331***      .20539     3.47  .0005      .31076   1.11586
      LR|   1.08943***      .19615     5.55  .0000      .70499   1.47388
   DENSY|    .26915***      .08399     3.20  .0014      .10454    .43376
     CVR|  -2.83093***      .74241    -3.81  .0001    -4.28602  -1.37583
     PDD|   -.06482***      .01884    -3.44  .0006     -.10174   -.02791
     A_1|  -2.38222***      .61411    -3.88  .0001    -3.58584  -1.17859
     A_2|  -1.76082***      .49182    -3.58  .0003    -2.72477   -.79687
     A_3|  -1.43530***      .31102    -4.61  .0000    -2.04490   -.82571
     A_4|   -.59980*        .30603    -1.96  .0500    -1.19960    .00001
     A_5|   -.60954**       .28877    -2.11  .0348    -1.17553   -.04355
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-----------------------------------------------------------------------------
Normal exit:  19 iterations. Status=0, F=    282.2716
-----------------------------------------------------------------------------
FIML Nested Multinomial Logit Model
Dependent variable                CHOICE
Log likelihood function      -282.27156
Restricted log likelihood    -496.29338
Chi squared [  12 d.f.]       428.04365
Significance level               .00000
McFadden Pseudo R-squared      .4312405
Estimation based on N =     270, K =  12
```

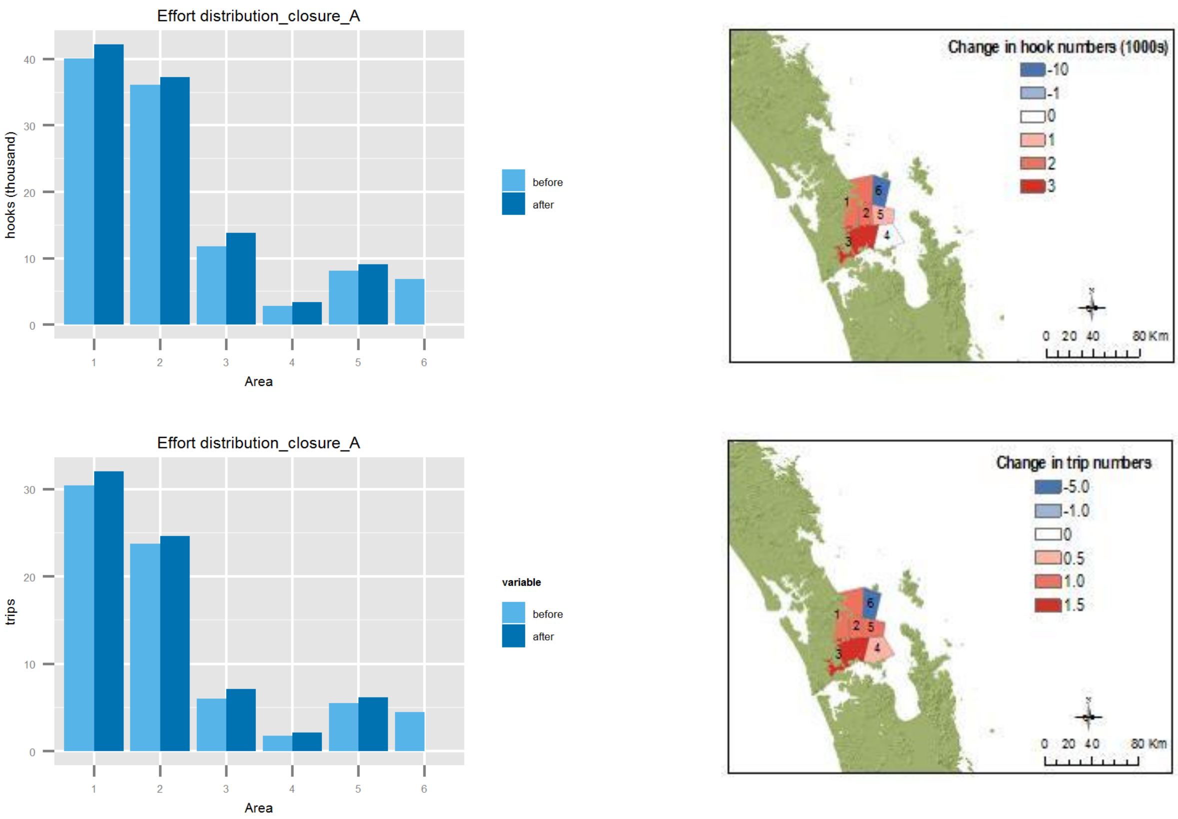
```
Inf.Cr.AIC  =    588.5 AIC/N =    2.180
Model estimated: Sep 03, 2014, 17:05:04
Constants only must be computed directly
               Use NLOGIT ;...;RHS=ONE$
At start values  -286.1192  .0134******
Response data are given as ind. choices
The model has 2 levels.
Random Utility Form 1:IVparms = LMDAb|l
Number of obs.=   270, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
        |Attributes in the Utility Functions (beta)
   VPUER|    1.29299***      .21368     6.05  .0000      .87419   1.71179
   VPUEY|     .86016***      .22459     3.83  .0001      .41998   1.30035
      LR|    1.19932***      .22265     5.39  .0000      .76293   1.63571
   DENSY|     .26598***      .09559     2.78  .0054      .07862    .45334
     CVR|   -2.96972***      .80550    -3.69  .0002    -4.54847  -1.39097
     PDD|    -.06269***      .01589    -3.95  .0001     -.09382   -.03155
     A_1|   -3.08918***     1.01949    -3.03  .0024    -5.08735  -1.09101
     A_2|   -1.87544***      .42852    -4.38  .0000    -2.71533  -1.03555
     A_3|   -2.39389***      .74887    -3.20  .0014    -3.86164   -.92614
     A_4|    -.59660*        .31260    -1.91  .0563    -1.20929    .01609
     A_5|    -.57277*        .29292    -1.96  .0505    -1.14688    .00134
        |IV parameters, lambda(b|l),gamma(l)
      N1|     .63026***      .11977     5.26  .0000      .39552    .86501
      N2|        1.0     .....(Fixed Parameter).....
        |Underlying standard deviation = pi/(IVparm*sqr(6))
      N1|    2.03495***      .38671     5.26  .0000     1.27702   2.79288
      N2|    1.28255     .....(Fixed Parameter).....
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
Fixed parameter ... is constrained to equal the value or
had a nonpositive st.error because of an earlier problem.
-----------------------------------------------------------------------------
```



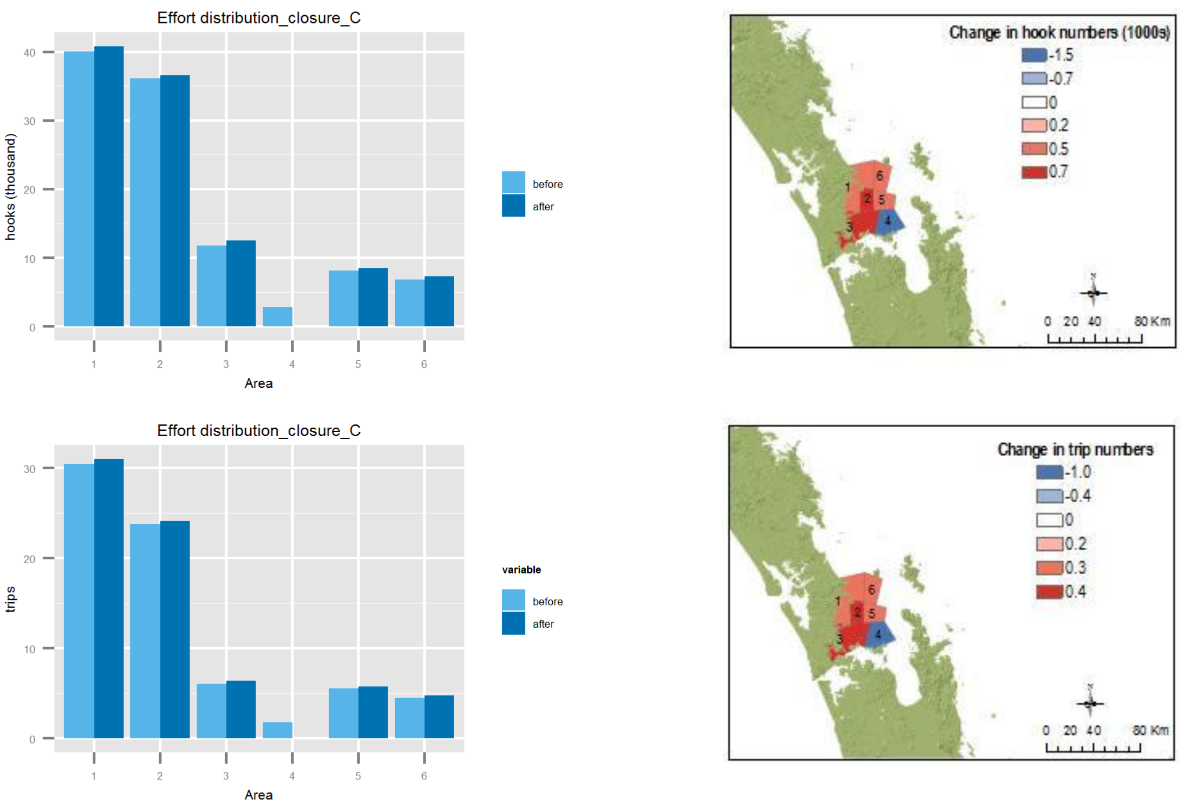
Apx Figure C.26 Out of sample fit at the annual level, observed vs. modelled distribution of effort for vessels fishing from Mahurangi/Sandspit



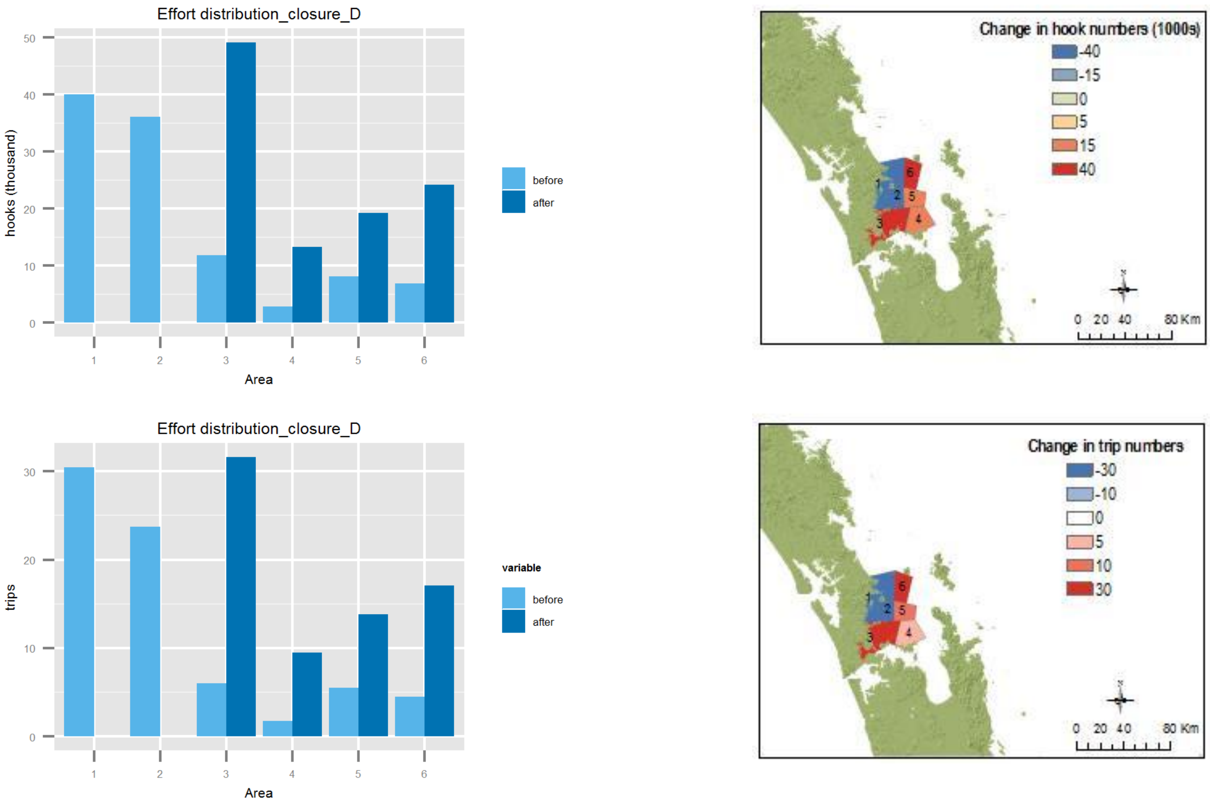
Apx Figure C.27 Out of sample fit at the monthly level, observed vs. modelled distribution of effort for vessels fishing from Mahurangi/Sandspit



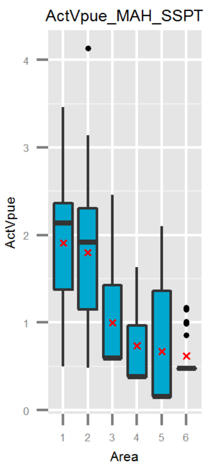
Apx Figure C.28 Predicted effort redistributions for the Mahurangi/Sandspit model under scenario A, trips to locations and numbers of hooks set



Apx Figure C.29 Predicted effort redistributions for the Mahurangi/Sandspit model under scenario C, trips to locations and numbers of hooks set



Apx Figure C.30 Predicted effort redistributions for the Mahurangi/Sandspit model under scenario D, trips to locations and numbers of hooks set



Apx Figure C.31 Actual VPUE values by location in 2011-12, red x indicates the mean

C.2 Single HGMP region model

MODEL OUTPUT

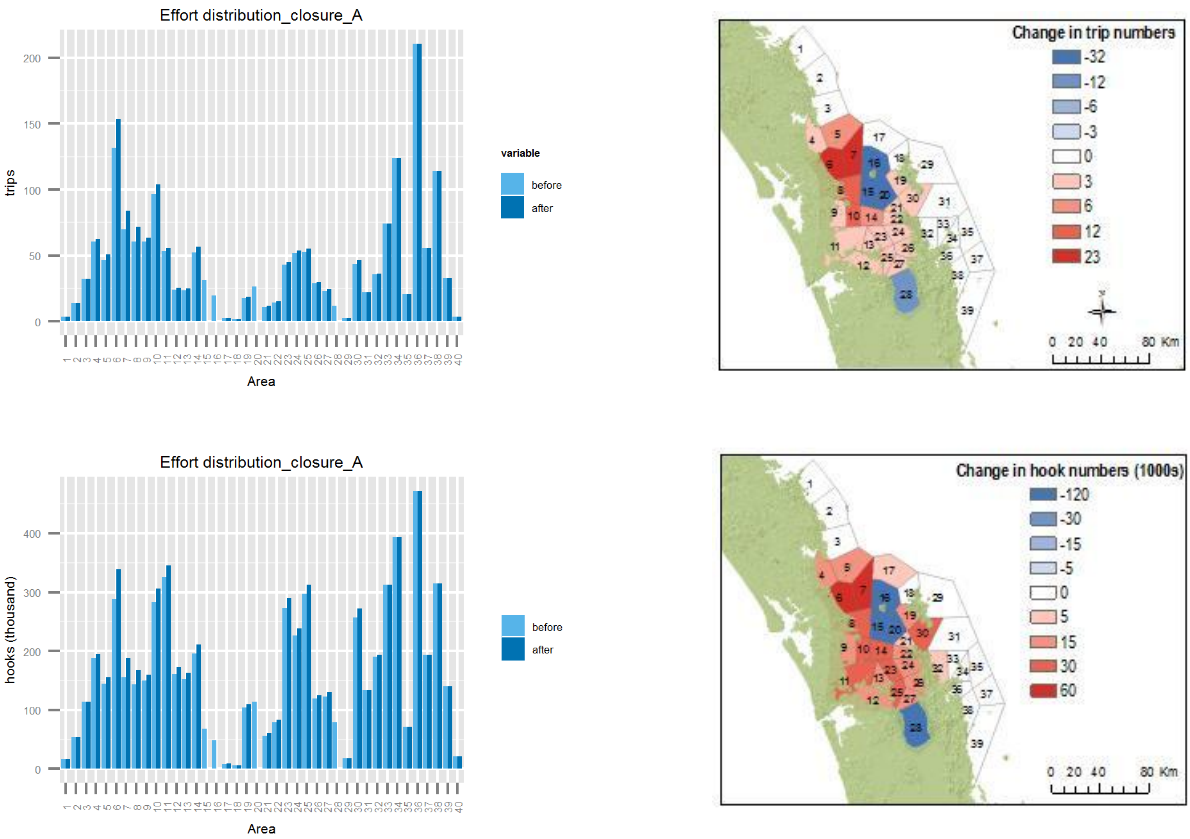
```
|-> NLOGIT; ? M5
    Lhs=CHOICE,CSET,ALTIJ;Choices=1,2,3,4,5,6,7,8,
    9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,
    24,25,26,27,28,29,30,
    31,32,33,34,35,36,37,38,39,40
    ;Rhs=vpueR,vpueY,LR,LY,DensR,CvR,CvY,PDL,
    PL,PDD,HWwind
    ;Rh2= one
    ;RU1
    ;maxit=200
    ;TREE= n1(9,10,27,28,19,20,25,26,33,34,11,12,17,18,29,30,23,24,13,14,31,32,21,22),
    n3(1,2,3,4,5,6,8,15,16,7,35,36,37,38), n2(39,40)
    ;ivset: (n1)=[1.0]
    ;checkdata$
+-----------------------------------------------------------+
| Inspecting the data set before estimation.                |
| These errors mark observations which will be skipped.     |
| Row Individual = 1st row then group number of data block |
+-----------------------------------------------------------+
No bad observations were found in the sample

Normal exit:   7 iterations. Status=0, F=    12960.46

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function    -12960.46076
Estimation based on N =    6808, K =  50
Inf.Cr.AIC  =  26020.9 AIC/N =    3.822
Model estimated: Sep 17, 2014, 19:39:50
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only must be computed directly
               Use NLOGIT ;...;RHS=ONE$
Chi-squared[11]           =  20712.45944
Prob [ chi squared > value ] =   .00000
Response data are given as ind. choices
Number of obs.=  6808, skipped    0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.       95% Confidence
  CHOICE|  Coefficient     Error       z    |z|>Z*          Interval
--------+--------------------------------------------------------------------
   VPUER|     .90050***    .03807   23.65  .0000       .82589    .97512
   VPUEY|     .37161***    .03291   11.29  .0000       .30711    .43612
      LR|    1.41157***    .03349   42.15  .0000      1.34593   1.47722
      LY|     .48632***    .04081   11.92  .0000       .40634    .56630
   DENSR|     .06964***    .01500    4.64  .0000       .04024    .09904
     CVR|   -1.03635***    .08921  -11.62  .0000     -1.21120   -.86149
     CVY|    -.37058***    .09835   -3.77  .0002     -.56335   -.17781
     PDL|     .02521***    .00398    6.33  .0000       .01740    .03302
      PL|    -.19737***    .05134   -3.84  .0001     -.29798   -.09675
     PDD|    -.06911***    .00295  -23.46  .0000     -.07489   -.06334
  HWWIND|    -.89948***    .09556   -9.41  .0000    -1.08677   -.71218
     A_1|     .27635       .31156     .89  .3751     -.33430    .88700
     A_2|    -.10137       .26473    -.38  .7018     -.62024    .41750
     A_3|     .25720       .23872    1.08  .2813     -.21068    .72508
     A_4|     .11206       .24626     .46  .6491     -.37059    .59471
     A_5|     .53041**     .23101    2.30  .0217      .07764    .98318
     A_6|     .56832**     .25117    2.26  .0237      .07604   1.06060
     A_7|     .15200       .25782     .59  .5555     -.35332    .65733
     A_8|   -1.95607***    .28467   -6.87  .0000    -2.51401  -1.39813
     A_9|    -.98192***    .26261   -3.74  .0002    -1.49662   -.46722
    A_10|    -.41493       .25324   -1.64  .1013     -.91127    .08141
    A_11|     .12926       .26385     .49  .6242     -.38787    .64639
    A_12|     .34913       .29077    1.20  .2299     -.22078    .91904
    A_13|     .02419       .26362     .09  .9269     -.49249    .54087
    A_14|     .15410       .24598     .63  .5310     -.32801    .63621
    A_15|    -.35069       .25703   -1.36  .1724     -.85445    .15308
    A_16|    -.09390       .25786    -.36  .7157     -.59930    .41149
    A_17|    -.07278       .34858    -.21  .8346     -.75599    .61043
    A_18|     .17923       .33615     .53  .5939     -.47960    .83807
    A_19|     .28916       .23470    1.23  .2179     -.17084    .74917
    A_20|     .26943       .24615    1.09  .2737     -.21303    .75188
    A_21|    -.05385       .24881    -.22  .8287     -.54150    .43381
```

```
    A_22|    -.05941         .25241      -.24  .8139      -.55411     .43530
    A_23|     .31797         .25025      1.27  .2039      -.17251     .80844
    A_24|     .35282         .24482      1.44  .1496      -.12703     .83267
    A_25|     .46191*        .25164      1.84  .0664      -.03130     .95512
    A_26|    -.08249         .26001      -.32  .7511      -.59210     .42713
    A_27|     .16495         .25802       .64  .5226      -.34076     .67066
    A_28|     .04935         .26614       .19  .8529      -.47228     .57098
    A_29|    -.29324         .38267      -.77  .4435     -1.04326     .45678
    A_30|     .86036***      .22052      3.90  .0001       .42815    1.29256
    A_31|     .26094         .24554      1.06  .2879      -.22031     .74219
    A_32|    -.00724         .23477      -.03  .9754      -.46738     .45290
    A_33|     .19944         .23822       .84  .4025      -.26745     .66634
    A_34|    -.11802         .24749      -.48  .6334      -.60309     .36704
    A_35|    -.32384         .24549     -1.32  .1871      -.80499     .15730
    A_36|    -.90953***      .26929     -3.38  .0007     -1.43732    -.38174
    A_37|     .04214         .23865       .18  .8598      -.42561     .50989
    A_38|    -.05371         .25083      -.21  .8305      -.54533     .43791
    A_39|    -.14254         .24134      -.59  .5548      -.61556     .33048
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-----------------------------------------------------------------------------

Normal exit:  60 iterations. Status=0, F=    12857.16

-----------------------------------------------------------------------------
FIML Nested Multinomial Logit Model
Dependent variable               CHOICE
Log likelihood function    -12857.15939
Restricted log likelihood  -27063.02015
Chi squared [  52 d.f.]     28411.72152
Significance level               .00000
McFadden Pseudo R-squared      .5249178
Estimation based on N =   6808, K =   52
Inf.Cr.AIC  =  25818.3 AIC/N =    3.792
Model estimated: Sep 17, 2014, 19:41:05
Constants only must be computed directly
               Use NLOGIT ;...;RHS=ONE$
At start values **********  .0080******
Response data are given as ind. choices
The model has 2 levels.
Random Utility Form 1:IVparms = LMDAb|l
Number of obs.=   6808, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.       95% Confidence
  CHOICE|  Coefficient       Error       z     |z|>Z*         Interval
--------+--------------------------------------------------------------------
        |Attributes in the Utility Functions (beta)
   VPUER|     .99186***      .04125     24.04  .0000       .91101    1.07271
   VPUEY|     .39426***      .03501     11.26  .0000       .32565     .46287
      LR|    1.44618***      .03551     40.73  .0000      1.37660    1.51577
      LY|     .52010***      .04193     12.40  .0000       .43793     .60228
   DENSR|     .08474***      .01587      5.34  .0000       .05364     .11584
     CVR|   -1.00506***      .09297    -10.81  .0000     -1.18727    -.82285
     CVY|    -.32980***      .10136     -3.25  .0011      -.52847    -.13113
     PDL|     .03139***      .00375      8.38  .0000       .02405     .03873
      PL|    -.27980***      .04806     -5.82  .0000      -.37400    -.18561
     PDD|    -.06981***      .00264    -26.42  .0000      -.07498    -.06463
  HWWIND|    -.91420***      .09498     -9.62  .0000     -1.10036    -.72803
     A_1|    1.66904***      .48345      3.45  .0006       .72149    2.61659
     A_2|    1.26676***      .46046      2.75  .0059       .36427    2.16925
     A_3|    1.55638***      .43867      3.55  .0004       .69661    2.41615
     A_4|    1.33677***      .44475      3.01  .0026       .46508    2.20846
     A_5|    1.76505***      .43288      4.08  .0000       .91662    2.61347
     A_6|    1.62701***      .45345      3.59  .0003       .73826    2.51575
     A_7|    1.22969***      .45906      2.68  .0074       .32996    2.12943
     A_8|   -1.07923**       .47809     -2.26  .0240     -2.01626    -.14220
     A_9|    -.50659**       .23099     -2.19  .0283      -.95932    -.05386
    A_10|     .05277         .22125       .24  .8115      -.38088     .48642
    A_11|     .58847**       .23284      2.53  .0115       .13212    1.04483
    A_12|     .85242***      .25860      3.30  .0010       .34558    1.35926
    A_13|     .52365**       .23776      2.20  .0276       .05765     .98964
    A_14|     .63755***      .21847      2.92  .0035       .20936    1.06574
    A_15|     .58394         .45524      1.28  .1996      -.30832    1.47619
    A_16|    1.08003**       .45309      2.38  .0171       .19199    1.96806
    A_17|     .25321         .33828       .75  .4541      -.40981     .91622
    A_18|     .51807         .32549      1.59  .1115      -.11987    1.15602
    A_19|     .69359***      .22620      3.07  .0022       .25024    1.13694
    A_20|     .72335***      .22271      3.25  .0012       .28684    1.15985
    A_21|     .35101         .23408      1.50  .1337      -.10778     .80979
    A_22|     .36573         .23481      1.56  .1193      -.09450     .82595
```

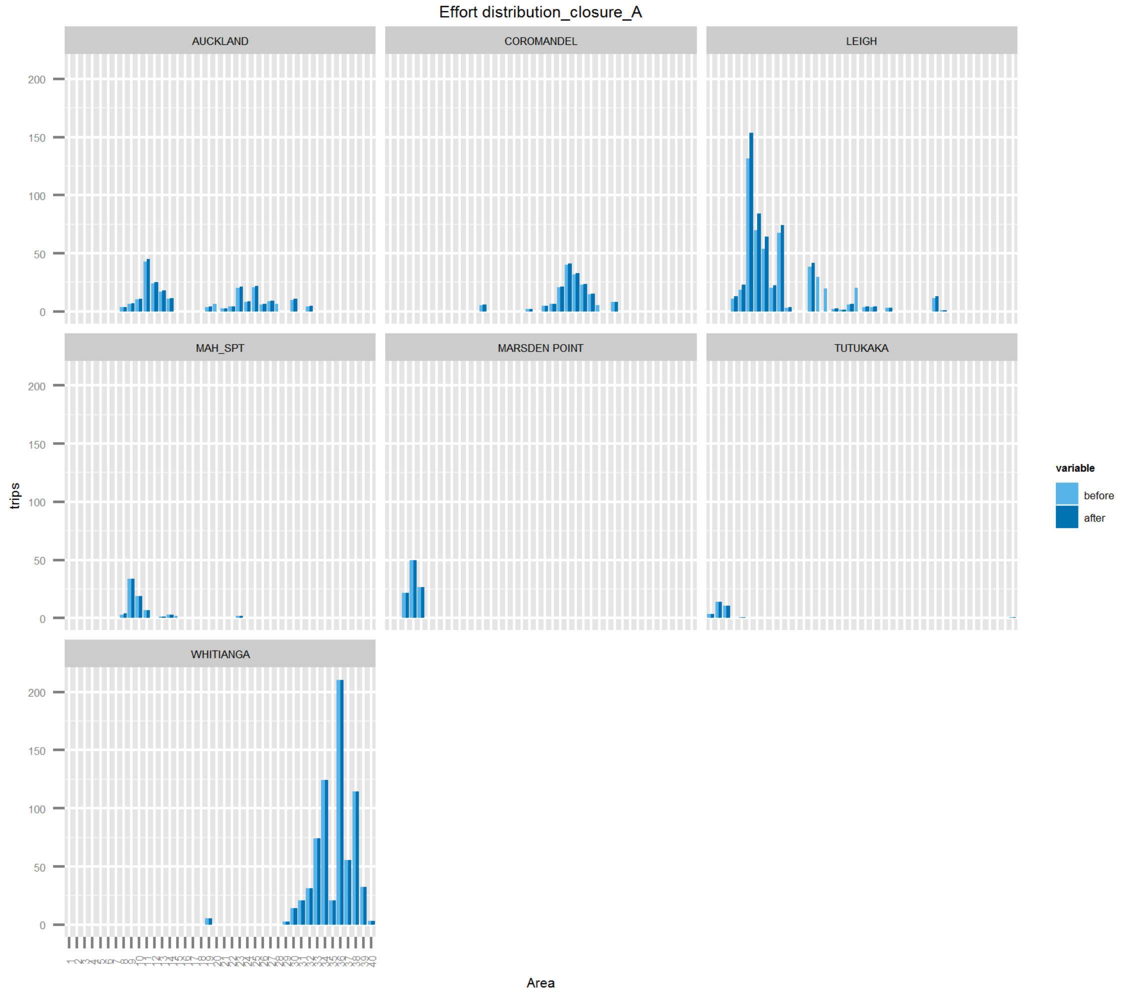
```
    A_23|     .79588***      .22631     3.52  .0004      .35232    1.23945
    A_24|     .76008***      .22296     3.41  .0007      .32309    1.19707
    A_25|     .91594***      .22690     4.04  .0001      .47123    1.36064
    A_26|     .33412         .23319     1.43  .1519     -.12292     .79116
    A_27|     .61257***      .23313     2.63  .0086      .15564    1.06950
    A_28|     .52287**       .24848     2.10  .0354      .03585    1.00989
    A_29|     .05829         .38322      .15  .8791     -.69280     .80938
    A_30|    1.24497***      .21077     5.91  .0000      .83187    1.65808
    A_31|     .65180***      .22980     2.84  .0046      .20140    1.10219
    A_32|     .48182**       .21132     2.28  .0226      .06765     .89599
    A_33|     .72871***      .20965     3.48  .0005      .31781    1.13961
    A_34|     .45932**       .21440     2.14  .0322      .03911     .87954
    A_35|     .56929         .43769     1.30  .1934     -.28857    1.42714
    A_36|    -.13955         .46086     -.30  .7620    -1.04283     .76373
    A_37|     .94212**       .43251     2.18  .0294      .09442    1.78982
    A_38|     .79210*        .44553     1.78  .0754     -.08112    1.66532
    A_39|    -.16931         .27540     -.61  .5387     -.70909     .37047
        |IV parameters, lambda(b|l),gamma(l)
      N1|        1.0    .....(Fixed Parameter).....
      N3|     .52730***      .03245    16.25  .0000      .46369     .59091
      N2|     .72555***      .04955    14.64  .0000      .62844     .82267
        |Underlying standard deviation = pi/(IVparm*sqr(6))
      N1|    1.28255    .....(Fixed Parameter).....
      N3|    2.43230***      .14970    16.25  .0000     2.13888    2.72571
      N2|    1.76768***      .12071    14.64  .0000     1.53109    2.00427
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
Fixed parameter ... is constrained to equal the value or
had a nonpositive st.error because of an earlier problem.
-----------------------------------------------------------------------------
```

C.2.1 CLOSURE SCENARIOS (A-D)

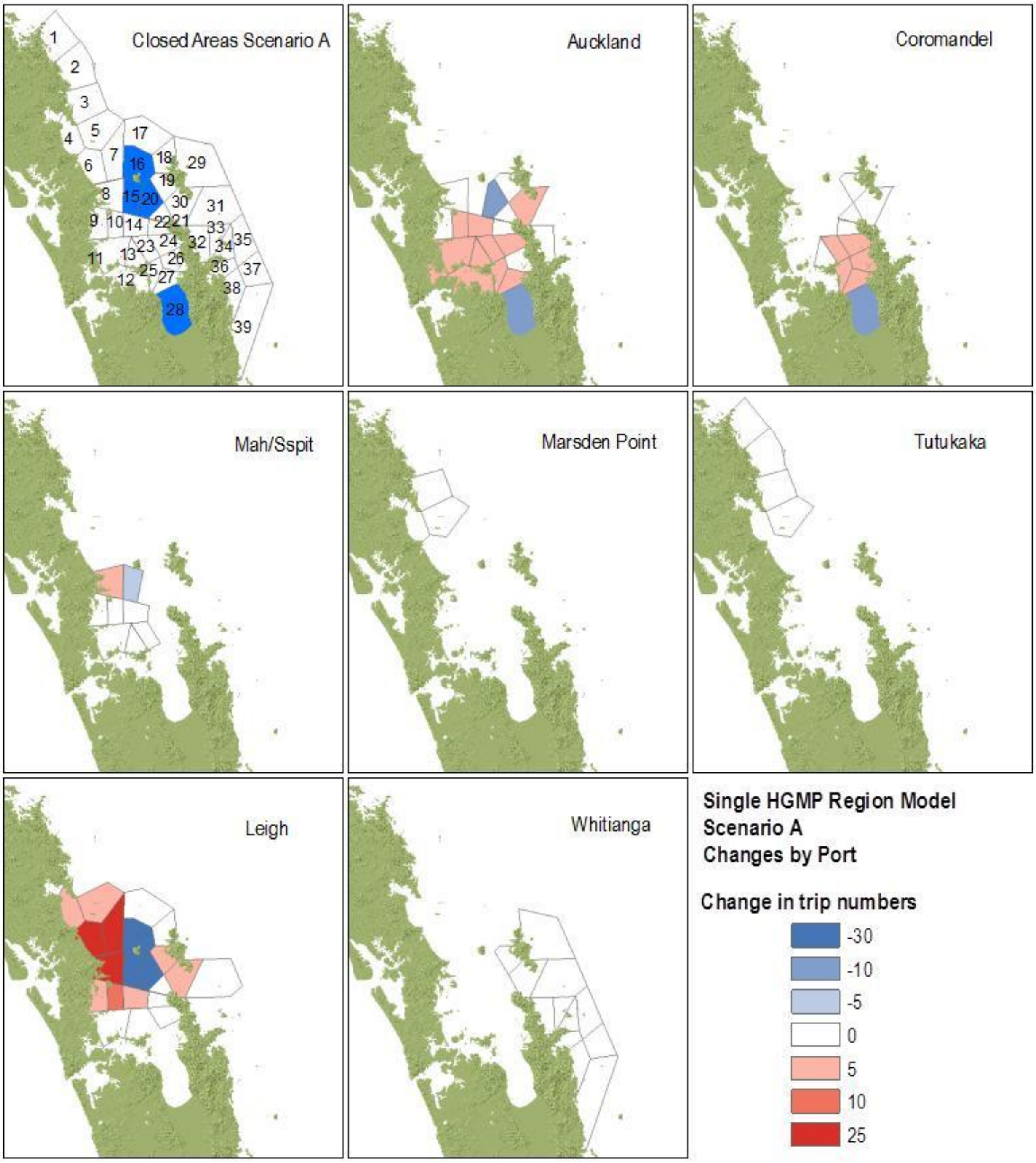
SCENARIO A



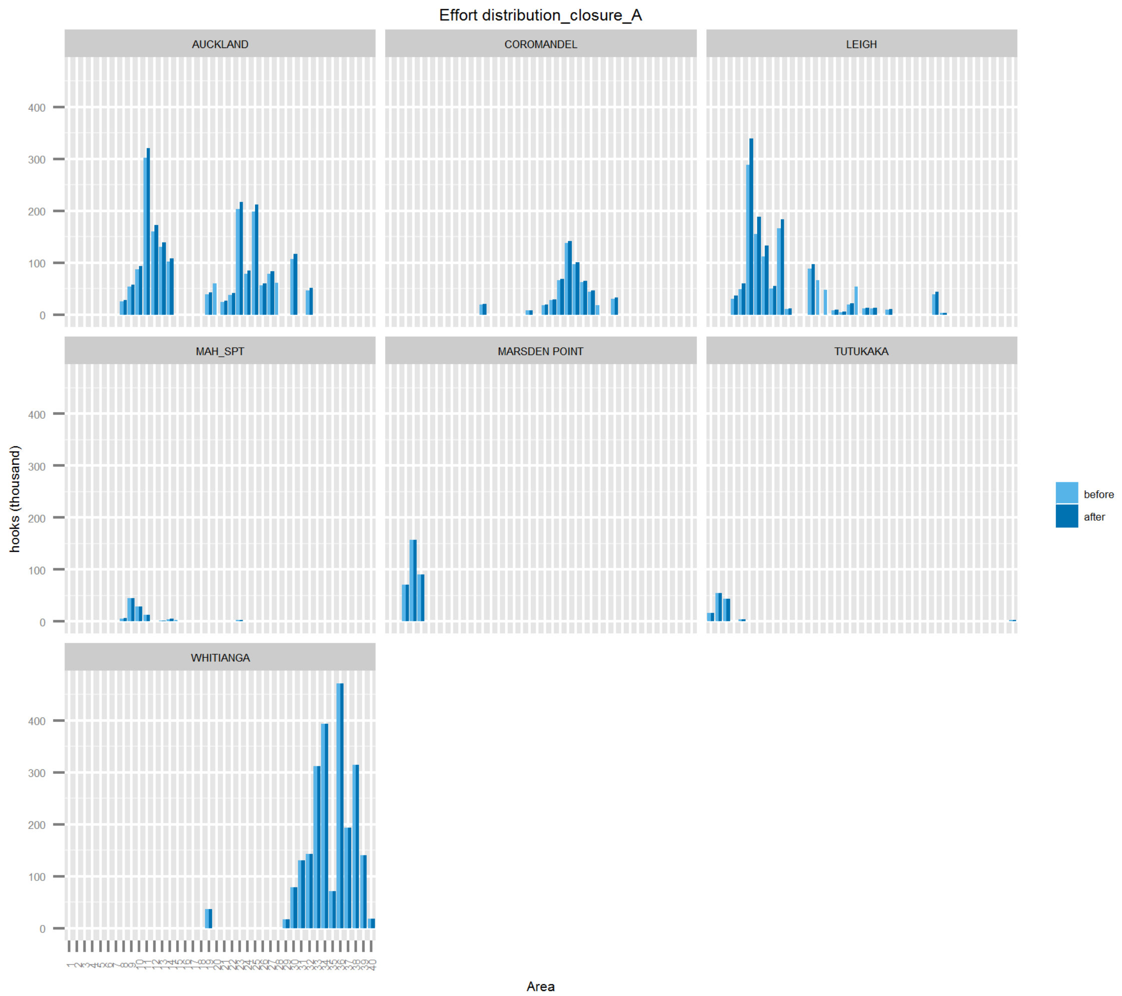
Apx Figure C.32 Predicted effort redistributions for the single HGMP region model under scenario A, , trips to locations and numbers of hooks set



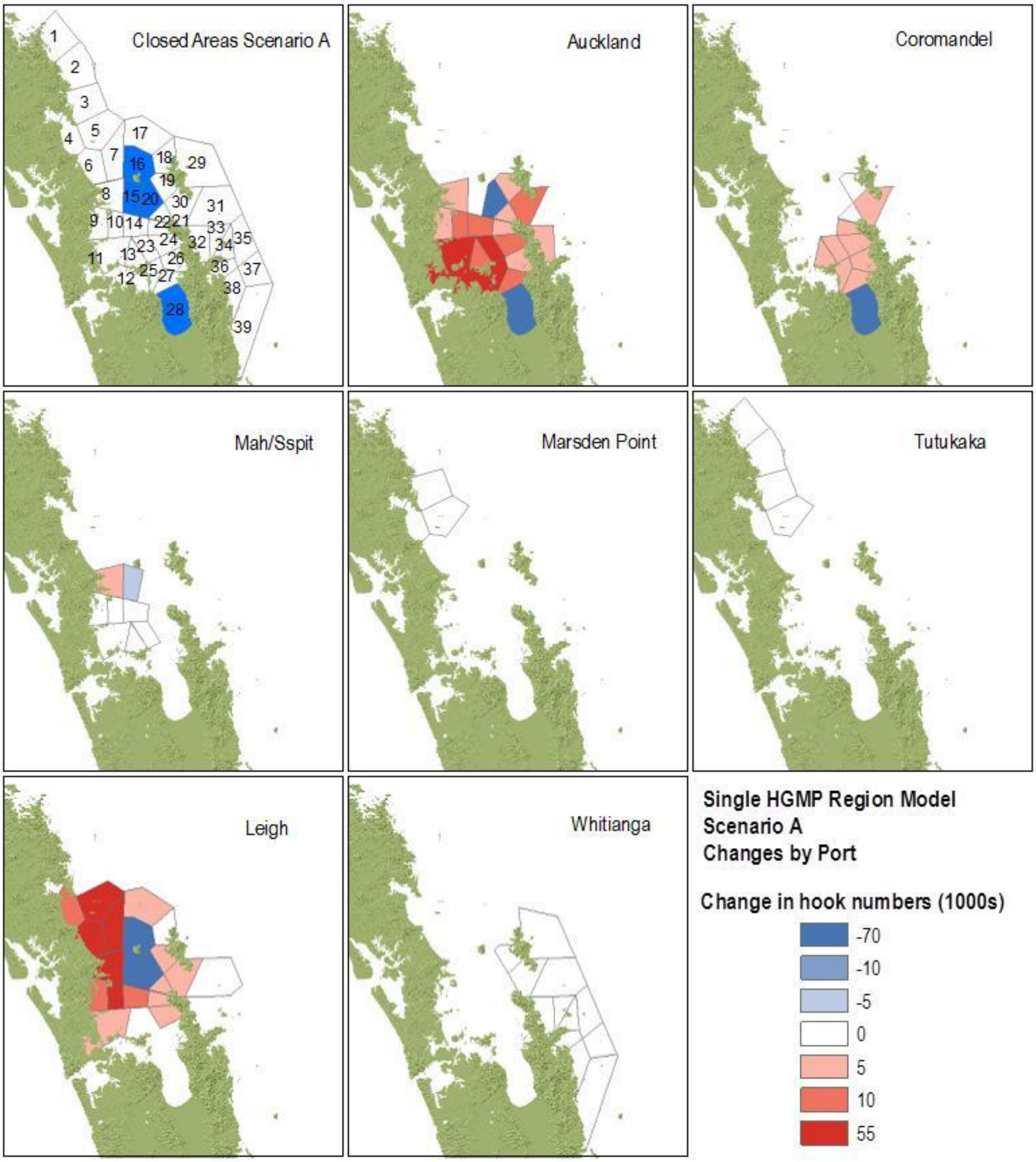
Apx Figure C.33 Port level predicted effort redistributions for the single HGMP region model under scenario A, trips to locations



Apx Figure C.34 Port level predicted effort redistributions for the single HGMP region model under scenario A, absolute change in numbers of trips

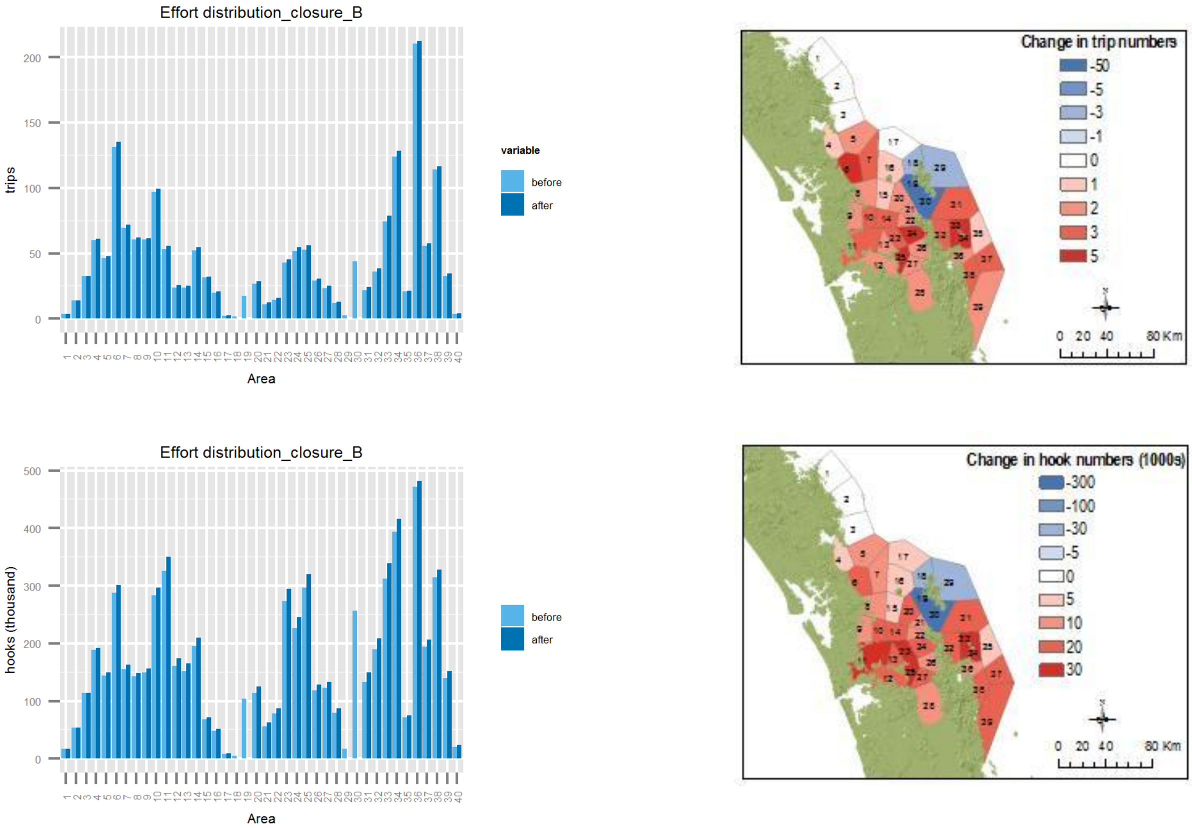


Apx Figure C.35 Port level predicted effort redistributions for the single HGMP region model under scenario A, numbers of hooks set



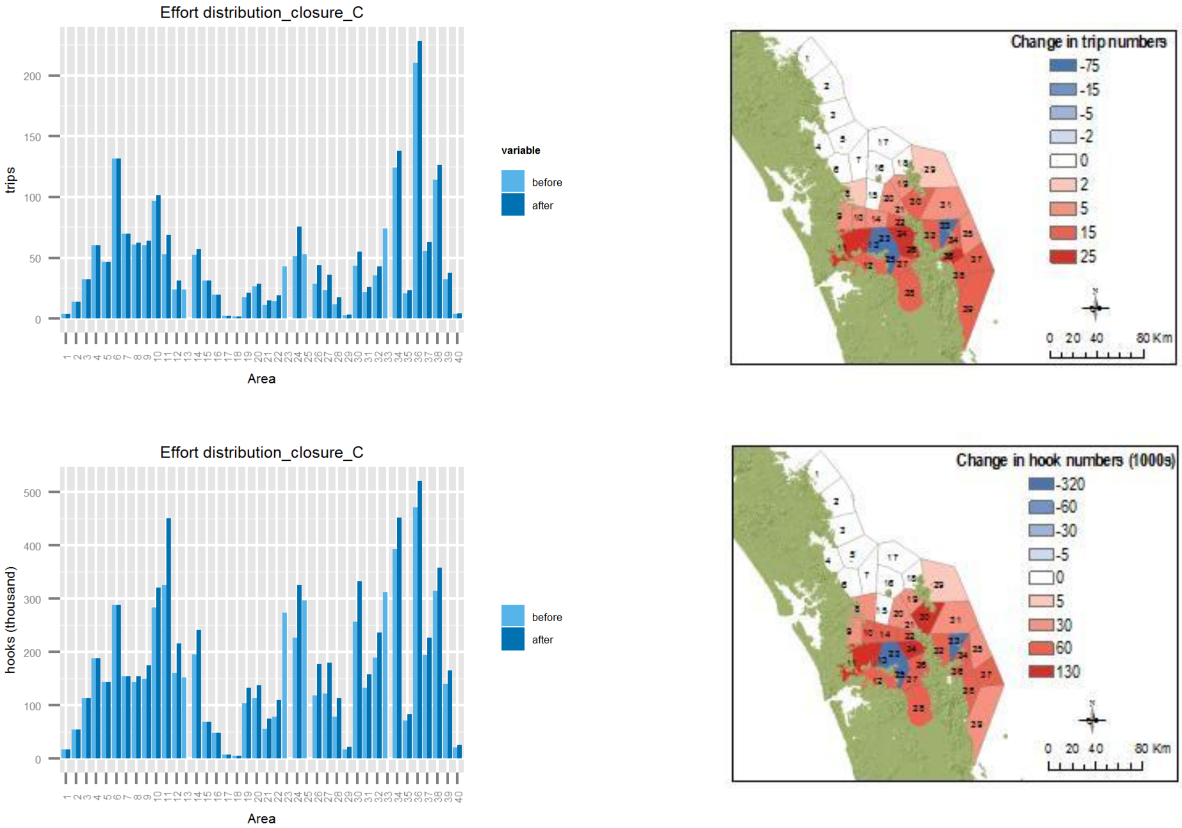
Apx Figure C.36 Port level predicted effort redistributions for the single HGMP region model under scenario A, absolute change in numbers of hooks set

SCENARIO B



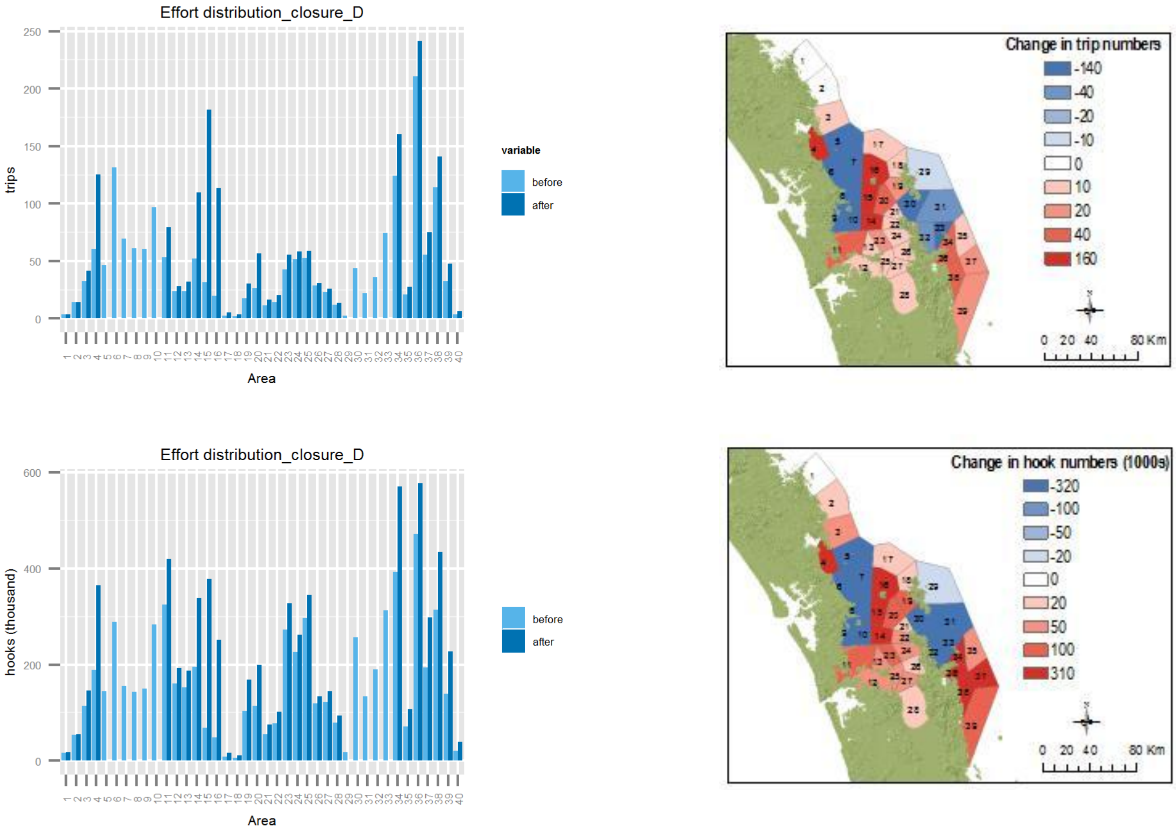
Apx Figure C.37 Predicted effort redistributions for the single HGMP region model under scenario B, trips to locations and numbers of hooks set

SCENARIO C

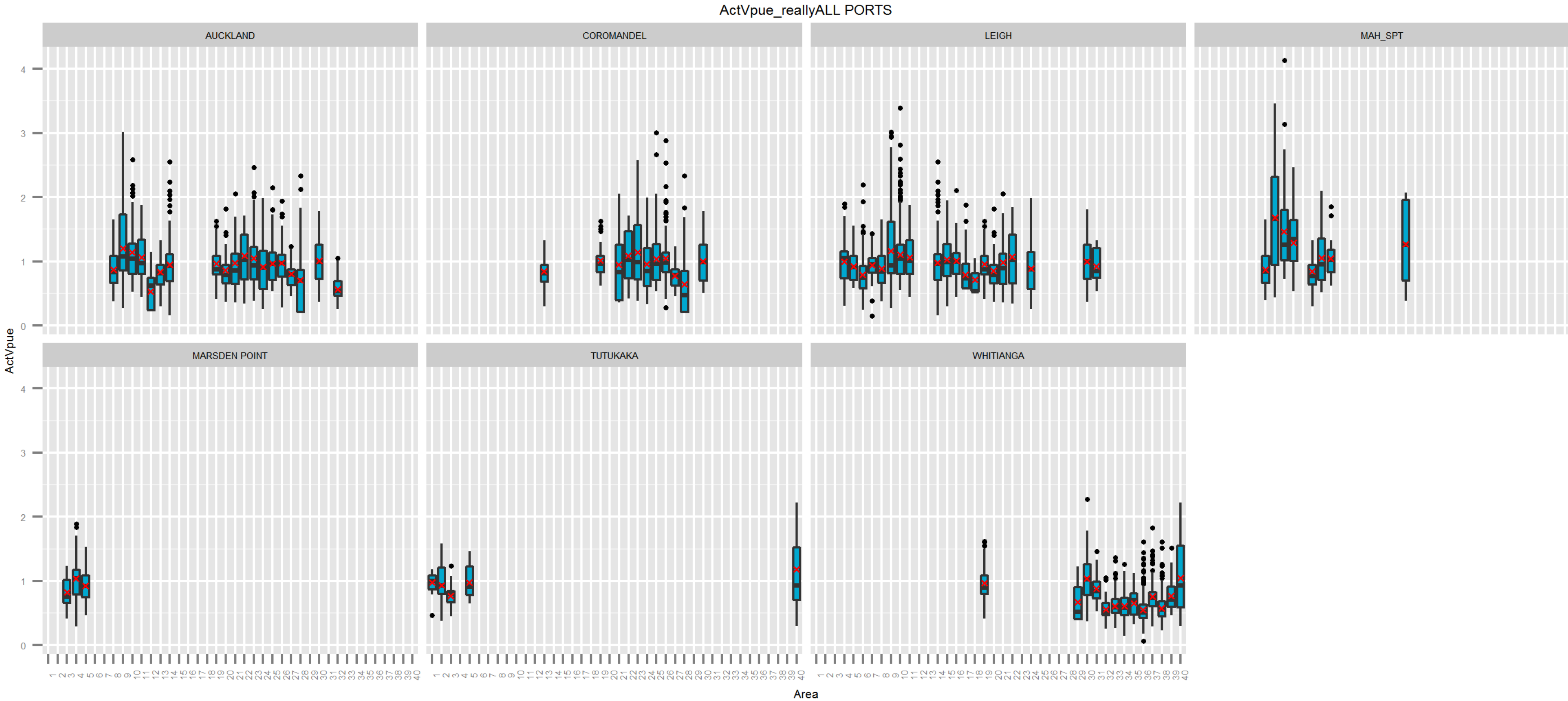


Apx Figure C.38 Predicted effort redistributions for the single HGMP region model under scenario C, trips to locations and numbers of hooks set

SCENARIO D



Apx Figure C.39 Predicted effort redistributions for the single HGMP region model under scenario D, trips to locations and numbers of hooks set



Apx Figure C.40 Actual VPUE values by location, red x indicates the mean

Appendix D Catalogue of R code

1. **Combine_old_and_new_data_1.R** - Merge the various data sources and periods.
   Requires: CSIRO_BLLEvents.RData, CSIRO_BLLEventsfy1213.RData BaseNamesFix.csv LandingNames2Fix.csv CSIRO_BLL_EstcatchMatrix_fy0712.RDat, CSIRO_BLL_EstcatchMatrix_fy1213.RData, PricesForR.csv
   Produces: BaseNames.csv, LandingNames2.csv, EVENTS_0713.csv, CATCH_0713.csv, UpdatedCLcombo.csv

2. **Identifying BLL vessels_2.R** - Look at how much individual vessels use BLL gear and the importance of using BLL in or around the HGMP (as a proportion of revenue). From this an initial list of vessels is derived (the "HGMP BLL fleet") for further investigation.
   Requires: UpdatedCLcombo.csv
   Produces: Dependence on BLL in HG regionL.csv, HG_BLL_VesNos.csv

3. **Clustering_and_individual_vessel_effort_plots_3.R** – Looks into where vessels are fishing and uses a clustering approach to begin defining the locations fished by the vessels identified above.
   Requires: EVENTS_0713.csv, HG_BLL_VesNos.csv, vesselData_CSIRO.RData
   Produces:

4. **Cleaning_effort_data_4.R** – further analysis of the data (again limited to the vessels of interest)
   Requires: EVENTS_0713.csv, HG_BLL_VesNos.csv, LandingNames2Fix.csv, vesselData.csv, UpdatedCLcombo.csv, ChoiceCellMembership.csv
   Produces: EventDistances_mean.csv, Trips_lat_lon.csv, BLL_fleet_summary_table_after_cleaning.csv, Locations of multiple event trips.csv, BLL effort and catch cleaned.csv

5. **Construction of parameter values_5 (min 5).R** - Create parameters and choice sets
   Requires: FuelPricesReal.csv, BLL effort and catch cleaned.csv, ChoiceCellMembership.csv, Location_areas_km2.csv, windSpeed.csv, windDirection.csv
   Produces: datacoverage_BLL_ReallyALL.csv, ChoiceSets_5_min_reallyAll.csv, BLL_NoFstYr_5_min_reallyAll.csv, BLL_NoFstLstYr_5_min_reallyAll.csv, BLL_ONLY_LstYr_5_min_reallyAll.csv

6. **Simulations_PORT NAME HERE (MX).R** – comparison of models ability to predict effort distribution and closure scenarios (this is a generic script that is modified to suit the model being run.
   Requires: BLL_NoFstLstYr_PORT.csv, BLL_ONLY_LstYr_PORT.csv
   Produces: Trip_changes_",PORT,"_closure_",Scenario,".csv, rev_fuel_changes_",PORT,"_closure_",Scenario,".csv, Hook_changes_",PORT,"_closure_",Scenario,".csv

Shortened forms

HGMP – Hauraki Gulf Marine Park

BLL – Bottom longline

SNA - Snapper

AIC – Akaike information criterion

LL – Log-likelihood

RUM – Random utility model

MNL – Multinomial logit

NL – Nested logit

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