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Challenges in Statistical Marine Ecology

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As a coastal nation, it is important for Canada that we understand the oceans around us and how they and their inhabitants are responding to changes induced either directly or indirectly by human activity. Within biology, marine ecology is the scientific study of marine-life habitat, populations, and interactions among organisms and the surrounding environment.

19.1 Introduction

Marine ecologists ask questions at various scales ranging from worldwide populations to the behavior of individual species or animals. Statistics are essential for answering these questions: from describing the study design and data collection, to providing models and methodology appropriate for answering the question(s) of interest, and finally in making available the necessary expertise to fully understand and interpret results.

In marine ecology, the scientific questions often concern the abundance of a particular species, how that abundance may depend on habitat or other species and how the abundance changes over space and/or time in response to environmental or human-induced changes. What are the features of marine ecological data that make them challenging statistically? First, data often include substantial random variation and other inaccuracies at least in part due to the difficulty of making accurate measurements of abundance in the marine environment. For instance, it is challenging to estimate the number of cod in a particular fishing zone and consequently we must often use surrogate and rather imprecise measures. Often data also vary quite dramatically over both space and time and series are commonly short and sparse. Furthermore, data on marine species or systems of interest usually need be linked to environmental measurements that are typically collected on different scales.

Given a clear marine ecological question of interest, the next step is to translate this into statistical terminology such that the study design, data collection and ensuing model framework are effective. Statistical models are used to represent important features of the ecological processes of interest. Such models are mathematical representations; for example, they might describe the changing numbers (abundance) of fish in a particular region of interest. There is a symbiotic relationship between the model and the data collected. That is, the model must be complex enough to capture the essential features of the process but simple enough that it can be fitted to the data. Typically a model will have some unknown quantities, referred to as states or parameters which we wish to estimate from the data. For instance if we want to fit a straight line to a simple two-dimensional dataset, then the slope and intercept are often the parameters of interest. We aim for states and parameters that have simple ecological interpretations, can be reasonably well estimated and for which we are able to assess the accuracy of estimates.

In this chapter, we describe two research projects that utilize novel statistical methodologies to answer important scientific questions. The goal of the first project is to describe how a collection of fish populations is changing over time in response to fishing and other sources of mortality. This is critical to sustaining some of our most valuable renewable resources.

The second project presents a statistical model for obtaining accurate estimates of abundance of the critically endangered hammerhead shark. Although both projects are concerned with estimating abundance of marine species, they require the development of very different statistical methods and rely on vastly different types of data. Further details are given below.

Young fish are very vulnerable to competition, predation, hydrography, temperature, and a host of other environmental factors that result in extraordinarily high levels of mortality. Their varying ability to survive and grow ultimately determines how many fish become part of the adult population (the part of the total population than can be legally fished). Understanding the dynamics of their growth period is therefore critical to understanding fish population dynamics and the management of fisheries resources. Yet, despite a century of fruitful investigation, much uncertainty remains in the understanding of stock replenishment. Here the focus is on the scientific question of whether the number of Atlantic cod joining the adult population has changed over time and, where observed, are such changes similar to those of proximate populations. The data used were extracted from a quality controlled global fish stock assessment database (Ricard et al., 2012) that was recently developed at Dalhousie University.

In the second project we note that for many endangered marine species, the only available data related to their abundance are counts of when they are caught unintentionally in a fishery (i.e., as bycatch). These data typically involve a large number of zero counts (indicating that none were caught as bycatch in a particular haul) and very few positive counts (obtained if one or more are caught as bycatch in a haul) and are based on hauls that occur within trips which are made by each of a number of vessels. Using these data, we need to answer the important question of whether we can accurately estimate the probability of bycatch as this is an important first step in attempting to protect endangered marine species (Lewison et al., 2004). The second project uses bycatch data on the hammerhead shark, obtained by Julia Baum—see Baum (2007), for further details—from the US National Marine Fisheries Service Pelagic Observer Program (`http://www.sefsc.noaa.gov/pop.jsp`). In the spring of 2013 these sharks, which are commercially valuable and whose numbers are thought to have been declining dramatically in recent years, were given added protection by CITES (the Convention on International Trade in Endangered Species of Wild Fauna and Flora) whose aim is to ensure that international trade in specimens of wild animals (and plants) does not threaten their survival.

19.2 Sustaining North Atlantic Cod Stocks

A fish stock is a group of fish of the same species that live in the same geographic area and mix enough to breed with each other when mature. Stock assessments provide fisheries managers with the information that is used in the regulation of a fish stock. Data used in stock assessments can be classified as fishery-dependent or fishery-independent. Fishery-dependent data are collected from both commercial and recreational fishing activities. There is a variety of methods for obtaining fishery-dependent data. The most common approach is to use records of the amount of fish sold with the numbers typically reported in total weight. Another common mode for acquiring fishery-dependent data is through portside sampling of the catch of both recreational and commercial fishermen. Other less common methods for obtaining data are through the use of onboard observers, self-reporting, telephone surveys, and vessel-monitoring surveys. Fishery-independent data are obtained in the absence of any fishing activity with the majority of these data collected by government agencies. A wide variety of methods are used to acquire fishery-independent data and sampling equipment can include trawls, seines, acoustic and/or video surveys. Stock assessments are often conducted using both fishery-dependent and fishery-independent data.

Traditional approaches to predicting the number of fish that will be present in a stock either in the current year or in future years have relied on a statistical model by Ricker (1954). Typically we refer to fish as belonging to a particular cohort or year class and want to estimate the number of new fish entering the cohort (recruits) based on the number of parent fish (spawners). We label cohort or year by t and want to predict the number of recruits in year t based on the number of spawners at time $t - \tau$, where τ represents the years required for a fish to mature. Estimates of the number of spawners and recruits for 10 different cod stocks corresponding to fishing regions off the coast of Nova Scotia and Newfoundland from a new quality controlled global fish stock assessment database (Ricard et al., 2012) developed at Dalhousie University were used. To write down the Ricker model for a collection of J stocks use $j \in \{1, \ldots, J\}$ as the stock label and t as the year label, where $t \in \{t_{j,0}, t_{j,0} + 1, \ldots, T_j\}$ (the start $t_{j,0}$ and end years T_j are stock-specific since the start and end points of the assessments differ by stock with some stretching back close to a century while others begin within the last 30 years). The Ricker model can then be written as

$$R_{j,t} = \alpha_j S_{j,t-\tau_j} \exp(-\beta_j S_{j,t-\tau_j} + \epsilon_{j,t}),$$

where $R_{j,t}$ is the number of recruits in stock j, in year t at age τ_j (age of maturity can depend on the particular stock) and $S_{t-\tau_j}$ is the number of spawners. When suitably scaled, α_j is referred to as the maximum reproductive rate, which is a measure of how productive the stock is at recruiting fish to the adult population and we see that as α_j increases the number of recruits increases. β_j is a parameter describing density-dependence and can be thought of as the inverse of the carrying capacity of the environment of the stock. As the carrying capacity increases, β_j decreases and the number of recruits increases due to the minus sign in front of it. The $e^{\epsilon_{j,t}}$ are Log-Normally distributed errors and represent all other factors which might affect recruitment. The model can be linearized by dividing through by the number of spawners and taking the natural logarithm, viz.

$$\log\left(\frac{R_{j,t}}{S_{j,t-\tau_j}}\right) = a_j - \beta_j S_{j,t-\tau_j} + \epsilon_{j,t}. \tag{19.1}$$

The natural logarithm of the ratio of recruits to spawners is termed survival and $a_j = \log(\alpha_j)$ is referred to as the productivity. In order to understand how productivity changes over time and how productivity in one stock is related to another, one can allow a_j to to vary over time leading to a so-called state space model (SSM). A SSM involves two equations: the first is the process equation which describes the underlying (yet unobserved) state that one would like to model, namely the productivity $a_{j,t}$; the second is the measurement equation relating the unobserved states to the observed measurements. Here Equation (19.1) is the measurement equation (with a_j replaced by $a_{j,t}$). For the process equation, a random walk on $a_{j,t}$ is used. That is, the productivity at time t is determined by the productivity at time $t-1$ plus a Normally distributed random error $\eta_{j,t}$ termed a process error (which can be either positive or negative) and is expressed as

$$a_{j,t} = a_{j,t-1} + \eta_{j,t}.$$

SSMs similar to the above have been fitted in the past but only to one stock at a time; see, e.g., Peterman et al. (2003) and Dorner et al. (2008). The method (Minto et al., 2013) allows one to simultaneously model multiple stocks (e.g., stocks in different geographic regions). That is, the multivariate SSM allows us to simultaneously estimate trends and correlations in productivity for multiple stocks. The formulation includes a correlation matrix (Q) describing the correlation of productivity across stocks. Where stocks are behaving similarly we would expect positive values in Q and conversely where they behave differently negative values would be expected. The method allows one to (i) test if productivity has changed over time; (ii) determine how productivity is correlated across stocks; and (iii) interpret the scale of productivity changes where they exist.

In order to estimate the states and parameters in the multivariate SSM, the Kalman Filter is used; see Harvey (1991) and Petris et al. (2009) for a description. SSMs are capable of dealing with missing values by interpolating using the process equation. This provides an opportunity to estimate historical trends in productivity for a given stock during a time period in which no data exist.

19.2.1 Results

By applying the multivariate SSM to 10 cod (*Gadus morhua*) stocks from different regions in the northwest Atlantic, we see that productivity has varied markedly through time. Furthermore, it was found that many stocks display lower productivity today, compared with historical averages. This indicates some fundamental changes in stock biology, or alternatively, in their environment. In the northwest Atlantic (Figure 19.1), the southern stocks of Georges Bank (GB), the Gulf of Maine (GOM), and the Southwestern Scotian Shelf (SWSS) are currently close to a historic minimum (based on hindcasts for Georges Bank and the Gulf of Maine). The Eastern Scotian Shelf (ESS), Southern (SGOSL) and Northern Gulf of St. Lawrence (NGOSL) stocks have potentially higher recent productivity than that observed or predicted at the earliest time points. All three stocks displayed markedly elevated productivity in the late 1970s, early 1980s. The Southern Newfoundland (SNEW) stock displayed increasing productivity to the 1980s and has been declining since. The Labrador Northern Newfoundland (LABNNEW) stock displayed constant productivity until the late 1980s, when it dipped precipitously prior to the cod fishing moratorium in 1992. A similar but more consistently decreasing trend was observed for the Southern Grand Banks (SGRAND) stock, again with a precipitous decline in the early 1990s. Both stocks are currently at depressed productivity levels, although forecasts suggest slow though uncertain productivity increases in both. The Flemish Cap (FLEM) stock displays differing productivity trends to those elsewhere in the northwest Atlantic; while other stocks reached a peak in productivity in the early 1980s, the Flemish Cap displayed a trough, similarly in the mid- to late-1990s.

Note that in Figure 19.1 results obtained by fitting a SSM to each stock individually are shown in light gray. A comparison of these estimated states with those of the multivariate SSM (shown in dark gray) shows similar trends for most stocks with overlapping confidence intervals. The confidence intervals

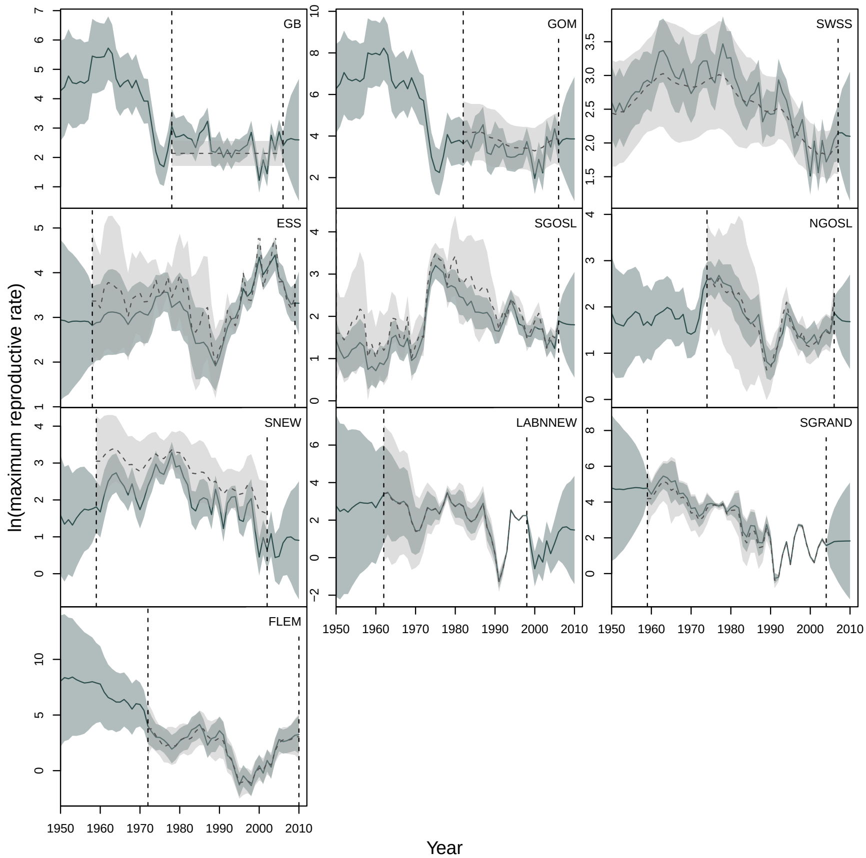

FIGURE 19.1: Estimated productivity (with 95% confidence intervals) from single-stock (light gray) and our multivariate (dark gray) fits to 10 Northwest Atlantic cod stocks. Dashed vertical lines represent the earliest and latest data points for each stock. Pre-dashed line fits are hindcasts. Post-dashed lines are forecasts.

are tighter for the multivariate SSM, thereby illustrating that one is better able to infer the productivity dynamics by borrowing information from other stocks. The method also generates hindcasts and forecasts that are not available if we consider each stock separately. In fact, single-stock models have long been viewed as too simplistic (Larkin, 1977) and there has been an increasing emphasis on ecosystem-based management (Link et al., 2011).

The correlation of the time-varying productivity across stocks showed marked patterns in the northwest Atlantic (Figure 19.2). Some strong correlations exist, e.g., the Georges Bank, Gulf of Maine and Southwestern Scotian

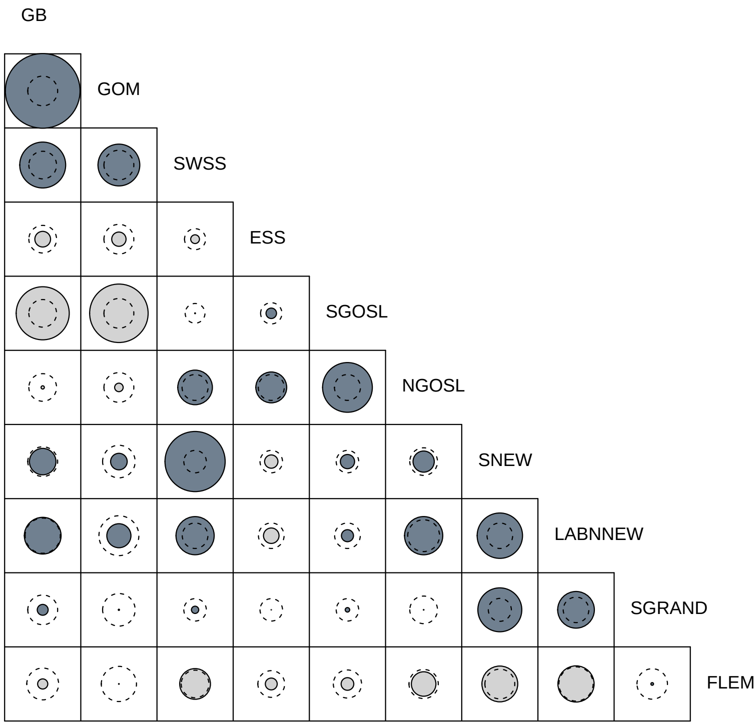

FIGURE 19.2: Estimated correlations in productivity for 10 Northwest Atlantic cod stocks. The strength of the correlation is represented by the radius of the circle, the direction by the color (light gray representing negative correlations and dark gray positive). Radii greater than that of the dashed circles are significant according to a statistical test.

Shelf stocks and further north, the Labrador Northern Newfoundland, Southern Newfoundland and Southern Grand Banks stocks displaying positive correlations. The Southwestern Scotian Shelf also displays positive correlations with distant stocks such as the Northern Gulf of St. Lawrence, Southern Newfoundland and Labrador Northern Newfoundland. Equally noticeable, however, is the isolation of several individual stocks from those adjacent. For example, the Eastern Scotian Shelf stock displays no or weakly negative correlations with the nearby stocks of Gulf of Maine and the Georges Bank. Similarly, the Southern Gulf of St. Lawrence stock displays no or negative correlation with all but the adjacent Northern Gulf stock (Figure 19.2). Outside the positive correlations already highlighted, the Southern Grand Banks displays weak correlations with all other stocks. Interestingly, the Flemish Cap displays weakly negative correlations with all stocks (Figure 19.2).

These statistical methods have made it possible to describe what is happening to productivity both within and between northwest Atlantic cod stocks. We found that productivity of northwest Atlantic cod, a key population parameter, varies markedly through time as well as across stocks and that these relationships change with geographic distance, identifying similar productivity regimes among neighboring stocks. The observed trends displayed some synchronicity across stocks, but also smaller scale variability that is not readily explained by current ecological hypotheses. The next step is to work with marine ecologists to attempt to understand why these ecological patterns are emerging.

19.3 Conserving the Endangered Hammerhead Shark

Marine species conservation is an important goal of ecologists. For many endangered species the only available data related to their abundance are counts of when they are caught unintentionally in a fishery; see Figure 19.3. We refer to this as bycatch data and here examine that of Hammerhead sharks obtained from the US National Marine Fisheries Service Pelagic Observer Program. Hammerhead sharks have garnered much attention recently due to CITES, which took decisive action in March of 2013 to halt their further decline. These bycatch data are complicated in that we have counts of bycatch of Hammerhead sharks recorded for each of a collection of hauls occurring during each of a number of trips by particular vessels. Such data are difficult to model with standard statistical methods for two main reasons: first, they involve a preponderance of hauls for which no Hammerheads are recorded (zero counts, see Figure 19.4); second, hauls are nested, i.e., they occur within trips which are nested within vessels, and this structure results in dependencies in the data that must be incorporated into the model structure for proper inference. Data with such features are commonly referred to by statisticians as clustered count data with many zero observations and are typical of endangered species data, particularly in marine environments.

In Cantoni et al. (2013) a statistical model was formulated for clustered count data with many zero observations. The formulation allows one to describe the bycatch of hammerhead sharks in terms of two random processes: one process determines the presence or absence of sharks in a haul, and in those hauls for which sharks are present, a second process determines the number of sharks. It deals with the clustering (also known as dependence) resulting from hauls made as part of the same trip and possibly trips made

FIGURE 19.3: A hammerhead shark as bycatch.

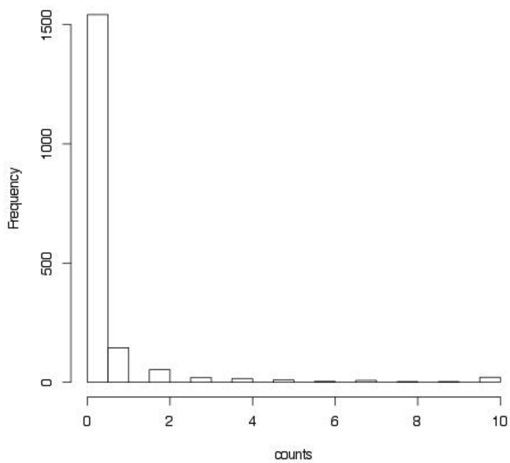

FIGURE 19.4: Histogram of the counts of hammerhead sharks caught as bycatch.

by the same vessel by introducing random effects. For instance, a trip random effect is an attempt to measure the effects on the bycatch which are particular to that trip and measure the extent to which the bycatch on one haul on the trip is correlated with the bycatch from another haul on the same trip. Parameters are introduced which control whether these random effects appear in one or both parts of the model. The two parts of the model are independent if these parameters equal zero and dependent otherwise.

Here we describe the model by supposing that there are c trips, with each trip i containing n_i, $i \in \{1,\ldots,c\}$, hauls (for simplicity we are ignoring the effect of vessel here). On the jth haul of the ith trip, one observes a count of Hammerhead shark bycatch, y_{ij}, along with other pieces of information, referred to as covariates. These include the year and season, the average hook depth, the area where the fishing is occurring as well as some measure of fishing effort. Some of these covariates will affect the presence or absence of a hammerhead while others will affect the number of hammerheads given their presence. Hence two (possibly overlapping) sets of covariates are allowed. Denote the values of the covariates in the jth haul of the ith trip as $\mathbf{x}_{ij}$ and $\mathbf{z}_{ij}$, $j \in \{1,\ldots,n_i\}$, $i \in \{1,\ldots,c\}$. The $\mathbf{x}_{ij}$ are the covariates which are anticipated to affect the presence or absence of a hammerhead while the $\mathbf{z}_{ij}$ are those affecting the number of hammerheads given their presence. This so-called hurdle model specifies that the counts y_{ij} are independent (given the random effects) with probabilities of the form:

$$\Pr(Y_{ij} = y_{ij} \mid \mathbf{u}_i, \mathbf{v}_i) = \begin{cases} 1 - p(\mathbf{x}_{ij}, \mathbf{u}_i) & y_{ij} = 0, \\ \\ p(\mathbf{x}_{ij}, \mathbf{u}_i) f\{y_{ij}, \lambda(\mathbf{z}_{ij}, \mathbf{u}_i, \mathbf{v}_i)\} & y_{ij} = 1, 2, 3, \ldots \end{cases}$$

where p is the probability of observing a positive count (i.e., “crossing the hurdle”), $f\{y_{ij}, \lambda(\mathbf{z}_{ij}, \mathbf{u}_i, \mathbf{v}_i)\}$ is the density of a distribution defined on the positive integers with parameter λ which is a function of the covariates and the random effects $\mathbf{u}_i$ and $\mathbf{v}_i$. Both $\mathbf{u}_i$ and $\mathbf{v}_i$ represent trip random effects with $\mathbf{u}_i$ being the effect of a trip on the presence/absence of sharks and $\mathbf{v}_i$ being the effect on the number given presence.

In many cases, it is of great interest to predict the effects of trips and/or vessels and other quantities that are functions of them. For example, we may be interested in determining which vessels tend to have more shark bycatch or which trips tend to result in more bycatch. We may also be interested in predicting the probability of bycatch for a particular haul, trip and vessel combination $\Pr(Y_{ij} > 0|\mathbf{u}_i)$, or the expected number of sharks comprising bycatch (given non-zero bycatch) $\mathrm{E}(Y_{ij}|Y_{ij} > 0, \mathbf{u}_i, \mathbf{v}_i)$ or, the expected abundance $\mathrm{E}(Y_{ij}|\mathbf{u}_i, \mathbf{v}_i)$. We may also be interested in the analogous quantities aggregated over all trips made by a particular vessel or also across all vessels; for instance, the probability of bycatch, the expected bycatch given non-zero bycatch, or the expected bycatch.

This approach was used to model 1825 bycatch counts made on 292 different trips, with from 1 to 21 hauls per trip. Each of the $c = 292$ trips was treated as a cluster; vessels potentially add another layer of clustering though not incorporated here. For these data, we had 85% zeros and the positive counts ranged from 1 to 46. The covariates thought to potentially influence both the probability of bycatch and its magnitude that were considered are: the year (YEAR), average or median hook depth (AVGHKDEP, from 6.40 to 182.88 meters), area (4 = South Atlantic Bight and 5 = Mid Atlantic Bight), and season (SEASON, with 464 observations in autumn, 543 in spring, 525 in summer and 293 in winter). The catch effort was measured using the logarithm of the number of hooks (TOTHOOK, ranging from 25 to 1548). Baum et al. (2003) provide a more complete description of these data.

19.3.1 Results

The fitted model showed that there are more variables which are significant in the abundance part than in the presence-absence part. This is quite common in ecological problems; more factors affect the abundance given presence than whether we observe a positive count or not. The variable YEAR is significant in both parts and has a negative effect. This means that sharks are observed less often through time, and even when they are present they are less abundant. With each additional year the odds of observing a positive count reduce by 5.7%. SEASON too plays a role in both parts, with spring and winter significantly different from autumn. The catch effort, log(TOTHOOK), does not affect the presence-absence, but is significant in the abundance part. The hook depth also affects the abundance given presence significantly. Furthermore, a new parameter that was included in the model formulation demonstrated that the two parts of the model were dependent on each other. This sort of information is critical for informing management decisions, since, by incorrectly fitting the two parts of the model separately, e.g., one could potentially underestimate the extent to which their abundance is decreasing through time.

Figures 19.5 and 19.6 show the predicted probability of presence $\Pr(Y_{ij} > 0|\mathbf{u}_i)$ and the conditional expectations $\mathrm{E}(Y_{ij}|Y_{ij} > 0, \mathbf{u}_i, \mathbf{v}_i)$ with their corresponding confidence intervals for the first five trips (identifers as shown). We can interpret these results quite precisely. For example, in Figure 19.5, we see that for trip 01A019 there are essentially two different groups of predictions. It turns out that this is due to two different values of AVGHKDEP for this trip.

In Figure 19.6, we observe that the length of the confidence intervals can be quite variable. For trip 01A019, the two much larger intervals correspond to a different combination of AVGHKDEP and log(TOTHOOK), which is significant in the abundance part of the model and therefore has an impact on the estimation of $\mathrm{E}(Y_{ij}|Y_{ij} > 0)$. Similarly, the longer interval for trip 01A029 corresponds to the sole observation of this cluster with a different value of AVGHKDEP. The smaller variations in length are due to the differences in log(TOTHOOK).

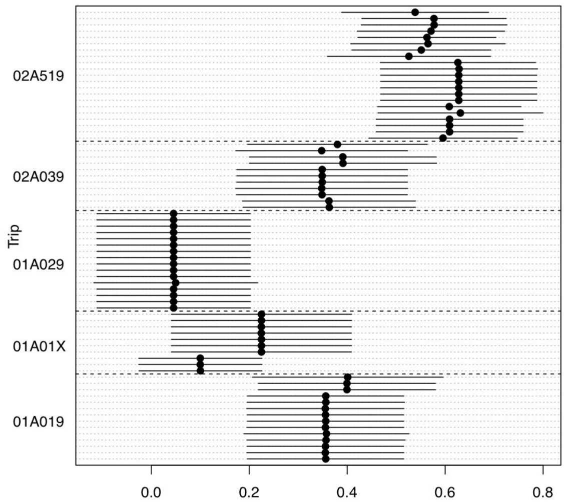

FIGURE 19.5: Confidence intervals for the probability of presence of hammerhead shark for the first five trips.

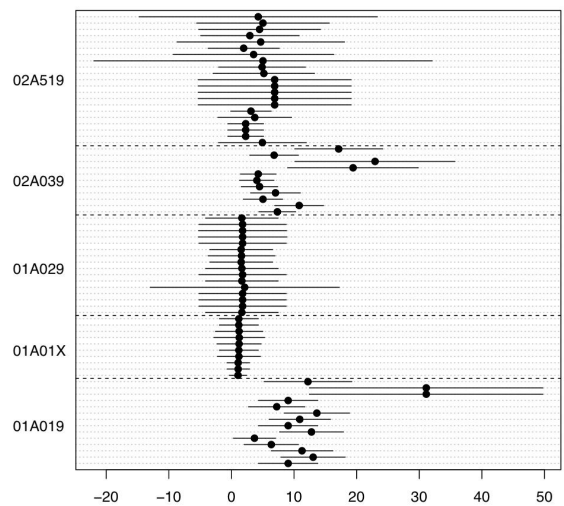

FIGURE 19.6: Confidence intervals for the expected number of hammerhead sharks present (given that bycatch has occurred) for the first five trips.

Tools to estimate abundance and predict important quantities like the probability of presence of critical endangered species have been much anticipated. We have demonstrated here how much can be learned in this regard from bycatch data. Future research will involve combining this information with measures of fishing intensity so as to attempt to fully describe abundance in regions of interest.

19.4 Conclusions

As we have illustrated with these two projects, we are able to gain insight into important questions in marine ecology by the careful construction of statistical models. As with many datasets in marine ecology, the structure is complex and there is also dependence among the observations which we need to accommodate in our models.

The development of the statistical model is determined by the scientific question of interest and the available data. The parameters to be estimated need to have clear ecological interpretations for the scientific question at hand. The confidence bounds on the parameters provide a measure of the accuracy of the estimates and information on the strength of the underlying ecological process in the data.

Our overall aim is to provide statistical models and tools necessary to understand the marine environment. This is especially important as data collection technologies continue to rapidly evolve leading to more sophisticated and complex data. For Canada, it is essential to understand how the oceans are changing, particularly the Arctic, as we continue to experience climate change.

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