

**SEA TURTLE BYCATCH
BY THE U.S. ATLANTIC PELAGIC LONGLINE FISHERY:
A SIMULATION MODELING ANALYSIS
OF ESTIMATION METHODS**

by:

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ABSTRACT

The U.S. pelagic longline fishery catches 98% of domestic swordfish landings but is also one of the three fisheries most affecting federally protected sea turtles (Crowder and Myers 2001, Witherington et al 2009). Bycatch by fisheries is considered the main anthropogenic threat to sea turtles (NRC 1990).

Accurate and precise bycatch estimates are imperative for sea turtle conservation and appropriate fishery management. However, estimation is complicated by only 8% observer coverage of fishing and data that are hierarchical in structure (i.e., multiple sets per trip), zero-heavy (i.e., bycatch is rare), and often overdispersed (i.e., larger variance than expected).

Therefore, I evaluated two predominant bycatch estimation methods, the delta-lognormal method and generalized linear models, and investigated improvements in uncertainty incorporation. I constructed a simulation model to evaluate bycatch estimation at two spatial scales under ten spatial models of sea turtle, fishing set, and observer distributions.

Results indicated that distributing observers relative to fishing effort and using the delta-lognormal-strata method was most appropriate. The delta-lognormal-strata 95% confidence interval (CI) was wider than statistically appropriate. The delta-lognormal-all sets pooled 95% CI was narrower but simulated bycatch was above the CI too frequently. Thus, I developed a

bycatch estimate risk distribution to incorporate uncertainty in bycatch estimates. It gives managers access to the entire distribution of bycatch estimates and their choice of any risk level.

Results support the management agency's observer distribution and estimation method but suggest a new procedure to incorporate uncertainty. This study is also informative for many similar datasets.

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overlap, there is strong evidence that the two medians differ (Chambers et al 1983). The box includes the first through third quartile. Whiskers extend to the most extreme data point which is no more than 1.5 times the interquartile range from the box. Dots represent outliers. In the (Turtles_{clump}, Sets_{clump-sets}) model, ten outliers were removed from the GLM-P box plot and ten outliers were removed from the GLM-NB box plot. In the (Turtles_{clump}, Sets_{random}) model, eleven outliers were removed from the GLM-P box plot and ten outliers were removed from the GLM-NB box plot. If these outliers were included, the boxplots would be too compressed to determine method performance.116

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A fishing set clump. The green cell indicates the center of the nine-by-nine cell fishing set clump. The black cells represent the fished cells. In this example there are four sets that fish five cells each. Notice that a set that begins in the middle of the clump can fish five cells in any of the four directions and remain inside the clump.128

FIGURE A1.2

A spatial replicate with clumped sets. The grid of light blue is 100-by-100 cells. There are five fishing set clumps that are nine-by-nine cells each. The fishing set clumps are consistent with the clump presented in Figure A1.1, except there is now a dark blue border around each clump. The border is four cells wide. It represents the area that could be fished by a set beginning at the edge of the clump.129

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Probabilities for placing turtles within a clump. Probabilities are assigned to X coordinates and Y coordinates independently so the center cell has the highest probability and probabilities decline with distance from the center. The range of random numbers that would be assigned to a coordinate are shown.132

FIGURE A1.5

The maximum amount of overlap allowed between two turtle clumps. This configuration prohibits a set from fishing in multiple turtle clumps.133

FIGURE A1.6

Border placement of uniformly random sets. A set could begin in any of the light blue cells, which range from coordinate four to ninety-five. This ensured that sets could cover five cells within the 100-by-100 cell grid. The purple border four cells wide demarcates where a set can fish if it begins on the edge of the light blue cells.136

FIGURE A1.7

A spatial replicate with a set clump. The grid is 100-by-100 cells. The green cell indicates the center of the clump. The medium blue cells compose the set clump. The dark blue cells around the set clump are a fishing set border. The border is four cells wide and indicates the cells that could be fished by a set that begins at the edge of the set clump. The light blue cells extend from cell number eight to ninety-one. The center of the set clump, the dark green cell, can be placed anywhere within the light blue cells. The light yellow cells bordering the light blue cells represent the extent of the set clump if the center of the clump is placed on the edge of the light blue cells. The light purple cells bordering the light yellow cells indicate where a set could fish if it started fishing at the edge of a set clump centered on the edge of the light blue cells.137

FIGURE A1.8

A fishing set clump. The green cell is the center of the clump. The black cells are the beginning cells of five fishing sets.138

FIGURE A1.9

A fishing set clump. The black cells are the beginning cells of five fishing sets. Based on the algorithm described above, $\text{DistanceSet}_0R = 81.93$, $\text{DistanceSet}_0L = 136.67$, $\text{DistanceSet}_0U = 102.86$, and $\text{DistanceSet}_0D = 123.30$. So $P(\text{Right}) = 0.327$, $P(\text{Left}) = 0.196$, $P(\text{Up}) = 0.260$, and $P(\text{Down}) = 0.217$140

FIGURE A1.10

The maximum amount of overlap allowed between two fishing set clumps. This configuration prohibits the overlap of sets from multiple set clumps.141

FIGURE A1.11

Algorithm for placing sets within a turtle clump. The number of turtles with each X and Y coordinate are tallied. The fraction of turtles with a given coordinate is used to determine the probability a set will begin in that coordinate. In this example, the orange cells are the nine-by-nine cell turtle clump. The yellow cell is the center of the clump. The black cells are the starting positions of five sets.143

FIGURE A1.12

Algorithm for determining the direction a set fishes in a turtle clump. The numbers in the cells indicate the number of turtles present. Consider the black cell in the top right portion of the clump. The grey cells show the possible fishing routes. The numbers of turtles that would be

encountered in each direction are used to calculate the probability of fishing in that direction. In this example, $\text{Animals}_R = 20$, $\text{Animals}_L = 222$, $\text{Animals}_U = 11$, and $\text{Animals}_D = 212$. So $P(\text{Right}) = 0.043$, $P(\text{Left}) = 0.477$, $P(\text{Up}) = 0.024$, and $P(\text{Down}) = 0.456$144

FIGURE A1.13

Turtles uniformly random and sets uniformly random

- Turtles could be placed in any cell, purple or light blue.
- To ensure that sets fished entirely within the grid, sets could start in any light blue cell and could move into the purple cells. The black cells indicate fished cells in one scenario.145

FIGURE A1.14

Turtles uniformly random and sets clumped

- Turtles could be placed in any cell, purple, yellow, or light blue.
- Fishing set clumps were placed so that sets fished entirely within the grid. The middle cell of set clumps could occur in any light blue cell. If the middle cell occurred on the border of the light blue cells, the clump extended into yellow cells. Sets could begin in any medium blue cell of the clump. Fishing could extend into the dark blue cells around the clump.
- No part of clumps could overlap so sets from multiple clumps did not overlap. The black cells indicate fished cells in one scenario.146

FIGURE A1.15

Turtles clumped and sets uniformly random

- Turtle clumps were placed so that the entire clump could fit within the grid. The middle cell of turtle clumps could occur in any light blue cell. If the middle cell occurred on the border of the light blue cells, the clump extended into yellow cells. Turtles could occur in any medium orange cell of the clump. The dark orange cells around the turtle clump indicate the fishing border.
- Sets could start in any cell except purple cells. Sets that began in the turtle clump could extend into the dark orange cells. The black cells indicate fished cells in one scenario.
- The dark orange cells of multiple clumps could overlap but the medium orange could not, so sets could not fish in multiple turtle clumps.147

FIGURE A1.16

Turtles clumped and sets clumped independently

- Turtle clumps were placed so that the entire clump could fit within the grid. The middle cell of turtle clumps could occur in any light blue cell. If the middle cell occurred on the border of the light blue cells, the clump extended into yellow cells. Turtles could occur in any medium orange cell of the clump. The dark orange cells around the turtle clump indicate the fishing border. Sets that began in the turtle clump could extend into the dark orange cells. The dark orange cells of multiple clumps could overlap but the medium orange could not, so sets could not fish in multiple turtle clumps.
- Fishing set clumps were placed so that sets fished entirely within the grid. The middle cell of set clumps could occur in any light blue cell. If the middle cell occurred on the border of the light blue cells, the clump extended into yellow cells. Sets could begin in

any medium blue cell of the clump. Fishing could extend into the dark blue cells around the clump. No part of set clumps could overlap so that sets from multiple clumps did not overlap. The black cells indicate fished cells in one scenario.

- There was no restriction on how turtle clumps and set clumps could overlap.148

FIGURE A1.17

Turtles clumped and sets clumped in the same area

- Turtle clumps were placed so that the entire clump could fit within the grid. The middle cell of turtle clumps could occur in any light blue cell. If the middle cell occurred on the border of the light blue cells, the clump extended into yellow cells. Turtles could occur in any medium orange cell of the clump. The dark orange cells around the turtle clump indicate the fishing border. Sets that began in the turtle clump could extend into the dark orange cells. The dark orange cells of multiple clumps could overlap but the medium orange could not, so sets could not fish in multiple turtle clumps.
- Sets began inside the medium orange turtle clump. They could extend into the dark orange cells. The black cells indicate fished cells in one scenario.149

FIGURE A1.18

Effort-based observer distribution. Suppose the pink cell was randomly selected to be the cell of high fishing effort. Then the two closest sets, marked with black and white hatches, were selected for observation.151

CHAPTER 1

LITERATURE REVIEW

L.1 THE BYCATCH PROBLEM

Global commercial fisheries discard an average of 27 million metric tons (17.9 to 39.5 million Mt) of fish each year, a significant proportion of the world's annual catch, which is around 100 million Mt (Alverson et al 1994, Hall et al 2000). Bycatch is defined under the Magnuson-Stevens Fishery Conservation and Management Act (MSFCMA) as "fish which are harvested in a fishery, but which are not sold or kept for personal use" (MSFCMA Section 3(2) 2007). The take of individuals of the target species but of an undesirable sex, size, or age class and the take of individuals of non-target species constitute bycatch (Lewison et al 2004a). Observed bycatch is either discarded or retained. Animals caught as bycatch may be released alive or dead, and individuals taken by the fishing gear but not observed are considered bycatch too (Crowder and Murawski 1998, NMFS 2007f). Any marine mammals or sea turtles interaction with pelagic longline gear constitutes bycatch.

The prevalence of bycatch is of concern for a number of reasons. Biodiversity can be affected if threatened and endangered species are caught incidentally. Ecological communities and food webs are altered by the removal of top predators or prey. Bycatch is economically undesirable as it generates no profit but incurs costs. Also bycatch generates conflict among fisheries, between fisheries and managers, and between fisheries and the public (Crowder and Murawski 1998, Hall et al 2000).

The shrimp trawl fishery has the highest ratio of bycatch to marketable catch among global fisheries and produces over one-third of global bycatch (Crowder and Murawski 1998,

Hall et al 2000). Bycatch by the pelagic longline fishery is also a concern. A longline is not a selective gear; baited hooks are set in the water column and catch whatever becomes hooked or entangled in the line (Crowder and Myers 2001). Therefore, bycatch of non-targeted billfish, sharks, marine mammals, sea turtles, and birds occurs. Bycatch of sea turtles by the U.S. pelagic longline fleet in the Atlantic, Gulf of Mexico, and Caribbean is the focus of this project because sea birds are not caught in this region of the fishery, the sea turtle bycatch rate is greater than the marine mammal bycatch rate, and sea turtles are of a greater conservation concern. The sea turtles caught by the pelagic longline fishery are listed under the Endangered Species Act (ESA) but the marine mammals are not.

L.2 THE PELAGIC LONGLINE FISHERY

L.2.1 HISTORY OF THE FISHERY

Pelagic longlining has been practiced worldwide since the 1800s when hooks were first mass produced (Crowder and Myers 2001, Gilman et al 2006). Today, pelagic longline fisheries range from small scale, subsistence fisheries known as artisanal fisheries to large, mechanized and industrialized fleets fishing not only in their nation's waters but in distant waters as well (Lewison et al 2004a, Gilman et al 2006). A wide variety of species are targeted by longline fisheries. Swordfish (*Xiphias gladius*), yellowfin tuna (*Thunnus albacares*), and bigeye tuna (*T. obesus*) are the primary targets of the U.S. Atlantic pelagic longline fishery. Albacore tuna (*T. alalunga*), bluefin tuna (*T. thynnus*), dolphinfish or mahi mahi (*Coryphaena* spp.), mako shark (*Isurus oxyrinchus*), thresher shark (*Alopias* spp.), and porbeagle shark (*Lamna nasus*) are among the secondary targets (Crowder and Myers 2001, Gilman et al 2006, NMFS 2007a).

L.2.2 PELAGIC LONGLINE GEAR CHARACTERISTICS

Fundamentally, pelagic longline gear consists of a horizontal mainline that is held at a certain depth by floats and a series of vertical lines with baited hooks that hang from the mainline (Witzell and Cramer 1995) (Figure 1.1). The mainline is about 47km long for U.S. vessels on average but can range from about 32km to 64km (Witzell 1999, Beerkircher et al 2004, Gilman et al 2006, NMFS 2007d). An average of 429 hooks are set, but the number can range from 200 to several thousand (Witzell 1999, Gilman et al 2006, NMFS 2007c). “Dead bait”, bait brought on the trip frozen, is almost exclusively used, and the bait is usually thawed before use. Atlantic mackerel (*Scomber scombrus*) and squid (*Illex spp.*) are commonly used (Beerkircher et al 2004). Typically the gear is left in the water for 6 to 10 hours (NMFS 2007b). Trips usually last 2-45 days, during which time the catch is kept fresh on ice (Crowder and Myers 2001, NMFS 2007c). On average, a trip lasts 9 days and involves 6 sets (NMFS 2006).

L.2.3 CATCH

The longline is a key fishing gear for catching swordfish, bigeye, and yellowfin tuna. Longlines caught about 98% of swordfish landings, 81% of bigeye tuna landings, and 43% of yellowfin tuna landings in the U.S. North Atlantic commercial fishery during 1996 (Crowder and Myers 2001, NMFS 2007e).

However, swordfish and tuna, the targeted species, constitute less than half of the total longline catch (Figure 1.2). Sharks and rays (29% of the catch) and finfish (14%) comprise the other most abundant categories, while the incidental capture of sea turtles, marine mammals, and sea birds make up only 1% of the total catch (Beerkircher et al 2004).

L.2.4 FISHERY MANAGEMENT

Atlantic Highly Migratory Species (HMS), such as swordfish and tuna, are managed by the Magnuson-Stevens Fishery Conservation and Management Act (MSFCMA) and the Atlantic Tunas Convention Act (ATCA) (NMFS 2006). The purpose of the MSFCMA is “to conserve and manage the fishery resources found off the coasts of the United States” (MSFCMA Section 2(b)(1) 2007). NMFS is charged with managing fisheries to maintain optimal yield (OY), rebuild overfished fisheries, and prevent overfishing (NMFS 2006). Bycatch minimization is also required under National Standard 9 of the MSFCMA (NMFS 2004b). Management policies must minimize bycatch to the extent practicable, and when bycatch cannot be avoided, policies must minimize the mortality of bycatch (Crowder and Murawski 1998, NMFS 2004b).

L.2.5 ECONOMICS AND HUMAN DIMENSIONS

In addition to rebuilding overfished fisheries, preventing overfishing, and minimizing bycatch, the MSFCMA also requires NMFS to assess the likely effects of management policies on fishermen and fishing communities (MSFCMA Section 301(a)(8)). The crews of over 100 vessels rely on revenues from the U.S. Atlantic pelagic longline fishery for their livelihoods. However, many longline firms are currently operating at the margins of financial sustainability (Crowder and Myers 2001). When the economics at the fleet-level are examined, it appears that swordfish landings peaked in weight in 1988 and in value in 1989. At this time, almost 5,200Mt of swordfish worth about \$37 million (unadjusted for inflation) were caught annually. However, the catch and revenue have declined in the 1990s and 2000s (Crowder and Myers 2001).

There is a strong market for swordfish and tuna in the U.S. The U.S. consumes about 25% of the world's swordfishing landings, making it the world's largest swordfish market (Ward and Elscot 2000, Crowder and Myers 2001). Only a very small amount of swordfish is exported from the U.S., while in 1999, 13,800Mt valued at \$72 million were imported from twenty-three countries (Crowder and Myers 2001, NMFS 2001). The U.S. exported 13,500Mt of tuna worth \$37.5 million and imported 200,000Mt of tuna valued at \$750 million in 1999 (Crowder and Myers 2001).

Because of the importance of the U.S. pelagic longline fishery for people and communities, it is necessary to consider how they are affected by management decisions. In the most recent HMS Fishery Management Plan (FMP), the effects of a number of potential closures were considered. Results indicate that existing closures may have contributed to the reported 15% decline in fishing effort, 10% decline in the number of directed and incidental permits, and the decline from 199 to 130 active pelagic longline permits from 2000 to 2004 (NMFS 2006).

L.3 PELAGIC LONGLINE BYCATCH

Although sea turtles and marine mammals make up less than 1% of the pelagic longline catch, these incidental captures are notable as these species are protected under the ESA and MMPA respectively. Observed sea turtle bycatch is much larger than observed marine mammal bycatch (Johnson et al 1999). For this reason and because out of the protected species that interact with the pelagic longline fishery the sea turtles are more threatened than the marine mammals, the incidental catch of sea turtles seems to receive more attention.

There are two major steps in addressing the bycatch problem: (1) characterize the bycatch and (2) reduce bycatch. Characterizing the bycatch includes identifying the species caught,

quantifying the magnitude of bycatch by species, determining the nature of the injuries sustained and the condition of release, and assessing the population level effects (Crowder and Murawski 1998). The population level effects of bycatch can be assessed by determining post-interaction mortality rates and how longline-related mortality affects population growth and demographics. Bycatch can be reduced by changing fishing practices – changing gear, fishing location, or fishing season.

L.3.1 INCIDENTALLY CAUGHT SPECIES

L.3.1.1 Sea turtles

Loggerhead sea turtles (*Caretta caretta*) and leatherback sea turtles (*Dermochelys coriacea*) comprise 94% of the sea turtle bycatch by Atlantic pelagic longlines, but green turtles (*Chelonia mydas*), Kemp's ridley turtles (*Lepidochelys kempii*), and hawksbill turtles (*Eretmochelys imbricata*) interact with the fishery at low levels (Crowder and Myers 2001). Loggerheads tend to actively consume baited hooks whereas leatherbacks more frequently become entangled in the gear or hooked externally (Witzell and Cramer 1995, Gilman et al 2006).

The dominant hypothesis regarding loggerhead development and migration suggests that they undergo trans-Atlantic developmental migrations. After hatchlings leave the beach, they are thought to be caught up in the Gulf Stream-Azores Current and North Atlantic Gyre and spend many years in this oceanic stage. During this time, they may primarily be pelagic, meaning they occupy the water column. It is believed that loggerheads transition from the oceanic stage to the neritic stage at 46-64cm curved carapace length (CCL) (average of 52cm straight carapace length (SCL)), which is reached after 7 to 11.5 years (average of 8.2 years) (Bolten 2003a, Bolten

2003b). The neritic zone is the inshore waters not exceeding 200m (Bolten 2003b). At this stage, loggerheads are primarily epibenthic or demersal, meaning they frequent the sea floor (Bolten 2003b). Older loggerheads may enter pelagic waters during seasonal migrations (Bolten 2003a).

In contrast, leatherbacks inhabit oceanic waters during their entire lives; they are pelagic and feed on jellyfish throughout their lives (Crowder and Myers 2001). Leatherback movements are not well understood, but they are known to be the most migratory sea turtle and to have the largest latitudinal range of all sea turtles (Plotkin 2003, NMFS-OPR 2007a).

Loggerheads are listed as threatened under the ESA and endangered by The World Conservation Union (IUCN), reflecting their high risk of extinction in the wild. Leatherbacks are listed as endangered under the ESA and are designated as critically endangered by the IUCN since they have an extremely high risk of extinction in the wild in the immediate future (IUCN 2006). The ESA defines a threatened species as “any species which is likely to become an endangered species within the foreseeable future throughout all or a significant portion of its range” and an endangered species as “any species which is in danger of extinction throughout all or a significant portion of its range” (ESA Section 3(6) 1973), and (ESA Section 3(19) 1973).

The ESA prohibits the taking of an individual of a listed species where “take” means “to harass, harm, pursue, hunt, shoot, wound, kill, trap, capture, or collect, or to attempt to engage in any such conduct” (ESA Section 3(18) 1973). However, allowances are made for incidental takes, takes that are “incidental to, and not the purpose of, the carrying out of an otherwise lawful activity”, such as incidental capture by a fishery (ESA Section 10(a)(1)(B) 1973). Incidental takes are not prohibited under the ESA if “the taking will not appreciably reduce the likelihood of the survival and recovery of the species in the wild” and if the taking is in compliance with an

Incidental Take Statement (ITS). The ITS issued by the NMFS specifies the impact of incidental takes on listed species and reasonable and prudent measures to minimize takes (ESA Section 10(a) (2)(A)).

L.3.1.2 Marine mammals

The long-finned pilot whale (*Globicephala melas*), short-finned pilot whale (*Globicephala macrorhynchus*), and Risso's dolphin (*Grampus griseus*) are the marine mammals that interact most with the Atlantic, Gulf of Mexico, and Caribbean pelagic longline fisheries (Crowder and Myers 2001). Pilot whales are caught more frequently than Risso's dolphins, and together they make up 89% of the marine mammal bycatch by the Atlantic pelagic longline fishery (Scott and Brown 1997, Crowder and Myers 2001).

Pilot whales have a world-wide range and frequent deeper waters (NMFS-OPR 2007c, NMFS-OPR 2007e). They feed primarily on squid from 305m or deeper, but octopus and fish may also be consumed (NMFS-OPR 2007d). In fact, pilot whales are frequently observed feeding on hooked fish, especially bigeye tuna (NMFS-OPR 2007f). Pilot whales form social aggregations of 20-90 individuals which can be over a kilometer long and include related females, their offspring, and males (ACS 2007a, MarineBio.org 2007, NMFS-OPR 2007d).

The Risso's dolphin inhabits tropical to warm temperate waters world-wide (NMFS-OPR 2005). They are pelagic, prefer offshore habitats, and primarily feed on squid at night; however, they have been known to prey on crustaceans and fish (ACS 2007b, CRRU 2007, OBIS-SEAMAP 2007). Risso's dolphin typically form groups of 3-30 individuals, but "super-pods" of several thousand animals have been observed (ACS 2007b). They move in echelon formation where individuals line up abreast and are evenly spaced, resulting in efficient foraging (CRRU

2007). Risso's dolphins may also associate with other species of cetaceans (OBIS-SEAMAP 2007).

The World Conservation Union (IUCN) classifies *G. melas* as lower risk and least concern and *G. macrorhynchus* as lower risk and conservation dependent, which means they would be considered threatened within 5 years if the existing conservation programs were ended. The IUCN classifies Risso's dolphin as data deficient, meaning the data are insufficient to assess the population's risk of extinction (IUCN 2006).

Risso's dolphin and pilot whales, and all marine mammals, are protected under the MMPA. The MMPA prohibits, with some exceptions, the take of marine mammals, where "take" is defined as above, and does not permit stocks to fall below their optimum sustainable population (MMPA Section 2(2) 1972, NMFS-OPR 2007b). With respect to incidental capture by fisheries, the MMPA requires the reduction of bycatch "to insignificant levels approaching a zero mortality and serious injury rate" (MMPA Section 118(b)(1) 1972). U.S. commercial fisheries are categorized under the MMPA according to the amount of marine mammal mortality and serious injury caused. The U.S. Atlantic, Caribbean, and Gulf of Mexico pelagic longline fishery is a Category I fishery, the category of highest marine mammal impact (Johnson et al 1999).

L.3.2 DATA TO ADDRESS THE BYCATCH PROBLEM

Data to estimate sea turtle and marine mammal bycatch are gathered from the Fisheries Logbook System and Pelagic Observer Program. Participation in the Fisheries Logbook System has been required since 1986. All vessel captains must keep logbooks, and fishing effort data are obtained from the logbooks. The Pelagic Observer Program was initiated in 1992. Observers

are placed on a subset of U.S. pelagic longline vessels, and they record information about interactions with marine mammals and sea turtles in addition to characterizing the catch in general.

L.3.2.1 Fisheries logbook system

The Atlantic Swordfish Fishery Management Plan has required permitted U.S. longline vessels to submit daily logbook reports since 1986 (Scott and Brown 1997, NMFS 2007b). Of all the information recorded in the logbook, the level of fishing effort is the most important for estimating sea turtle and marine mammal bycatch, and the number of hooks is the most common metric for effort. Data identifying the target species, bait type, set and haulback times and positions, length of gangions and floatlines, number of light sticks, number of hooks, number of each species caught, number of animals retained, number of animals discarded alive or dead, and nature of interactions with protected species are obtained from the daily logbook reports (DiNardo 1993, Witzell 1999, NMFS 2007b). The Trip Summary form provides information on the date and port of departure and return, costs, unloading dealer and location, number of sets, and number of crew (NMFS 2007b). The Southeast Fisheries Science Center (SEFSC) manages this database (Scott and Brown 1997). Generally, the logbooks report effort and catch data, and to some degree, protected species interactions (Crowder and Myers 2001, NMFS 2007b).

For a number of reasons, logbook reports of protected species interactions are not treated as conclusive (Witzell and Cramer 1995). Underreporting of protected species interactions, species misidentification, and improper use of logbook forms may contribute to biases in the logbook data (Johnson et al 1999, Walsh 2000). Protected species bycatch may be underreported because fishermen naturally have a tendency to remember marketable catch better or from fear of

Federal regulation (Witzell and Cramer 1995). Alternatively, fisherman may report marine mammal and sea turtle bycatch, but they may misidentify the species. Also, changes in logbook reporting procedures could lead to reporting errors. Prior to 1992, sea turtle takes were recorded as hard shell turtle or leatherback, but after 1992 species-specific records were required (Crowder and Myers 2001).

Logbook records provide an unreliable source of bycatch data, and observer data are used to mitigate this problem (Yeung 1999). While logbook and observer data show some similar trends – high turtle catch in 1995 and low catch in 1997, for example – bycatch estimates made from observer data are larger than bycatch levels reported in logbook data (Johnson et al 1999). Observer data demonstrate the existence of error in logbook data, but the direction and magnitude of logbook error cannot be determined due to the low observer coverage (Scott and Brown 1997, Johnson et al 1999, Crowder and Myers 2001, Lewison et al 2004a).

L.3.2.2 Pelagic observer program

The 1991 amendments to the Fishery Management Plan for Swordfish promulgated the Pelagic Observer Program (Scott and Brown 1997). The Northeast Fisheries Science Center (NEFSC) established an observer program in 1991, and the SEFSC instituted an observer program in 1992 (Witzell and Cramer 1995). The NEFSC and SEFSC ran separate observer programs before 1997 at which time the SEFSC assumed control of the entire Atlantic observer program (Beerkircher et al 2004). The observer program mandates systematic sampling of the U.S. pelagic longline fleet in the Atlantic (Scott and Brown 1997).

The observer's goal is to collect data that can serve as a representative basis for estimating total catch composition, including retained and discarded catch and targeted and

incidental catch (Scott and Brown 1997). Observers are charged with a number of objectives: estimate the number of individuals caught per species, collect biological data on the individuals caught, observe fishing methods and compliance with regulations (Crowder and Murawski 1998). The data collected by observers can be used to characterize the nature of the catch, estimate total bycatch and take rates, and identify factors correlated with catch (DiNardo 1993).

A number of forms are used by observers to collect effort and catch data (Beerkircher et al 2004).

1. Longline Gear Log – Includes records on type of mainline, length of dropline, number and length of gangions, type of hook, number of buoys, number of high-flyers, and number of radio beacons (Figure 1.1)
2. Longline Haul Log – Includes records on set and haulback location, time, and duration; vessel speed during set; environmental conditions; and type of bait
3. Individual Animal Log – Includes records on the species caught, condition of the catch (alive, dead, damaged, unknown), biological characteristics of the catch (length, weight, sex), and fate of the catch (kept, thrown back, finned, etc.). There is also a comments section where observers may note the injury and release condition (Yeung 1999).
4. Sea Turtle Life History Form – Since 1999 the Sea Turtle Life History Form has been used to record more detailed information about sea turtle bycatch events. On this form observers record fishing location and gear characteristics, turtle species, condition of the turtle, dimensions of the turtle, information on any tags present, and release condition. Photographs may also be included (Yeung 1999).
5. Incidental Take Log – Includes records of marine mammal or marine bird bycatch. The species, condition, and length of the animal are recorded. Whether a photograph was

taken of the animal and gear characteristics such as the presence of a light stick can also be noted.

The goal in selecting vessels for observation is to obtain a representative sample of the fleet. In the Atlantic, observers are deployed according to a simple random sampling design based on reported effort (Witzell and Cramer 1995). Vessels are selected in proportion to the amount of fishing reported in the prior year-area-quarter and are sampled without replacement within a year-quarter. Quarter refers to one of the four calendar quarters, and area refers to one of the Atlantic fishing areas (Figure 1.3). Also, six grouped fishing areas (NAREA) were created for estimating bycatch, and three major ocean regions (MAREA) were created for reporting and testing of the estimation method's sensitivity to pooling (Scott and Brown 1997).

Prior to 1999, only vessels targeting swordfish or tuna were observed, but since 1999, all vessels using pelagic longline gear have been observed. While this includes vessels targeting sharks or mahi mahi, they remain a small percentage of all pelagic longline vessels (Beerkircher et al 2004).

Before 2002, a target observer coverage of 5% was set based on the available resources and estimated sampling costs rather than on predicted bycatch estimate precision (Scott and Brown 1997, Johnson et al 1999). Since 2002 the target coverage has been 8% (Beerkircher et al 2004). The Observer Program has had varying success in meeting this target. From 1992 to 2002, an average of 86% of the targeted number of sets were observed (Beerkircher et al 2004), and this equates to an average of 4.2% coverage from 1992 to 2001 (NMFS 2004a). Since 2001, the average coverage has been 7.1%. The strata with characteristically low observer coverage, CAR, NED, SAR, NCA, TUN, TUS, are also the strata furthest offshore (Yeung et al 2000, NMFS-SEFSC 2001, Garrison 2003).

L.3.3 ESTIMATING BYCATCH

L.3.3.1 Difficulties

Overall low observer coverage and sparse coverage of some strata can lead to biases. Sea turtle and marine mammal bycatch is a rare event, there is a high degree of spatial and temporal variation in the system, and there is inter-vessel variability. If these facts are not taken into consideration when distributing observers and making estimates, they can become sources of bias. On average, at least one sea turtle is caught on about 10% of the observed sets (Scott and Brown 1997, Johnson et al 1999, Musick and Godley 2007). Marine mammal bycatch is even rarer; only 2.4% of observed sets catch at least 1 marine mammal (Scott and Brown 1997, Johnson et al 1999). Therefore, when few sets are observed, very few bycatch events are observed, and it is very difficult to make fleet-wide estimates based on these data. However despite this, the observed coefficients of variation for annual estimates of loggerhead and leatherback bycatch have sometimes met the requirements for accuracy set by NMFS by being less than 30% (Garrison 2005, Walsh and Garrison 2006).

Further complicating estimation is the high degree of spatial and temporal variation in fishing behavior, marine mammal and sea turtle distribution and behavior, and thus bycatch. When some quarter-area strata have low coverage, the high degree of variability in the system makes it difficult to extrapolate observations to estimate bycatch in these strata. Also, inter-vessel variability and the fact that fishermen may change their fishing behavior when an observer is onboard must be considered as potential sources of bias (Crowder and Myers 2001, Babcock and Pikitch 2003). Because of inter-vessel variability, error can be introduced when observations from a few vessels are extrapolated to make fleet-wide estimates (Crowder and Myers 2001). Finally, if fishermen change where they fish, which species they target, how they

set their gear, or how they sort the catch when an observer is present, the observer data may not be representative of the fleet (Hall 1999, Liggins et al 1997). Thus, estimates made from these data would be biased (Babcock and Pikitch 2003). The characteristics of the system must be considered when collecting data and using them to make estimates so that they do not become sources of bias.

L.3.3.2 The importance of accurate and precise estimation

Although there are many difficulties associated with estimating sea turtle and marine mammal bycatch, it is required by regulation, and accurate and precise estimates are necessary both for the conservation of the species and for appropriate management of the fishery. According to NMFS's interpretation of the ESA and MMPA, the agency must estimate annual U.S. pelagic longline bycatch of sea turtles and marine mammals. The pelagic longline fishery is authorized by a Biological Opinion under Section 7 of the ESA, and the Biological Opinion includes an Incidental Take Statement specifying expected turtle take by the fishery (Table 1.1). The expected level of take must be compared to annual estimates of bycatch, and if the fishery exceeds the anticipated level of take, ESA Section 7 Consultation is triggered. The Service assesses whether the fishery is jeopardizing the survival of the species, and consequently, how the fishery is allowed to proceed (McCracken 2004, USFWS 2007). Estimates of total bycatch are also useful in developing recovery and management plans (Witzell and Cramer 1995).

The MMPA mandates that marine mammal mortality and serious injury be reduced below Potential Biological Removal (PBR) (Garrison 2003). The PBR identifies anthropogenic mortality levels that permit a protected species to remain stable or recover (Wade 1998). Serious injury and mortality are allowed until these takes impair the stock's ability to recovery to its

maximum net productivity level (Crowder and Myers 2001, Angliss and DeMaster 1997). Estimates of population size, growth rates, conservation status, and data uncertainty influence the PRB calculation (Crowder and Murawski 1998, Crowder and Myers 2001).

L.3.3.3 Correlated factors to facilitate estimation

Making accurate bycatch estimates can be difficult given the low observer coverage and the high degree of variation in oceanographic conditions, species abundance and behavior, and fishing practices across fishing areas, seasons, and years (Yeung 2001). Luckily, understanding patterns in fishing practices and factors correlated with bycatch can assist with the efficient distribution of observers and with estimation.

L.3.3.3.1 Fishing patterns

In the U.S. Atlantic pelagic longline fishery, many patterns can be found among effort, gear characteristics, targeting practices, fishing location, and season. Understanding these patterns can assist in distributing observers and estimating sea turtle and marine mammal bycatch. U.S. vessels fish in different areas of the Atlantic during different seasons, and patterns in effort can be found by bathymetric features (Crowder and Myers 2001). Effort is highest in southern regions of the Atlantic in the winter (Musick and Godley 2007). While effort is distributed more or less evenly among calendar quarters in the GOM, effort in NEC and NED reaches a high in the 3rd quarter and a low in the 1st quarter. Effort in OFS and CAR exhibits the opposite trend, and effort in the SEC peaks in the 2nd quarter (NMFS-SEFSC 2001). A spatial analysis also found that fishing effort is highest within continental shelves (200-1000m depth) and slopes (1000-3000m depth), especially around the 200m and 1000m isobaths, and in areas

with strong bathymetric gradients (Crowder and Myers 2001). Not only does effort vary by fishing area, but target species does as well. Tunas are generally targeted in the GOM, MAB, and NEC whereas swordfish are targeted in the CAR, FEC, SAB, SAR, NED, NCA, TUN, and TUS (Beerkircher et al 2004). Also, gear configuration and fishing methodology vary depending on the target species and location of fishing (Beerkircher et al 2004). When targeting swordfish, longlines are set overnight at shallow depths (10-100m), and squid bait is used. Often a light stick is attached several meters above the hook on every second or third branchline. In contrast, when tuna are targeted, longlines are set at dawn and hauled in at late afternoon or evening. The longlines are set at 30-150m except when targeting bigeye tuna, then gear is set at 100-400m (Crowder and Myers 2001).

L.3.3.3.2 Bycatch patterns

Identifying correlations between sea turtle and marine mammal bycatch and target species, time of day, season, fishing area, and habitat features can facilitate observer distribution and bycatch estimation. Considering fishing seasons and locations with historically high levels of bycatch could also help identify patterns. I will only discuss patterns in sea turtle bycatch since they interact with pelagic longlines more frequently than marine mammals and they are of a higher conservation concern.

Sets targeting swordfish are responsible for most sea turtle takes (Crowder and Myers 2001). Studies employing hook timers also indicate that leatherbacks are more frequently hooked at night (Watson et al 2004, Gilman et al 2006). In contrast, loggerheads may have a greater hooking rate during the day since they tend to detect bait visually (Báez et al 2007). Loggerheads and leatherbacks are taken year-round, but the majority of takes seem to occur from

June to November (Witzell 1999, NMFS-SEFSC 2001, Crowder and Myers 2001). Most loggerhead catches occur in waters 28-32°C, while most leatherback catches occur in waters 25-31°C (Gilman et al 2006, Musick and Godley 2007). Bycatch data suggest that loggerheads are more abundant in waters deeper than 3000m and in areas with little bathymetric relief (Crowder and Myers 2001). Leatherback catch is high in deep water with low bathymetric relief far from continental shelves and slopes (Witzell 1999, Crowder and Myers 2001).

The fishing area with the highest annual bycatch has varied substantially from 1995 to 2006. All areas except the NCA, TUN, and TUS have been cited as having high loggerhead bycatch in at least 1 area-quarter-year strata, and the low observer coverage of these areas likely contributes to this trend. However, loggerhead bycatch has been consistently high in the MAB, NEC, NED, and GOM (Witzell and Cramer 1995, Williams et al 1996, Johnson et al 1999, Witzell 1999, Garrison 2003, Garrison and Richards 2004, Garrison 2005, Walsh and Garrison 2006). Likewise, all areas except the CAR, SAR, NCA, TUN, and TUS have had high leatherback bycatch. The GOM is often reported to be the area of highest leatherback bycatch, but there are also consistently high bycatch levels in the MAB, NEC, and NED (Williams et al 1996, Witzell and Cramer 1995, Johnson et al 1999, Witzell 1999, Garrison 2003, Garrison and Richards 2004, Garrison 2005, Walsh and Garrison 2006, Musick and Godley 2007). The NED in particular has high levels of bycatch because of its circulation and thermodynamic features that result in high productivity.

There appear to be associations between habitat and the incidence and magnitude of loggerhead and leatherback bycatch. Environmental features such as major current systems and temperature, chlorophyll, or salinity gradients strongly influence the distribution of target species and sea turtles (Bigelow et al 1999, Polovina et al 2000, Lewison et al 2004b). These currents

and frontal regions are often associated with enhanced productivity and prey aggregation, and some bathymetric features have the same effect (Witzell 1999, Crowder and Myers 2001). For example, pelagic longlining and turtle abundance are high around the warm-core rings that spin off from the Gulf Stream onto the cool northeast slope water (Williams et al 1996, Witzell 1999).

L.3.4 ESTIMATION METHODS

The NMFS Southeast Fisheries Science Center (SEFSC) has estimated marine mammal and sea turtle bycatch by the U.S. Atlantic longline fishery since 1992, and the Pacific Islands Fisheries Science Center (PIFSC) began estimating sea turtle bycatch by the Hawaii-based longline fleet in 1994. A variety of methods have been used by the SEFSC and PIFSC to estimate bycatch, but no standard method has been developed (Table 1.2). Each method extrapolates observer data to make fleet-wide estimates based on varying assumptions (Crowder and Myers 2001).

Generally the estimation methods can be broken into two categories: sample-based estimators and model-based predictors. Sample-based estimators raise observed bycatch rates to fleet-wide estimates based on total reported effort. While effort may be quantified by vessel size, number of vessels in the fleet, number of days fishing per vessel, number of trips per vessel, number of sets per trip, or number of hooks per set (Crowder and Myers 2001); the number of hooks has been used most frequently (Yeung 1999). Sample-based estimators assume sampling probabilities but for the most part avoid assumptions regarding the target population structure and features being estimated. Sample-based estimators are usually less efficient than model-based predictors, which assume a statistical model of bycatch. Empirical data are used to

develop an approximating model for bycatch, and an estimator is based on the assumed prediction model (McCracken 2004).

The different methods used by the SEFSC and PIFSC will be highlighted here, but more information can be found in the Methods Section and Appendix B. These methods are not only used to estimate sea turtle bycatch by the U.S. pelagic longline fishery but are also used in many diverse disciplines to estimate rare events with zero-heavy data.

L.3.4.1 Sample-based estimators

L.3.4.1.1 Survey sampling method

The most basic sample-based estimation procedure is the survey sampling method. Stratum-specific observer data are used to calculate a rate of bycatch as the number of takes divided by the number of hooks. Extrapolations are then made by multiplying the estimated take rate by the total number of hooks to estimate fleet-wide bycatch (Skillman and Kleiber 1998). It was one of the first methods used by the PIFSC but is no longer employed.

L.3.4.1.2 Delta-lognormal method

The delta lognormal method has been consistently used by the SEFSC. It accommodates a predominant group of zero observations by including a probability of zero catch, and non-zero observations are assumed to be lognormally distributed (Pennington 1983, Ortiz et al 2000, NMFS-SEFSC 2001). The delta-lognormal method will be used extensively in this study. More details can be found in Appendix B, section A2.2.

L.3.4.1.3 Horvitz-Thompson estimator

The Horvitz-Thompson estimator has been used by the PIFSC since 2004 when the fishery was reopened with increased observer coverage (McCracken 2004). Responses are weighted by a probability of inclusion in the sample so that the higher the probability of selection, the less weight the response is given (Patterson 2008). This method was not used by the SEFSC because observer coverage was too low.

L.3.4.2 Model-based predictors

While in sample-based estimators bycatch rates are calculated by dividing observed takes by observed effort and then raising to the total level of effort, in model-based predictors models describing the relationship between environmental or fishing conditions and bycatch are used to estimate unobserved bycatch.

L.3.4.2.1 Classification and regression tree (CART)

In classification and regression trees (CART) analysis, the model is initially designed with as many variables as possible and later pruned to contain only the most important explanatory variables (Skillman and Kleiber 1998). Classification trees can be advantageous because they do not assume additivity, but bycatch data must be redefined as a Bernoulli variate where the presence or absence of bycatch is modeled rather than the magnitude of bycatch (McCracken 2004). While the PIFSC used CART in early bycatch estimation, now the PIFSC only recommends CART for identifying explanatory variables, not for predicting bycatch (McCracken 2004).

L.3.4.2.2 Generalized linear model (GLM)

The GLM extends the classical linear model by using a distribution other than the normal distribution and using any monotonic differentiable link function. The GLM most commonly used for count data, the log-linear model, assumes a Poisson error distribution (McCullagh and Nelder 1989). In the past, NMFS has used fishing area, data source (observer or logbook), light stick use, gear depth, month, latitude, sea surface temperature, day of the year, and number of hooks as explanatory variables (Witzell and Cramer 1995, McCracken 2000, McCracken 2004). The GLM will be used in this study. More details can be found in Appendix B, section A2.1.

L.3.4.2.3 Generalized additive model (GAM)

In a GAM, a flexible additive function replaces the GLM's linear predictor (McCracken 2004). While a GLM is fit by estimating parameters, a GAM is fit estimating a smoothing function (Hastie and Tibshirani 1990). In GLMs, regressors are related to the response with linear functions of covariates, but the additive smoothing functions of a GAM can be any shape from a straight line to a nonparametric curve (Hastie and Tibshirani 1990, McCracken 2000, Schimek and Turlach 2000, McCracken 2004, Venables and Dichmont 2004, Wood 2006).

L.3.4.2.4 Models to address overdispersion and excess zeros

Several other estimation methods have been used to estimate rare events from data with many zeros and overdispersion. In count data, the variance is often larger than the mean, a case known as overdispersion. Overdispersion arises when observations are not independent or there is some clumping in the data, for example if animals aggregate in good habitat or because of social behavior (McCracken 2000, Lindsey 2004, Fahrmeir and Echavarría 2006). Further,

overdispersion is likely when modeling subunits in hierarchical data since the subunits are clumped within primary units, as sets are grouped within trips (McCracken 2004). If overdispersion is not addressed, standard errors can be seriously underestimated and the form of the linear predictor can be misinterpreted (McCracken 2000, Rideout et al 2001, Potts and Elith 2006). Excess zeros can also complicate estimation. Models designed to accommodate excess zeros do not explicitly address overdispersion, but overdispersion may be reduced (Potts and Elith 2006).

The quasi-likelihood model, generalized linear mixed model (GLMM), and GLM or GAM with a negative binomial distribution can account for overdispersion. The quasi-likelihood model is a GLM extension to deal with overdispersion. The distribution is not specified exactly; a model is specified for the mean and for the relationship between the mean and variance, and a dispersion parameter based on the data is included (Wedderburn 1974, McCracken 2000, McCracken 2004, Potts and Elith 2006). A generalized linear mixed model (GLMM) includes an extra component of variation in the model to account for the increased dispersion (Venables and Dichmont 2004). A GLMM linear predictor has both fixed terms and random variates (Venables and Dichmont 2004). When data are hierarchical, the GLMM model is particularly suitable (McCracken 2004). GLMMs are often appropriate when the parameters occur naturally in groups, and they have several independent places where a stochastic element enters the model (Venables and Dichmont 2004). The negative binomial distribution includes a parameter not present in the Poisson distribution, the dispersion parameter. So while the mean and variance are assumed equal in the Poisson model, the negative binomial model defines the variance as a multiple of the mean (White and Bennetts 1996, Welsh et al 1996, Thurston et al 2000, Lindsey 2004, Venables and Dichmont 2004, Potts and Elith 2006, Sileshi 2006).

The zero-inflated Poisson (ZIP) model, zero-inflated negative binomial (ZINB) model, and conditional model address data with excess zeros (Wedderburn 1974, Welsh et al 1996, White and Bennetts 1996, Thurston et al 2000, Dobbie and Welsh 2001, Rideout et al 2001, Fletcher et al 2005, Warton 2005, Fahrmeir and Echavarría 2006, Weiss 2006). The first component of both models includes only zero counts. The second component of the conditional model only includes positive counts, but the second component of the zero-inflated model may include zero and positive counts. The assumption in the conditional model that zero counts only occur in the first component of the model is suitable when factors can be divided into those that influence presence/absence and those that influence abundance (Weiss 2006). The zero-inflated model assumes some zero counts are observed by chance as the Poisson distribution predicts, and the rest are generated by a different mechanism (Rideout et al 2001, Weiss 2006). Biologically this can be understood as observing zero counts from sampling unsuitable habitats and observing zero counts by chance from sampling a site suitable for the animal but without an individual present (Weiss 2006). The goal in both conditional and zero-inflated models is to develop separate regression models for presence/absence and abundance.

L.3.4.3 NMFS's selection of estimation methods

So far several estimation methods employed by the NMFS SEFSC and PIFSC have been discussed. However, there has been relatively little discussion about which is most appropriate. The SEFSC has used the delta-lognormal approach in the majority of their estimation reports but not because it was shown to be the most appropriate method after a systematic analysis. The delta-lognormal method is used to maintain consistency with prior reports (Fairfield and Garrison 2008).

Although sea turtle bycatch has been estimated since 1992, the first report to systematically examine different methods for their suitability was written in 2000 (McCracken 2000). After considering a diversity of models, McCracken concluded that the rarity of observed bycatch was the factor demanding the most attention, not overdispersion. The NBD, GLMM, and ZIP models require more information from the data and more complex algorithms for model fitting (McCracken 2004). McCracken found that parameter estimates did not converge in the GLMM and negative binomial linear model (McCracken 2004). However, the log-linear model and its GAM and quasi-likelihood counterparts fit the data well, and they converged quickly. Thus, McCracken concluded these were the most appropriate method for modeling turtle bycatch for that dataset (McCracken 2004).

L.3.5 ASSUMPTIONS AND POTENTIAL BIASES

In addition to considering assumptions in estimation methods, assumptions regarding the quality of the data and data structure must be considered. There may be missing or inaccurate data. Logbook records are not always complete. NMFS has attempted to address this by substituting missing values with the values recorded on neighboring days or with the most frequently recorded value (Scott and Brown 1997). Underreporting of effort in the logbooks is also possible, and this would result in a negative bias in bycatch estimates. However, observed gear characteristics and effort seems consistent with reported effort (Garrison 2003).

There are gaps in observer coverage. There are some quarter-area-year strata with reported effort but very little observer coverage. Each stratum should have at least 20 to 30 observations to make precise and unbiased bycatch estimates, and a minimum of 3 observations is required to estimate stratum variance (Babcock and Pikitch 2003). If there is insufficient

observer data for a stratum, data are pooled. This increases the sample size but resolution is lost and biases may be introduced. Pooling can decrease estimate variance, but pooling also assumes that the sample data are representative of the region. Such an assumption can obscure important differences and trends (Yeung et al 2000). A number of different pooling procedures have been considered by the SEFSC to address these issues. The current approach is to use the mean bycatch rate observed in the quarter-area stratum since 2004 if a stratum has effort but no observer coverage (Fairfield and Garrison 2008). Fairfield and Garrison reasoned that there is likely more variation between quarters and geographic areas than across years.

Also, observer data have a hierarchical structure that may introduce two kinds of stochastic dependence among sets within a trip: (a) bycatch from sets within a trip may be more similar than bycatch across trips and (b) bycatch from sets that are spatially or temporally close may be more similar. Thus, sets are not independent. If trips were modeled, independence could be assumed, but resolution would be lost at the set level. Therefore, it is preferable to model sets, but the hierarchical nature of the data should be accounted for so that results are not misleading. Set dependence should be modeled if explanatory variables do not explain the dependence among sets (McCracken 2000).

Finally, turtle misidentification is a possible problem. Takes of hawksbill, green, and Kemp's ridley sea turtles have been recorded by observers and in logbooks, but it is unlikely for individuals of these species to occur in waters fished by the U.S. pelagic longline fleet (Yeung et al 2000, NMFS-SEFSC 2001). There was also some photographic evidence of misidentification (Witzell and Cramer 1995). Also, it is possible for an animal to have multiple longline interactions, so estimates should be interpreted as the number of interactions rather than the number of animals interacting with the gear (Witzell and Cramer 1995).

L.3.6 RESULTS FROM PAST ESTIMATION REPORTS

When the bycatch estimates from 1992 to 2007 are examined some patterns emerge (Figure 1.4). However, it is important to note the large confidence intervals and the underlying uncertainty in annual bycatch levels and inter-annual trends. It appears that loggerhead takes reached a high in 1995 but have been lower since then (Garrison 2005). Estimated leatherback takes increased from 1998 until their peak in 2004, before the circle hook regulations were implemented (Garrison 2005).

There were substantial decreases in both loggerhead and leatherback bycatch in 2005 (Walsh and Garrison 2006). These reductions could be due in part to the switch to circle hooks in the later part of 2004, to a decrease in effort following Hurricanes Katrina and Rita, or to a decline in turtle populations (Walsh and Garrison 2006). Other inter-annual sources of variability such as environmental conditions could have contributed as well.

Changes in the amount of leatherback bycatch since 2005 are not clear, but the level of bycatch has clearly dropped from its high levels in the early 2000s. Loggerhead bycatch seems to have increased since 2005, and there is no clear difference between post-2004 bycatch levels and the levels of the mid-1990s and early 2000s.

L.3.7 POPULATION-LEVEL EFFECTS OF FISHERY INTERACTIONS

The purpose of estimating bycatch and managing the fishery to control bycatch is so that the fishery does not jeopardize protected species. Therefore, understanding the number of interactions is an important first step, but understanding the effect of interactions on the survival of individuals is essential. Sea turtles are often alive when released from longline gear, but post-

interaction mortality is largely unknown. The number of fatalities from interacting with the longline fishery is biologically the most important estimate, not the number of captures.

NMFS should assess population-level effects of fisheries bycatch on sea turtles and marine mammals (Crowder and Myers 2001). However, very little is known about their population sizes, population trends, and key growth parameters (Crowder and Myers 2001). This makes any estimation of population-level effects of fisheries interactions difficult. But we do know that the life history characteristics of sea turtles and marine mammals make their populations especially vulnerable to fishery-related mortality. With a late age of maturity and low reproductive rate, it can take the population a long time to recover from high levels of anthropogenic mortality (Hall et al 2000, Lewison et al 2004b). Even low levels of bycatch may affect population viability (Crowder and Myers 2001). While many aspects of sea turtle and marine mammal biology are not fully understood, the little information we have about population structure, size, and trends is useful in understanding the effects of longline takes.

Not only does our incomplete understanding of sea turtle biology hamper our ability to assess the impact of pelagic longlines on sea turtle populations, but it is also impaired by our meager knowledge about the degree of post-longline hooking mortality. The vast majority of turtles interacting with longline gear are released alive. However, how these turtles fare after being released is poorly understood. Satellite tags have been attached to some turtles when released from longline gear, but although these studies have potential, they have not conclusively revealed the fate of turtles released alive from longlines (Sasso and Epperly 2007). Because survival rates could vary by species, in different areas of the Atlantic, in different seasons, in different years, and with different injuries and release conditions, it is difficult to draw many conclusions from these studies so far. Yet discounting post-interaction mortality would seriously

underestimate the impact of longlining on sea turtle populations (Yeung 1999). Experts in longline gear deployment and sea turtle biology, anatomy/physiology, veterinary medicine, satellite telemetry established post-interaction mortality criteria at the Workshop on Marine Turtle Longline Post-Interaction Mortality (Ryder et al 2006). Mortality rates were hypothesized for loggerheads and leatherbacks based on the nature of the injury and the release condition (Table 1.3). Leatherbacks have higher estimated mortality rates for a given injury/release condition than loggerheads because of their fragile tissue, bone structure, and increased susceptibility to entanglement and anoxia. Also larger turtles have a greater risk of injury during boarding or handling (Ryder et al 2006). Not only are populations affected by direct mortality, but cumulative long-term declines in fitness could affect the health of the population. Sub-lethal injuries such as forced submergence, hook ingestion, external hooking, or entanglement could result in increased stress, decreased growth, delayed development and maturation, and ultimately decreased reproductive potential (Crowder and Murawski 1998, Ryder et al 2006).

Despite the uncertainty about sea turtle biology and the post-longline interaction effects, some have suggested that sea turtle interactions with longline gear must be reduced for the long-term survival of these species (Ryder et al 2006). From demographic models it has been determined that the large juvenile and subadult are the most critical loggerhead lifestages, but these are some of the lifestages that interact with longlines (Crouse et al 1987, Crowder and Murawski 1998, Crowder et al 1994, Heppell 1997, Mazaris et al 2006). It is disconcerting that turtles being taken by the pelagic longline fishery are among the lifestages to which the population growth rate is most sensitive (NMFS-SEFSC 2001).

L.3.8 BYCATCH MITIGATION

Two general approaches may be taken to reduce the impact of the longline fishery on sea turtles and marine mammals: (1) reduce the number of interactions and (2) reduce mortality from interactions. With respect to sea turtles, regulated time/area closures, voluntary avoidance of areas with high bycatch, and some gear modifications can reduce the number of interactions while gear modifications and improved handling techniques can reduce mortality from interactions (Crowder and Myers 2001, Gilman et al 2006).

The NED, including the productive Grand Banks, was partially closed in 2000 because of high turtle bycatch levels, and it remained completely closed to commercial pelagic longline vessels from June 2001 to June 2004 when it was reopened with gear restrictions (Garrison 2003, Garrison and Richards 2004, Garrison 2005, Gilman et al 2006). The NED was opened to fishing if 18/0 or larger circle hooks with an offset not exceeding 10 degrees and whole Atlantic mackerel or squid bait are used (NMFS 2004a). Vessels fishing outside the NED must follow the NED-specific requirements modified to allow 16/0 or larger non-offset circle hooks and whole finfish bait (NMFS 2004a). The change from J-hooks to exclusive use of circle hooks went into effect in the third quarter of 2004 (Garrison 2005, Walsh and Garrison 2006). Studies have suggested that, when compared to J-hooks, circle hooks decrease the bycatch rate and the severity of injury when bycatch occurs (Watson et al 2004, Watson et al 2005). The size and shape of the circle hook and the orientation of the barb may reduce external hooking and make esophagus and gut hooking rarer; when loggerheads attempt to consume the bait, they are more likely to be hooked in the mouth than swallow the hook (Watson et al 2005, Gilman et al 2006).

Instead of mandated closures, voluntary avoidance of areas with high bycatch in combination with a cap on bycatch has potential. Experience has shown that if a vessel catches a

turtle, avoiding that area will reduce the chances of catching another turtle (Williams et al 1996, Gilman et al 2006). This observation has led to a voluntary fleet communication program in the U.S. North Atlantic where sea turtle encounters, sea turtle sightings, and sightings of oceanographic features known to be correlated with high turtle abundance are reported in real-time so that vessels can avoid these areas and thus avoid exceeding a government-set cap on bycatch. Observer data suggest that this program has reduced turtle CPUE by 50% (Gilman et al 2006).

When a sea turtle is caught, longline crews must follow safe handling and release guidelines (NMFS 2004a). Vessels are required to carry and use sea turtle release equipment and to comply with regulations for their use when handling incidentally caught turtles. The gear required is a long-handled line clipper or cutter, a long-handled dehooker for ingested hooks, a longhandled dehooker for external hooks, a long-handled device to pull an “inverted V”, a dipnet, a standard automobile tire, a short-handled dehooker for ingested hooks, a shorthandled dehooker for external hooks, long-nose or needle-nose pliers, a bolt cutter, a monofilament line cutter, and two different types of mouth openers and mouth gags (including either a block of hard wood, a set of three canine mouth gags, a set of two sturdy dog chew bones, a set of two rope loops covered with hose, a hank of rope, a set of 4 PVC splice couplings, or a large avian oral speculum) (NMFS-SEFSC 2001, NMFS 2004a). These required tools and procedures facilitate the removal of hooks and lines and thus reduce the post-interaction mortality rate (NMFS-SEFSC 2001).

Some of these practices, such as single threading of bait, use of 18/0 circle hooks, and use of fish bait, are also thought to maintain or increase the CPUE of the target species, making these policies widely appealing (Gilman et al 2006). In many cases policies must be designed

specifically for the fishery because the variability in the fishery and environment may lend different approaches to be more effective and commercially viable in different areas (Gilman et al 2006).

L.3.9 COMPARISON WITH OTHER FISHERIES

When interpreting the impact of the U.S. pelagic longline fishery on sea turtle and marine mammal populations, it is important to put interactions with this fishery in context by comparing them with other sources of anthropogenic mortality. This does not discount the potential seriousness of longline interactions; it merely puts these interactions in a wider context so population-level effects can be more clearly examined. For example, the commercial shrimp trawl fishery is thought to be the most significant source of anthropogenic sea turtle mortality in the southeast Atlantic and Gulf of Mexico. Of all commercial fisheries the Atlantic pelagic longline fishery has the greatest impact on pilot whales and Risso's dolphins (Crowder and Myers 2001).

L.4 INTERNATIONAL CONTEXT

When considering the effects of the pelagic longline fishery on marine mammal and sea turtle populations it is important to remember that many nations besides the U.S. fish in the Atlantic. In fact, U.S. effort is a small proportion of total longline effort in the Atlantic. Further, it is important to remember that since marine mammals and sea turtles have a wide range, the fishing activities in many oceans and seas affect these populations.

L.4.1 EFFORT AND TARGETED CATCH

Twenty-six nations besides the U.S. fish in the western North Atlantic with pelagic longlines, and the U.S. fleet contributes 5 to 8% of the total effort and about 5% of the total catch (NMFS-SEFSC 2001, Crowder and Myers 2001, NMFS 2007d). These estimates may even be high as a large proportion of U.S. data are included but other nations may not report fishing statistics as consistently (NMFS-SEFSC 2001). Japan, Taiwan, and Spain have the largest fleets in the Atlantic (Crowder and Myers 2001, NMFS-SEFSC 2001, Lewison et al 2004b).

L.4.2 BYCATCH OF SEA TURTLES AND MARINE MAMMALS

It is believed that the U.S. fleet is efficient compared to most foreign fleets; in other words, targets species make up a greater percentage of the U.S. catch. However, the efficiency of foreign fleets is not well known (NMFS-SEFSC 2001). Several fisheries in the Atlantic, besides the U.S. fleet, collect effort and catch data. But they are of varying quality, and few have systematic observer programs or report incidental catch in any capacity. Twenty-four nations have reported a recent pelagic longline catch, but only 13 have reported effort (Long and Schroeder 2004). While France, Greece, Italy, and Spain have observer programs and have collected high quality bycatch data (Long and Schroeder 2004), artisanal effort and bycatch is largely unknown (Lewison et al 2004a). This lack could be significant as artisanal fisheries are expected to have a high turtle take rate because of their fishing location, methods, and gear (Gilman et al 2006). Further, effort and bycatch of illegal, unregistered, or unreported (IUU) vessels are not known. This is not inconsequential as IUU vessels are thought to catch around 85,000Mt of tuna and swordfish (Lewison et al 2004b). To put this estimate in context, the U.S.

Atlantic Highly Migratory Species fisheries landed 2,974Mt of tuna and 1,958Mt of swordfish in 2004 (NMFS 2006).

Catch data from over 40 nations and bycatch data from 13 international observer programs were utilized by Lewison et al (2004b) to estimate the global level of sea turtle bycatch by pelagic longlines in 2000. The minimum bycatch estimate, made considering a fraction of the total hooks, suggested about 60,000 loggerheads and 9,000 leatherbacks were taken in 2000, but when extrapolated to consider all hooks, two estimation methods gave 220,000-250,000 loggerheads and 50,000-60,000 leatherbacks caught worldwide. No mortality estimates were made.

Due to the internationality of fisheries and the distribution of sea turtles and marine mammals, international agreements must be a focus of conservation efforts. International agreements such as the Convention on the Conservation of Migratory Species of Wild Animals (CMS) and the FAO Code of Conduct for Responsible Fisheries will help achieve international cooperation in managing fisheries and reducing bycatch (Lewison et al 2004a). The Inter-American Convention for the Protection and Conservation of Sea Turtles is the only international treaty exclusively addressing sea turtle conservation (NMFS-OPR 2007a).

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CHAPTER 2

SIMULATION MODEL

INTRODUCTION

The U.S. Atlantic pelagic longline fishery targets swordfish and tuna but occasionally catches protected species of marine mammals and sea turtles. The loggerhead sea turtle (*Caretta caretta*) is threatened and the leatherback sea turtle (*Dermochelys coriacea*) is endangered under the Endangered Species Act (ESA). Risso's dolphin (*Grampus griseus*) and pilot whales (*Globicephala* spp.) are protected under the Marine Mammal Protection Act. In this thesis, I will focus on the catch of sea turtles since they are a greater conservation concern, but results should be applicable to marine mammal bycatch as well.

Every year the National Marine Fisheries Service (NMFS) Southeast Fisheries Science Center (SEFSC) estimates the number of individuals of each protected species caught by the U.S. Atlantic pelagic longline fishery. These annual bycatch estimates have serious implications. If an estimate exceeds the species' incidental take statement (ITS), consultation under the ESA is reinitiated. If it is determined that fishing jeopardizes the continued existence of the species, alternative measures must be taken (NMFS 2004, USFWS 2007). In the past, the NMFS regulated a change from J hooks to circle hooks and has used time and area closures to reduce bycatch (Fairfield and Garrison 2008). In the Pacific, the Hawaii-based swordfish longline fishery was completely closed from 2000 through 2003 because of sea turtle bycatch (Dalzell 2000, Pradhan and Leung 2006).

Bycatch estimates are calculated from two sources of data: logbooks kept by the captains of fishing vessels and records kept by observers. Generally, bycatch is estimated by identifying

some relationship between fishing effort or environmental characteristics and the number of turtles caught on observed sets and extrapolating that relationship to estimate bycatch on unobserved sets. The information about observed sets comes from the records kept by observers, and data regarding unobserved set is obtained from logbooks. Each captain is required to keep a logbook and record information about fishing gear, location, effort, target, and catch. While logbooks include effort and catch data, the reports of protected species interactions are not considered conclusive (Witzell and Cramer 1995, Crowder and Myers 2001, NMFS 2007). Observers provide a more accurate report of protected species interactions. The observer's goal is to collect data that can serve as a representative basis for estimating total catch composition, including retained and discarded catch and targeted and incidental catch (Scott and Brown 1997). The current SEFSC procedure is to place observers on fishing vessels randomly based on the level of fishing effort in each time-area stratum in the previous year (Figure 1.3) (Fairfield and Garrison 2008, Beerkircher et al 2004). However, the SEFSC's target annual observer coverage is only eight percent of all fishing sets (Fairfield and Garrison 2008, Beerkircher et al 2004).

Although bycatch estimates are essential to sound fisheries management and species conservation, there are many statistical complications and many potential methods. There has been little work analyzing the suitability of methods for estimating sea turtle bycatch by the pelagic longline fishery, and there is no consensus regarding the most appropriate method. Some of the frequently occurring data characteristics that must be addressed by an estimation method are overdispersion (greater variance than expected), excess zeros (many observed sets without bycatch), and hierarchical observations (fishing sets within trips).

The National Marine Fisheries Service (NMFS) Southeast Fisheries Science Center (SEFSC) and Pacific Islands Fisheries Science Center (PIFSC) have used a variety of estimation

methods in the twenty years these centers have been estimating bycatch by the pelagic longline fishery (Table 1.2). Currently, the SEFSC estimates bycatch in time-area strata with the delta-lognormal method. The SEFSC has used this method since 1997, and continues to use this method primarily to maintain consistency among years (Scott and Brown 1997, Fairfield and Garrison 2008). In the PIFSC, many more estimation methods have been used, and there has been a greater emphasis on model-based estimation, as opposed to sample-based estimators such as the delta-lognormal method (McCracken 2000). A generalized linear model (GLM) emerged as the recommended method in the PIFSC until 2004 when the fishery reopened with high observer coverage, much higher than the level of observer coverage in the Atlantic fishery (McCracken 2004).

The SEFSC's estimates made with the delta-lognormal method have wide confidence intervals, and their accuracy is unknown (Figure 2.1). Consequently, it is difficult to determine the level of bycatch in one year and the trend over time, which impedes management. NMFS's ability to estimate bycatch and thus manage the fishery and conserve protected species may be improved if estimation methods are analyzed and the most suitable estimation method is identified.

In this thesis, I developed a spatial simulation model to replicate different fishing scenarios and applied some of the most common estimation methods to evaluate their performance under these different fishing conditions. I used the delta-lognormal method, a generalized linear model with a Poisson error distribution (GLM-P), and a GLM with a negative binomial error distribution (GLM-NB), each at two levels of data pooling. Analyzing the performance of various estimation methods under different fishing conditions highlighted their

strengths and weaknesses and could lead to more accurate point estimates and narrower confidence intervals, which in turn could improve management.

OBJECTIVES

The objectives of this thesis are:

1. To determine estimation method performance with observers distributed relative to fishing effort, the SEFSC's current procedure.
2. To determine if distributing observers in bycatch hotspots improves bycatch estimation.
3. To evaluate the SEFSC's 95% confidence interval and investigate ways to improve the incorporation of uncertainty in bycatch estimates.

METHODS

This study addressed three main objectives: (1) to evaluate the accuracy and precision of several of the predominate methods for estimating sea turtle bycatch by the pelagic longline fishery, (2) to evaluate the effect of observer distribution methods on bycatch estimation, and (3) to incorporate a quantification of risk in bycatch estimates.

First, I built a spatial model in which sea turtles and fishing sets were distributed in different fishing scenarios. Observers were placed on 8% of the sets according to the SEFSC's procedure of placing observers in proportion to fishing effort, and bycatch estimates were made. I evaluated the performance of each estimation method under each fishing scenario to identify method suitability.

Next, I modeled the same sea turtle and fishing set spatial models but with observers placed in bycatch hotspots. I estimated bycatch with each method under each fishing scenario to assess whether a bycatch-based distribution of observers improves bycatch estimation compared to an effort-based distribution of observers.

Finally, since the SEFSC typically uses bycatch point estimates without considering uncertainty to manage the pelagic longline fishery (P. Richards pers. comm. 7 May 2009), I incorporated a measure of risk in bycatch estimates.

I discuss the methods involved in each objective below. More details regarding how I constructed the spatial simulation model can be found in Appendix A. More details on the theory behind the estimation methods and how I applied the estimation methods in the simulation model can be found in Appendix B.

M.1 SPATIAL MODELS

To meet the objectives of this study, I built a spatial simulation model representing different fishing scenarios. Sea turtle – fishery interactions were simulated in each spatial model, and each estimation method was evaluated by comparing the estimate to the simulated total take. Modeling several spatial fishing scenarios enabled a more comprehensive evaluation of estimation methods. Each estimation method was evaluated under five spatial fishing scenarios. Also, much remains unknown about how sea turtles are distributed in space, how fishermen decide where to fish, and the nature of sea turtle – fishing vessel interactions in time and space. Therefore, I designed several spatial fishing scenarios to address the uncertainty and variation in sea turtle – fishery interactions (Table 2.1).

M.1.1 SEA TURTLE DISTRIBUTIONS

I gathered available data on sea turtle spatial distributions and densities and used this information to model two sea turtle spatial distributions under which to evaluate estimation methods: clumped and uniformly random.

M.1.1.1 Biological theory

Biologically, a clumped spatial distribution could occur because of variable habitat; turtles occur in desirable habitat and are not present in undesirable habitat. Turtles could also clump due to social aggregation.

A uniformly random spatial distribution could occur if there is no habitat effect; either the habitat does not vary or habitat varies but does not influence turtle presence. Also, turtles are unaffected by the presence of other turtles under a random spatial distribution turtles.

M.1.1.2 Empirical evidence

The main fishery-independent method to investigate at-sea turtle distributions is satellite tracking. However, data are limited. Few turtles are tracked because satellite tags are expensive, \$3,000 to \$6,000 each. Also, satellite tags transmit for at most one year (Coyne et al 2009). Satellite tags are attached to the carapaces of turtles, so nesting females have most frequently been tagged, although there has been some tagging of turtles at sea (James et al 2005). The behavior of turtles in pelagic water is of primary interest when studying bycatch by the pelagic longline fishery. Under the predominate theory, pelagic waters are used by leatherbacks at all ages and by juveniles loggerheads (Bolten 2003, Plotkin 2003). Therefore, satellite data may be biased by a disproportionately high number of nesting females and an under-representation of immature turtles developing in pelagic waters.

Lacking sufficient satellite tagging data, spatial and temporal patterns in bycatch can be studied. Gardner et al (2008b) found that catch distributions vary seasonally. For most of the year loggerhead and leatherback catch locations are not completely random, and there seems to be increased clumping from July through October. Clumping is more pronounced with loggerheads than leatherbacks (Gardner et al 2008b). Other studies have shown that environmental features like major current systems and temperature, chlorophyll, or salinity gradients seem to influence turtle clumping (Bigelow et al 1999, Polovina et al 2000, Lewison et al 2004). Currents, frontal regions, and some bathymetric features are often associated with enhanced productivity and prey aggregation, and turtles exhibit a clumping pattern in response as they forage (Williams et al 1996, Witzell 1999, Crowder and Myers 2001, Gilman et al 2006).

While there are data indicating that turtles clump, there is very little information about the size or density of clumps. Through an analysis of bycatch distributions, Gardner et al (2008b) found turtle catch distributions spanning 30 to 200km. Sea turtle density has been estimated from aerial surveys, but these estimates are highly uncertain. Sea turtles are only sighted on aerial surveys when they surface, and they are surfaced for a small proportion of time, around 10% (Keinath et al 1994). Hence, the number of turtles sighted is expected to be much smaller than the number of turtles present, but there is no reliable index to convert the number sighted to a total number present. Goodman et al (2007) estimated a mean surface density of 0.615 turtles/km² in the summer and 0.0616 turtles/km² in the fall off North Carolina. Keinath et al (1994) estimated a loggerhead surface density of 0 to 0.372 turtles/km² and a leatherback surface density of 0 to 0.07 turtles/km² off North Carolina depending on the season and year. Accounting for the percent of time at the surface, Keinath et al (1994) estimated total loggerhead density to be up to 2.952 turtles/km² and leatherback density to be up to 0.532 turtles/km². McDaniel et al (2000) also observed a sea turtle density of 0.525 turtles/km² in the Gulf of Mexico off the Florida Keys. A density of 0.5 turtles/km² was assumed for the model because this is an intermediate estimate, and it is computationally convenient.

M.1.1.3 Model application

There is evidence that turtles clump, especially in productive areas of the ocean, but turtle distributions seem to vary over time and with different species. Different species may clump to a greater or lesser degree at different times of the year and in different areas of the ocean. Therefore, I modeled clumped and non-clumped distributions. The non-clumped distribution is referred to as “uniformly random” to indicate that turtles were placed randomly according to a

uniform probability distribution function. This is in contrast to the ecological notion of a uniformly spaced distribution in which each animal maximizes its distance from all other animals, resulting in an equal spacing of animals (Figure 2.2). An evenly spaced distribution was considered but ruled out because it did not seem as biologically plausible as the other two distribution patterns.

M.1.1.3.1 Clumped

While constructing turtle clumps in the simulation model I attempted to incorporate the limited empirical data on the size and density of sea turtle clumps, but since the structure of turtle clumping is still highly uncertain, I also structured clumps to facilitate model computations. Turtles were modeled as most dense in the center-most cell of the clump and gradually decreased in density with distance from the center of the clump. The full details of modeling clumped sea turtles can be found in Appendix A, section A1.2.2.

M.1.1.3.2 Uniformly random

I modeled a non-clumped distribution according to a uniform random distribution. This served as an informative null. The full details of modeling a uniformly random distribution of sea turtles can be found in Appendix A, section A1.2.1.

M.1.2 FISHING SET DISTRIBUTIONS

NMFS data suggest that fishing sets are clumped in space. The reason for this clumping, however, is not fully understood. I modeled two mechanisms behind the clumped distribution, and I modeled a uniformly random distribution as a null.

M.1.2.1 Biological theory

Ocean productivity is not uniform. There are fronts and bathymetric features with associated highly productivity that may attract fishermen. Fishermen may be clumping together in productive areas that attract targeted swordfish and tuna. These productive areas may also attract foraging sea turtles, resulting in sets and turtles being clumped in the same areas (Bigelow et al 1999, Witzell 1999, Polovina et al 2000, Crowder and Myers 2001, Lewison et al 2004, Gardner et al 2008b). Sets and turtles may clump in the same area if turtles, targeted fish, and fisherman all congregate in productive areas of the ocean.

Fishermen may also take cues from other fishermen. They may be clumping because of peer influence, and this distribution may imperfectly match the presence of fish and turtles attracted to productive areas. Turtles may also occur in areas not actively fished. This results in sets clumped independent of turtle presence. Sets and turtles may clump independently if sets imperfectly locate productive areas or if turtles occur in other areas.

Sets could occur randomly if there is no habitat or peer influence. This would be expected if fishing conditions were uniform across the ocean.

M.1.2.2 Empirical evidence

In the SEFSC's annual bycatch estimation reports, the locations of reported and observed pelagic longline fishing sets are plotted. From examining the set distributions from 2005 through 2007, it appears that fishing sets are clumped (Figure 2.3). There are prominent clumps around the Grand Banks, continental shelf, and northern Gulf of Mexico, for example.

M.1.2.3 Model application

While it appears that fishing sets are clumped, the reason for this clumping is not fully understood. The location and degree of clumping seems to vary slightly from year to year, and some fishing areas have more clumping than others. I modeled two mechanisms behind the clumping of sets and also modeled a uniformly random distribution of sets.

M.1.2.3.1 Clumped

I modeled two states of clumped fishing sets: (1) sets clumped in the same areas as turtles, and (2) sets clumped independent of turtle presence. The full details can be found in Appendix A, sections A1.3.2 and A1.3.3.

M.1.2.3.2 Uniformly random

In addition to these two clumped distributions, I also modeled a uniform random distribution of fishing sets as a null. The full details can be found in Appendix A, section A1.3.1.

M.1.3 OBSERVER DISTRIBUTION – EFFORT

The NMFS SEFSC pelagic longline observers are responsible for documenting finfish bycatch, characterizing fishery behavior, and quantifying interactions with protected species (Fairfield-Walsh and Garrison 2007). Currently, the NMFS SEFSC distributes observers in the pelagic longline fishery relative to the amount of fishing effort in the previous year in each calendar quarter-fishing area strata (Figure 1.3) (Beerkircher et al 2004, Fairfield and Garrison

2008). I attempted to simulate this observer distribution in the model. The details of model application can be found in Appendix A, section A1.5.1.

M.1.4 FIVE SPATIAL MODELS

In this simulation model, turtles could be clumped or uniformly random. Sets could be clumped in the same area as turtles, clumped independent of the turtle distribution, or uniformly random. This resulted in five plausible combinations. All permutations were modeled except the case of turtles uniformly random and sets clumped where turtles are clumped since this is not possible (Table 2.1).

M.1.5 PROBABILITY OF TURTLE CAPTURE

After turtles and fishing sets were distributed, interactions were modeled. To quantify the number of takes, the number of turtles that occurred in fished areas was tallied. Then a probability of capture given co-occurrence was applied. These probabilities were based on 2005 through 2007 NMFS observer data (Walsh and Garrison 2006, Fairfield-Walsh and Garrison 2007, Fairfield and Garrison 2008). The full details can be found in Appendix A, section A1.6.

M.2 ESTIMATION METHODS

For a particular simulation model, a sea turtle distribution was selected and a fishing set distribution was selected. A probability of take was applied to each potential sea turtle – fishing set interaction to determine the number of takes. Observers were placed at 8% coverage and collected data. The number of takes on unobserved sets was tallied in the simulation. Simulated observer data and logbook data were used to estimate bycatch with several prominent estimation

methods. Each estimation method was evaluated by comparing the estimate to the number of simulated unobserved takes. This was repeated for each spatial fishing model to evaluate each estimation method under a range of fishing scenarios.

The performance of the delta-lognormal method and generalized linear model (GLM) were evaluated in this simulation model. The delta-lognormal method was selected because it has been used consistently by the NMFS SEFSC since 1997 (Table 1.2). The GLM was selected because it was determined to be one of the most suitable methods for estimating sea turtle bycatch based on model diagnostics and scientific judgment (McCracken 2000, McCracken 2004). A Generalized Additive Model (GAM) was also recommended, but I focused on the GLM since it is a more basic model and McCracken (2000) found no advantage of the GAM over the GLM. The SEFSC also used a GLM for their first bycatch estimation report and is currently exploring the use of a GLM for future bycatch estimation (Witzell and Cramer 1995, L. Garrison pers. comm. 7 May 2009).

More details on the theory of the delta-lognormal method and the GLM as well as how I applied these methods to the simulation model can be found in Appendix B.

M.2.1 GENERALIZED LINEAR MODEL (GLM)

M.2.1.1 NMFS application

Witzell and Cramer (1995) of the SEFSC estimated sea turtle bycatch with a GLM based on the Poisson error distribution assumption. Spatial fishing area, data source (logbook or observer), light stick use, and gear depth were considered as potential explanatory variables.

After considering a diversity of bycatch estimation models in 2000, McCracken of the PIFSC found no advantage of GAMs over GLMs and thus recommended GLMs. In her 2004

report, she suggested GLMs or GAMs. Good data fitting occurred with the log-linear model and its GAM and quasi-likelihood counterparts, and they converged quickly. McCracken also concluded the rarity of observed bycatch, not overdispersion, was the factor demanding the most attention (McCracken 2004).

M.2.1.2 Model application

When I estimated sea turtle bycatch, the number of takes served as the response variable. The set of potential explanatory variables consisted of all data categories recorded both by NMFS observers and in NMFS logbooks. The observed number of takes in the simulation and explanatory variable values selected from the NMFS dataset were used to fit a GLM. For more details on the selection of explanatory variable values, refer to Appendix B, section A2.1.2.1. More information about the GLM fitting procedure can be found in Appendix B, section A2.1.2.2.

I modeled two GLMs, one with a log link function and a Poisson error distribution, the other with a negative binomial error distribution. The Poisson distribution is the most common and straightforward distribution for counts of rare events (Lindsey 1997, McCracken 2000). However, zero-heavy count data are often overdispersed, variance larger than the mean (McCracken 2000, McCracken 2004). Poisson models cannot handle overdispersion, but negative binomial models are appropriate (Welsh et al 1996, Thurston et al 2000, Lindsey 2004, Venables and Dichmont 2004).

The GLM was used with the unobserved sets' explanatory variables, which were selected from the NMFS dataset, to estimate the number of takes on unobserved sets. I estimated bycatch

at two spatial levels: bycatch in each stratum and all strata pooled. Refer to Appendix B, section A2.1.2.3 for more information on predicting bycatch with the GLM.

- **Potential explanatory variables**

The data categories common between observer data and logbooks were considered as potential explanatory variables. It is important that data are recorded in both sources because in real life application, the model would be fit with data from observed sets, and data from logbooks would be used to predict take on unobserved sets. The common data are haul number, mainline length, target species, light stick presence, number of hooks, date, latitude, longitude, sea surface temperature (SST), and fishing area.

Variable values were pulled from real sets observed by NMFS from 2005 through 2007 and assigned to each simulated set. When a simulated set had bycatch, I assigned variable values from a SEFSC observed set with bycatch. Likewise, when a simulated set did not have bycatch, variables from a SEFSC observed set without bycatch were assigned. Further, variable assignment was designed to reflect the modeled spatial distribution. When modeled sets were clumped, variable values were selected from SEFSC observed sets that occurred close in time and space. Finally, I modeled strata based on the SEFSC's time-area strata estimation procedure. Therefore, sets in a modeled stratum had variable values from SEFSC observed sets close in time and space. This was similar to the procedure for selecting variable values for clumped sets, but this affected more sets (all the sets in a stratum not just the sets in a clump) and applied to the models where sets were not clumped. See Appendix B, section A2.1.2.1 for more details.

- **Model selection**

Initially I fit a saturated model, and I used an Akaike information criterion (AIC) stepwise procedure to select the model (McCracken 2004). See Appendix B, section A2.1.2.2 for more details.

- **Bycatch estimation**

Once the model was selected and fit, the explanatory variable values from the simulated unobserved sets were used as the regressors in the model to predict the number of turtles caught on each unobserved longline set i according to

$$\hat{Y}_i = \exp\left(\hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \cdots + \hat{\beta}_p x_{ip}\right) \quad (1)$$

where:

\hat{Y}_i = the predicted number of turtles caught on set i

x_{ij} = the variable value for regressor j on set i

β = parameter estimates

The predicted bycatch per unobserved set was summed across sets within a stratum or across all pooled sets to estimate take on unobserved sets. I added this estimate to the number of observed takes (Y_i) to arrive at a total annual estimate of bycatch (\hat{Y}_+) (McCracken 2000, McCracken 2004):

$$\hat{Y}_+ = \sum_{i=1}^n Y_i + \sum_{i=1}^{N-n} \hat{Y}_i \quad (2)$$

where:

\hat{Y}_i = the predicted number of turtles caught on set i

Y_i = the observed number of turtles caught on set i

n = the number of observed sets

N = the total number of sets

M.2.2 DELTA-LOGNORMAL

M.2.2.1 NMFS application

The NMFS SEFSC has used the delta-lognormal method to estimate bycatch since 1997 (Scott and Brown 1997). They estimate bycatch for each time-area stratum and sum these estimates to obtain an annual estimate (Fairfield and Garrison 2008).

However, the SEFSC has also investigated the effect of pooling data across time and space on bycatch estimates. They found that pooling did not significantly affect point estimates but increased precision (Yeung 1999). I also chose to investigate this estimation method. Pooling data across strata could be a useful approach for addressing the problem of little or no observer coverage in some strata. It may also help narrow the width of confidence intervals.

M.2.2.2 Model application

In the simulation model, I estimated bycatch for each time-area stratum, and I pooled data across all time-area strata to estimate bycatch.

○ **Strata-level estimate**

Making strata-level bycatch estimates is the standard procedure used by the NMFS SEFSC. Therefore, I estimated bycatch in the simulation model with this method.

• ***Bycatch point estimate***

The delta-lognormal method essentially estimates bycatch as the product of the proportion of sets with bycatch and the average rate of bycatch for those sets (Yeung 2001).

The mean bycatch rate was calculated as (Pennington 1983, Fairfield and Garrison 2008):

$$C_t = \frac{m_t}{n_t} e^{L_t} G\left(\frac{S_{L_t}^2}{2}\right) \quad (3)$$

where:

t = time-area stratum

m_t = the number of sets with observed bycatch in time-area stratum t

n_t = the number of observed sets in time-area stratum t

L_t = the mean of the \log_e -transformed number of turtles taken by 1,000 hooks when bycatch occurred in time-area stratum t

$S_{L_t}^2$ = the sample variance of the \log_e -transformed bycatch rate in time-area stratum t

G = the cumulative factor from the Poisson distribution given as:

$$G\left(\frac{S_{L_t}^2}{2}\right) = 1 + \frac{m_t - 1}{m_t} \left(\frac{S_{L_t}^2}{2}\right) + \sum_{j=2}^{\infty} \frac{(m_t - 1)^{2j-1}}{m_t^j (m_t + 1)(m_t + 3) \dots (m_t + 2j - 3)} * \frac{\left(\frac{S_{L_t}^2}{2}\right)^j}{j!} \quad (4)$$

While the sum is infinite, only a finite number of terms (j) are used. Terms are added sequentially until a term contributes less than 0.0001 (Fairfield and Garrison 2008).

However, if there was only one observed set with bycatch ($m_t = 1$), the mean bycatch rate was calculated as (Fairfield and Garrison 2008):

$$C_t = \frac{e^{L_t}}{n_t} \quad (5)$$

The mean bycatch rate (C_t) was multiplied by the total effort in stratum t (in thousands of hooks) to estimate total bycatch in that stratum. The stratum effort was determined by summing the number of hooks per set assigned by the GLM potential explanatory variable procedure. More details are available in Appendix B, section A2.1.2.1.

$$N_t = C_t * \left(\frac{\sum_{i=1}^{m_t} \text{hooks per set}_i \text{ with bycatch} + \sum_{j=1}^{n_t-m_t} \text{hooks per set}_j \text{ without bycatch}}{1,000} \right) \quad (6)$$

To obtain an annual estimate of bycatch (N), the stratum-specific estimates (N_t) were summed across all strata (t) (Fairfield and Garrison 2008).

- ***Variance estimate***

The variability of both the rate of bycatch and the proportion of sets with bycatch influenced the variance of the estimate (Scott and Brown 1997).

The variance of the delta estimator was calculated as (Fairfield and Garrison 2008):

$$\text{var}(C_t) = \frac{m_t}{n_t} \left(e^{2L_t} \left[\frac{m_t}{n_t} \left[G\left(\frac{S_{L_t}^2}{2}\right) \right]^2 - \left(\frac{m_t-1}{n_t-1}\right) G\left(\frac{m_t-2}{m_t-1} S_{L_t}^2\right) \right] \right) \quad (7)$$

If there was only one observed set with bycatch ($m_t = 1$), the variance of the delta estimator was calculated as (Fairfield and Garrison 2008):

$$\text{var}(C_t) = \left(\frac{e^{L_t}}{n_t} \right)^2 \quad (8)$$

An annual measure of variation was calculated by summing the stratum-specific bycatch rates (C_t) and stratum-specific variance estimates ($\text{var}(C_t)$) across all strata (t) to obtain an overall average bycatch rate (C) and variance estimate ($\text{var}(C)$). Then the coefficient of variation (CV) was calculated as (Fairfield and Garrison 2008):

$$CV = \frac{\sqrt{\text{var}(C)}}{C} \quad (9)$$

- ***Confidence interval***

A 95% confidence interval was constructed around the annual bycatch point estimate N . The lowerbound was (Fairfield and Garrison 2008):

$$\text{CI lower bound} = \frac{N}{e^{\left[1.96\sqrt{\ln(1+CV^2)}\right]}} \quad (10)$$

and the upperbound was:

$$\text{CI upperbound} = N e^{\left[1.96\sqrt{\ln(1+CV^2)}\right]} \quad (11)$$

○ **Pooled estimate**

In 1999, the NMFS SEFSC investigated the effect of pooling data across strata on bycatch estimates (Yeung 1999). Yeung found that bycatch point estimates were relatively insensitive to pooling, but estimate precision improved considerably. The only pooling currently done by the SEFSC occurs when there are no observed sets in a stratum. Then that stratum's mean bycatch rate from previous years is used.

However, the SEFSC estimates bycatch for a stratum when there is only one observed set with one turtle caught. Perhaps pooling sets across strata would improve estimation in situations like this. Doing this would mean variation among strata would be ignored; the strata would be assumed to have the same bycatch rates, but pooling strata would increase the sample size on which bycatch estimates are made. I pooled sets across all time-area strata and made a total annual bycatch estimate.

• ***Bycatch point estimate***

The mean bycatch rate was calculated as:

$$C = \frac{m}{n} e^L G\left(\frac{S_L^2}{2}\right) \quad (12)$$

where:

m = the number of sets with observed bycatch among all sets observed that year

n = the number of sets observed that year

L = the mean of the \log_e -transformed number of turtles taken by 1,000 hooks when bycatch occurred

S_L^2 = the sample variance of the \log_e -transformed bycatch rate

G = the cumulative factor from the Poisson distribution given as:

$$G\left(\frac{S_L^2}{2}\right) = 1 + \frac{m-1}{m} \left(\frac{S_L^2}{2}\right) + \sum_{j=2}^{\infty} \frac{(m-1)^{2j-1}}{m^j (m+1)(m+3)\dots(m+2j-3)} * \frac{\left(\frac{S_L^2}{2}\right)^j}{j!} \quad (13)$$

While the sum is infinite, only a finite number of terms (j) are used. Terms are added sequentially until a term contributes less than 0.0001 (Fairfield and Garrison 2008).

If there was only one observed set with bycatch ($m = 1$), the mean bycatch rate was calculated as:

$$C = \frac{e^L}{n} \quad (14)$$

The mean bycatch rate (C) was multiplied by the total effort in that year (in thousands of hooks) to estimate total annual bycatch. The effort (1,000s of hooks) was determined by summing the number of hooks per set assigned by the GLM potential explanatory variable procedure. For more details, see Appendix B, section A2.1.2.1.

$$N = C * \left(\frac{\sum_{i=1}^m \text{hooks per set}_i \text{ with by catch} + \sum_{j=1}^{n-m} \text{hooks per set}_j \text{ without by catch}}{1,000} \right) \quad (15)$$

- *Variance estimate*

The variance of the delta estimator was calculated as:

$$\text{var}(C) = \frac{m}{n} (e^{2L}) \left[\frac{m}{n} \left[G\left(\frac{S_L^2}{2}\right) \right]^2 - \left(\frac{m-1}{n-1}\right) G\left(\frac{m-2}{m-1} S_L^2\right) \right] \quad (16)$$

If there was only one observed set with bycatch ($m = 1$), the variance of the delta estimator was calculated as:

$$\text{var}(C) = \left(\frac{e^L}{n} \right)^2 \quad (17)$$

The coefficient of variation was calculated as:

$$CV = \frac{\sqrt{\text{var}(C)}}{C} \quad (18)$$

- *Confidence interval*

The confidence interval was calculated by the same procedure as discussed for the strata-level estimation.

M.2.3 EVALUATION OF ESTIMATION METHODS

Incorporating the different potential turtle distributions, set distributions, estimation methods, and spatial scales of estimation produced thirty potential models (five spatial models

with six estimation configurations each) (Figure 2.4). Each of the thirty potential models was run with 1,000 simulations.

The performance of each of the estimation methods was evaluated in each of the spatial models by comparing the estimated amount of bycatch to the total amount of bycatch simulated.

In addition to evaluating estimation methods using point estimates, I also examined confidence intervals. I calculated confidence intervals for the estimation methods identified as most suitable based on their point estimates. I examined the width of the confidence intervals and the percent of the simulations in which the total simulated take fell outside the confidence interval.

M.3 OBSERVER DISTRIBUTION - BYCATCH

The second objective of my thesis was to examine the effects of observer distributions on bycatch estimation. Distributing observers relative to fishing effort, which may not be correlated to bycatch rate, could bias bycatch estimates. Instead, focusing observers on areas of high protected species bycatch would likely increase the sample size from which estimates are made, which could increase the accuracy of point estimates and reduce the width of confidence intervals.

As discussed above, I investigated which estimation method was most suitable with observers distributed by effort, the current NMFS procedure. Next, I examined whether there were any improvements in estimation from distributing observers in bycatch hotspots. I ran the 30 potential models (5 spatial models with different sea turtle and fishing set distributions and 6 estimation methods each) again but this time with observers distributed relative to bycatch. Details on the bycatch-based observer placement procedure can be found in Appendix A, section

A1.5.2. The 30 models with observers placed in proportion to fishing effort and the 30 models with observers placed in proportion to bycatch were compared to evaluate bycatch estimate accuracy relative to the simulated amount of bycatch.

M.4 INCORPORATING RISK IN ESTIMATES

M.4.1 THE NMFS SEFSC'S USE OF RISK

In the SEFSC's annual bycatch reports, a bycatch point estimate is made, and the upper bound and lower bound of a 95% confidence interval is estimated. Yet only the point estimate is used in year to year management to determine the fishery's performance relative to the incidental take statement; there is no additional consideration of uncertainty or risk in year to year bycatch management (P. Richards pers. comm. 7 May 2009). Given how complicated estimation of bycatch in the U.S. Atlantic pelagic longline fishery is, it would be prudent to include a quantification of risk in annual bycatch estimates.

M.4.2 INCLUDING RISK IN THE SIMULATION MODEL

I developed a bycatch estimate risk curve that gives bycatch estimates at corresponding levels of accepted risk. For example, if a manager decided it was acceptable to have a 5% risk that the actual level of bycatch is greater than the estimate, the corresponding risk-adjusted bycatch estimate could be located on the bycatch estimate risk curve. Unlike the traditional approach of a point estimate and 95% CI, the bycatch estimate risk curve give a manager access to the entire bycatch estimate distribution.

I calculated the bycatch estimate risk curve in two ways. First, I used the traditional formula for a confidence interval but changed the z-score to obtain different risk levels. The

second method used results from the simulation model (Figure 2.5). In each of the 1,000 simulations of the model(s) determined to be most suitable according to the procedures discussed in sections M.2.3 and M.3, I calculated the ratio of simulated total bycatch to estimated bycatch. Then I created a cumulative distribution function (CDF) of those ratios (Figure 2.6). The Y axis of the CDF represented the different levels of risk in terms of probability that take will be no greater than the estimate. The X axis of the CDF provided “risk inclusion scalars”, which are the ratios of actual take to estimated take that when multiplied by the bycatch estimate will adjust it to give an estimate incorporating the desired level of risk. The CDF of risk inclusion scalars can be used to create a bycatch estimate risk curve by multiplying a bycatch point estimate by each of the risk inclusion scalars (Figure 2.7).

If multiple models were found to be equally suitable, CDFs were created for each, and the risk inclusion scalars were averaged across the CDFs. For example, if two models were determined to be equally suitable, the two risk inclusion scalars corresponding to a 5% level of risk would be averaged to give one risk inclusion scalar for a 5% level of risk. This would be done for the risk inclusion scalars at all risk levels.

$$S_{a,r} = \frac{\sum_{m=1}^q S_{m,r}}{q} \quad (19)$$

where:

$S_{a,r}$ = the risk inclusion scalar at risk level r averaged across all suitable models

$S_{m,r}$ = the risk inclusion scalar for model m at risk level r

q = the number of suitable models

The two bycatch estimate risk curve methods, varying z-score and risk inclusion scalar CDF, were compared by creating risk curves for the SEFSC's 2007 estimate of sea turtle bycatch.

RESULTS

First I modeled five combinations of sea turtle and fishing set distributions with observers placed according to fishing effort. I attempted to estimate bycatch with six methods, resulting in thirty simulation models (Figure 2.4). I evaluated estimation method performance in each of the thirty models to identify biases and suitability.

Next, I studied the effect of distributing observers based on bycatch on the ability to estimate bycatch. I modeled the five sea turtle and fishing set distributions with observers distributed relative to bycatch and estimated bycatch with the six bycatch estimation methods. Estimate method performance was evaluated in these thirty models and compared to the thirty models in which observers were distributed relative to fishing effort.

Finally, the most realistic spatial model(s) and most suitable estimation method(s) were identified and methods for including uncertainty were explored. A strata-based 95% confidence interval, a 95% CI for all sets pooled, and bycatch estimate risk curves were generated. Risk inclusion scalars were applied to the 2007 NMFS SEFSC bycatch estimates to create a bycatch estimate risk curve. A second bycatch estimate risk curve was calculated by varying the z-score in the traditional CI formula, and the two methods were compared.

R.1 POINT ESTIMATES

An estimation method performs well if point estimates are accurate (estimates on average give the true value) and precise (any given estimate is not very far off from the true value). The accuracy of an estimation method can be assessed by making many estimates, calculating the ratio of estimate to true value for each, and finding the median ratio. If the estimation method is unbiased, the median ratio should be one. The precision of the estimation method can be

measured by examining the interquartile range (IQR) of ratios. If the IQR is small, the estimation method is precise.

R.1.1 MODELS WITH OBSERVERS DISTRIBUTED BY EFFORT

The delta-lognormal method outperformed the GLM in this study (Figure 2.8). Focusing on the three most probable spatial models, ($Turtles_{clump}$, $Sets_{clump-turtles}$), ($Turtles_{clump}$, $Sets_{clump-sets}$), and ($Turtle_{random}$, $Sets_{clump-sets}$), the three models with sets clumped in some configuration, revealed that the delta-lognormal method gave the least biased bycatch point estimates. While the delta-lognormal estimate of strata was the most accurate method in the ($Turtles_{clump}$, $Sets_{clump-turtles}$) and ($Turtle_{random}$, $Sets_{clump-sets}$) models, the delta-lognormal estimate of pooled sets was most accurate in the ($Turtles_{clump}$, $Sets_{clump-sets}$) model. Only in the null spatial model, ($Turtle_{random}$, $Sets_{random}$) with sets and turtles distributed uniformly random, did the GLM outperform the delta-lognormal method. Note also that the GLMs tended to produce more outliers than the delta-lognormal method. There was no significant difference between the GLM-P and the GLM-NB. The precision of the estimation methods did not vary significantly, so accuracy became the standard on which to evaluate method performance.

The delta-lognormal method was shown to give more accurate and equally precise estimates as the GLM methods in the three models with clumped sets. In two of those models, strata-level estimates were most accurate, and in the third, estimates for all sets pooled were most accurate. While the delta-lognormal method was consistently preferred, there was not a consistently preferred spatial scale of estimation.

Upon closer examination of these three models, it appears that the ($Turtles_{clump}$, $Sets_{clump-sets}$) model had an unrealistically low observed bycatch rate (Figure 2.9). In the two spatial

models with little observed bycatch, ($Turtles_{clump}, Sets_{clump-sets}$) and ($Turtles_{clump}, Sets_{random}$), there were also many simulations with no observed bycatch (Table 2.2). When there is no observed bycatch, no bycatch estimate can be made. If the ($Turtles_{clump}, Sets_{clump-sets}$) model is eliminated from consideration, strata-level estimates were the most accurate in the two remaining models with sets clumped. In summary, the delta-lognormal method with strata-level estimation was shown to be the most accurate and precise method for estimating bycatch when observers are distributed relative to fishing effort (Figure 2.10). Next, method performance under a bycatch-based observer distribution will be examined.

R.1.2 MODELS WITH OBSERVERS DISTRIBUTED BY BYCATCH

The delta-lognormal method outperformed the GLM when observers were distributed in bycatch hotspots, as it did when observers were distributed relative to fishing effort, and there was no advantage of the bycatch-based observer distribution over the effort-based observer distribution. Observers could truly be distributed relative to bycatch in only three of the five spatial models, and estimation methods only gave reasonable bycatch estimates in one of those three spatial models, ($Turtles_{clump}, Sets_{clump-turtles}$) (Figure 2.11). The delta-lognormal method of strata-level estimation was the most accurate estimation method in this model, and it had similar precision to the other estimation methods. The GLMs tended to have more extreme outliers than the delta-lognormal methods.

When turtles were distributed uniformly random as in the ($Turtle_{random}, Sets_{random}$) and ($Turtle_{random}, Sets_{clump-sets}$) models, there were no bycatch hotspots, so observers were distributed randomly. Hence, estimation methods performed similarly in these models and the models where observers were distributed relative to fishing effort. Observers were distributed relative to

bycatch hotspots in the $(\text{Turtles}_{\text{clump}}, \text{Sets}_{\text{clump-turtles}})$, $(\text{Turtles}_{\text{clump}}, \text{Sets}_{\text{clump-sets}})$, and $(\text{Turtles}_{\text{clump}}, \text{Sets}_{\text{random}})$ models, but bycatch estimates were biased extremely high in the $(\text{Turtles}_{\text{clump}}, \text{Sets}_{\text{clump-sets}})$, and $(\text{Turtles}_{\text{clump}}, \text{Sets}_{\text{random}})$ models. This only left the $(\text{Turtles}_{\text{clump}}, \text{Sets}_{\text{clump-turtles}})$ model in which observers were distributed relative to bycatch hotspots and relatively accurate bycatch estimates were made.

When observers were distributed by effort in the $(\text{Turtles}_{\text{clump}}, \text{Sets}_{\text{clump-sets}})$, and $(\text{Turtles}_{\text{clump}}, \text{Sets}_{\text{random}})$ models, estimating bycatch was problematic because there were few observed takes. In models with observers distributed based on bycatch, the observed bycatch rates were more realistic (Figure 2.12) and the GLMs converged, but data from observers were not representative of unobserved sets. Observers saw a high proportion of all takes, so estimates based on their data overestimated bycatch. On the other hand, estimation methods were relatively unbiased in the $(\text{Turtles}_{\text{clump}}, \text{Sets}_{\text{clump-turtles}})$ model because sets were always in bycatch hotspots.

In summary, the delta-lognormal method with strata-level estimates performed the best in realistic spatial fishing models with observers distributed relative to bycatch hotspots (Figure 2.13). The delta-lognormal method with strata-level estimates was also identified as the most suitable method when observers were distributed based on fishing effort. Further, the bycatch-based observer distribution did not improve bycatch estimation and was actually less applicable than the effort-based observer distribution.

R.2 METHODS WITH CONVERGENCE PROBLEMS

Some estimation methods only converged in a small percentage of the simulations and not all of the generated estimates were reasonable. Estimation methods with convergence

problems or that gave unreasonable estimates are not presented in the results. I eliminated these methods for being unreliable.

The GLM-P and GLM-NB would not converge for strata-level estimation. These methods could estimate bycatch in some of the more heavily fished strata, but a bycatch estimate is needed in each stratum for these methods to be suitable. Therefore, the GLM-P and GLM-NB methods were only considered for estimation of all sets pooled.

The GLM-P and GLM-NB estimation methods did not converge in some simulations of the ($Turtles_{clump}$, $Sets_{clump-sets}$) and ($Turtles_{clump}$, $Sets_{random}$) models when all sets were pooled. Further, not all the bycatch estimates were reasonable. The actual amount of bycatch in these models was in the tens, but bycatch estimates ranged from the tens and hundreds to over a billion.

There were still warnings given in the models where the GLM-P and GLM-NB converged and produced reasonable estimates. Numerically zero fitted rates occurred in the GLM-P fitting procedure, and the iteration limit was reached in the procedure estimating the dispersion parameter, ϕ , for the GLM-NB.

R.3 CONFIDENCE INTERVALS

In addition to producing an accurate and precise point estimate, a bycatch estimation method must be able to generate a suitable measure of uncertainty, such as a confidence interval (CI). Since the delta-lognormal method outperformed the GLMs in producing point estimates, I eliminated the GLMs from consideration and only examined the confidence intervals of the delta-lognormal methods. Also, since distributing observers based on bycatch did not enhance estimation, CIs were only examined for the models with observers distributed by effort.

For every spatial model, the 95% confidence interval based on the mean bycatch rate and bycatch rate variance calculated from all sets pooled was narrower than the CI from estimating bycatch by strata (Table 2.3). In the two spatial models thought to be most realistic, ($Turtles_{clump}$, $Sets_{clump-turtles}$) and ($Turtle_{random}$, $Sets_{clump-sets}$), the CI based on all sets pooled was around 60% of the point estimate. However, the CI from strata was around 90% of the point estimate (Table 2.3).

While using a CI calculated from all sets pooled decreased the width of the CI, it led to more instances in which the actual take did not fall within the CI. A 95% CI based on 1,000 simulations is expected to have 25 simulations where the actual take falls below the CI and 25 simulations where the actual take is above the CI. The strata-based CI for the more realistic spatial models had far fewer than 25 estimates above and 25 estimates below; the strata-based CI was too conservative (Table 2.4). The CI from all sets pooled performed well in the ($Turtle_{random}$, $Sets_{clump-sets}$) model but underestimated bycatch more than expected in the ($Turtles_{clump}$, $Sets_{clump-turtles}$) model.

R.4 INCORPORATING RISK

I calculated risk inclusion scalars and applied them to the 2007 SEFSC sea turtle bycatch estimates. The resulting bycatch estimation risk curve indicated that the 2007 SEFSC bycatch estimate corresponded to the level of 58% risk. The scalar-based bycatch estimate risk curve always gave larger estimates than the bycatch estimate risk curve calculated by varying the CI z-score.

An effort-based observer distribution, the strata-based delta-lognormal method, and the ($Turtles_{clump}$, $Sets_{clump-turtles}$) and ($Turtle_{random}$, $Sets_{clump-sets}$) spatial models were determined to be

the most suitable. Therefore, I created CDFs of the actual take to estimated take ratio for these two models (Figure 2.14) and averaged the two resulting groups of risk inclusion scalars (Figure 2.15). I applied these risk inclusion scalars to the SEFSC's 2007 estimates of sea turtle bycatch and plotted the bycatch estimate risk curve (Figure 2.16). The scalar-based risk curve showed that the 2007 SEFSC point estimates only had an approximately 42% probability that take was no greater. Further, the lower bound of the SEFSC 95% CI corresponded to 99.4% risk, and the upper bound of the SEFSC 95% CI corresponded to 3.2% risk (Figure 2.17).

A second bycatch estimate risk curve was plotted by changing the z-score in the CI (Figure 2.18). For any risk level, the bycatch estimate was smaller with the varying z-score bycatch estimate risk curve than with the scalar-based bycatch estimate risk curve.

DISCUSSION

D.1 GENERAL APPLICATION TO ZERO-HEAVY DATA ANALYSIS

Bycatch by commercial fisheries is generally believed to be the main anthropogenic threat to sea turtles, and the pelagic longline fishery is considered one of the three fisheries most affecting sea turtles (NMFS and USFWS 2007, Witherington et al 2009). Therefore, improving estimates of the number of turtles caught by the pelagic longline fishery and increasing our understanding of post-interaction mortality is essential to sea turtle conservation. Improving the accuracy of bycatch estimates will also lead to more efficient fishery management.

Not only does an increased understanding of the delta-lognormal method and the GLM improve sea turtle conservation and fishery management, but it also has application to many other fields with zero-heavy data. The rare event of protected species bycatch can be compared to the rare events of industrial injuries, transportation accidents, product innovations, drug discoveries, or receiving patents (Pradhan and Leung 2006). As such, disciplines as wide ranging as meteorology, epidemiology, medicine, occupational health, and econometrics commonly deal with zero-heavy data (Stefánsson 1996, Martin et al 2005). Presence/absence data and count data are some of the most commonly collected data types. Both often contain many zeros, and count data also often have a skewed distribution (Martin et al 2005, Sileshi 2006). GLMs and delta-lognormal methods are among the most commonly used methods for these kinds of data.

Recently, interest in methods for analyzing data with excess zeros has increased (Martin et al 2005). However, the challenges of complex datasets are still not always met. It is not uncommon for scientists to use familiar statistical methods even though it is nearly impossible to meet the model assumptions (Walters 2003, Sileshi 2006). Additionally, transformations are

often employed in ecology to overcome violations in the error's assumed variance-mean relationship, but this will not ameliorate zero-heavy data (Martin et al 2005). Not accounting for excess zeros and using models with inappropriate assumptions can result in biased estimates and incorrect conclusions, as was seen in the simulation model when GLM assumptions were violated in the ($Turtles_{clump}$, $Sets_{clump-turtles}$) and ($Turtle_{random}$, $Sets_{clump-sets}$) models (Martin et al 2005).

Data complexities must be addressed, but often there is not one model that is clearly most appropriate (Sileshi 2006). Models must be compared to select a model that is most suitable for the data and the required output (Sileshi 2006). This study cannot recommend one method for addressing all zero-heavy data, but it does emphasize the importance of recognizing variance across time and space, shows the necessity of representative samples and sample size, and demonstrates that the delta-lognormal method is less biased than the GLM in this system.

D.2 CONCLUSIONS FROM SIMULATION MODEL

The simulation model of sea turtle bycatch by the U.S. Atlantic pelagic longline fishery generated many informative results regarding spatial distributions, observer placement, accuracy of bycatch point estimates, and methods for quantifying uncertainty. Likely reasons why these results were obtained and what the results mean for sea turtle and pelagic longline fishery management will be explained.

D.2.1 SPATIAL MODELS

The real-world spatial distribution of sea turtles and the reason for the clumping of sets are not well understood, and the simulation model results do not resolve the question either. The

most realistic spatial models included both sea turtle distributions and both clumped set distributions.

D.2.2 POINT ESTIMATE

D.2.2.1 Observers based on effort

The delta-lognormal method with strata estimates was the most appropriate method for estimating sea turtle bycatch by the U.S. Atlantic pelagic longline fishery when observers were distributed based on fishing effort (Figure 2.8). It consistently outperformed the GLM-P and GLM-NB. However, in two spatial models, the strata-based delta-lognormal method was most accurate, and in two spatial models, the delta-lognormal method with estimates from all sets pooled was most accurate.

Any set selected at random will be representative of unobserved sets in the spatial models in which the strata-based delta-lognormal method was most accurate, (Turtles_{clump}, Sets_{clump-turtles}) or (Turtle_{random}, Sets_{clump-sets}). In the (Turtles_{clump}, Sets_{clump-turtles}) model, all sets fish where turtles are present. In the (Turtle_{random}, Sets_{clump-sets}) model, each set has the same probability of encountering a turtle since turtles have a uniformly random distribution.

In these two spatial models there were also enough observed takes within strata to make relatively unbiased strata-specific estimates. Strata did not have to be pooled to achieve larger sample sizes, so differences between strata could be captured and biases associated with pooling were avoided.

GLMs could not be used to estimate bycatch in strata because they would not converge in the less heavily fished strata, so GLMs were only used to estimate bycatch in all sets pooled. The GLM estimates of all sets pooled performed as well as the delta-lognormal method with

estimation from all sets, indicating that the GLM is not capturing strata-specific differences. Although GLM estimates cannot be made for each stratum, the differences across strata should be captured through the explanatory variable values. However, with bycatch being such a rare event and such a low level of observer coverage, the relationship between environmental and fishing conditions and the amount of bycatch is probably not well established across the fishery.

In the ($Turtles_{clump}$, $Sets_{clump-sets}$) and ($Turtles_{clump}$, $Sets_{random}$) models, the two models in which the delta-lognormal method with pooled sets was most suitable, turtles were clumped but sets did not mimic their clumping pattern. The main result of this appears to be a low level of observed bycatch and a low level of total bycatch. Under these two spatial models, some sets would not be expected to encounter any turtles while other sets would be expected to encounter an abundance of turtles, but the frequency of encountering turtles is low in this model. When there are so few observed takes (Table 2.2), no estimation method will perform well. Also, when some sets interact with many turtles and others do not encounter any turtles, observing a small percent of sets would not provide a representative account of turtle interactions.

With such a small number of observed takes, the GLMs would not converge for either strata-level estimates or estimates of all sets pooled; only the two delta-lognormal methods could be used to generate bycatch estimates. Strata-level delta-lognormal estimates were biased because the vast majority of strata had no observed bycatch. When there are only three observed takes and those takes occur in two strata, for example, estimating bycatch for all sets introduces less bias than making strata-specific estimates.

The GLM was the most appropriate estimation method in the null spatial model, ($Turtle_{random}$, $Sets_{random}$), and the GLM-P and GLM-NB performed equally well. The delta-lognormal method with strata estimates was more accurate than the delta-lognormal method with

estimates of all sets pooled, which suggests that considering strata differences improved estimation. The performance of the two delta-lognormal methods is consistent with the (Turtles_{clump}, Sets_{clump-turtles}) and (Turtle_{random}, Sets_{clump-sets}) models, but in this case, the GLM outperformed both delta-lognormal methods. The most likely explanation is that the completely randomized spatial model did not violate the GLM assumptions, but violations of GLM assumptions introduced biases in the (Turtles_{clump}, Sets_{clump-turtles}) and (Turtle_{random}, Sets_{clump-sets}) models. One GLM-P assumption that was probably violated is that of counts being independent and randomly distributed in space (McCracken 2000, Sileshi 2006). The GLM-NB did not perform better than the GLM-P, perhaps because overdispersion was not an issue (White and Bennetts 1996, McCracken 2000, Sileshi 2006). Model-based predictors such as the GLM assume a statistical model of turtle takes that represents the process generating the response variable (number of takes) from explanatory variables (environmental or fishing characteristics) (McCracken 2000, McCracken 2004). However, the delta-lognormal method is a sample-based estimator that assumes sampling probabilities but is essentially free of assumptions about the population structure and estimated characteristics (McCracken 2000).

D.2.2.2 Observers based on bycatch

The delta-lognormal method with strata estimates was also found to be the most appropriate method for estimating sea turtle bycatch by the U.S. Atlantic pelagic longline fishery when observers were distributed based on bycatch. Further, an observer distribution based on bycatch conferred no benefit compared to an observer distribution based on fishing effort.

The only spatial model in which observers could be distributed based on bycatch and relatively unbiased bycatch estimates were produced was the (Turtles_{clump}, Sets_{clump-turtles}) model.

The strata-based delta-lognormal method performed the best in this spatial model, and the delta-lognormal method for all sets pooled was more accurate than the GLMs. These results suggest that the GLMs' assumptions were violated in the ($Turtles_{clump}$, $Sets_{clump-turtles}$) spatial model and a clear functional relationship between environmental or fishing conditions and the number of takes is not being captured.

Not only does the observer distribution based on bycatch not improve estimate accuracy but it would be extremely difficult to apply in the actual fishery. When the SEFSC assigns observers to fishing vessels, the SEFSC knows which spatial area the vessel will be fishing in but does not know where within that area the vessel will go. With such a rough idea of where fishing will occur, it is virtually impossible to pinpoint which vessels will be in bycatch hotspots. Also, it would be difficult to anticipate where bycatch hotspots would occur. The SEFSC could look at historic observer data to develop a hypothesis about areas of high bycatch, but there is a low level of observer coverage and fishing and turtle distributions vary within and across years. Accurately predicting where turtles will be interacting with vessels in a particular calendar quarter would still be difficult.

D.2.3 DEALING WITH UNCERTAINTY

D.2.3.1 Confidence intervals

The confidence intervals calculated from all sets pooled were narrower than the confidence intervals from the strata-level estimates since the variance in bycatch rates is larger when calculated for strata than when calculated for all sets pooled.

Considering the CI width as a percent of the bycatch point estimate highlighted how wide, and thus uninformative, the standard CI based on strata is. Narrowing the CI with

calculations from all sets pooled helps address the issue, but it is compounded by a higher amount of extreme underestimation than desired. For protected species conservation, extreme underestimation is more problematic than extreme overestimation. It is important to know a lower bound estimate for protected resource conservation; there is a lower threshold that if crossed, puts the species in jeopardy. That the threshold is crossed is more important than by how much it is crossed. To reconcile the CI width and amount of extreme underestimation I propose using a bycatch estimate risk distribution for a more flexible and precise inclusion of uncertainty.

D.2.3.2 Bycatch estimate risk distribution

In all cases, the estimates from the traditional 95% CI calculated from the strata-level delta lognormal method were less than the estimates produced from the risk inclusion scalars (Figure 2.18). This could be an effect of the strata-level delta-lognormal method's bias. As seen in the box plots comparing estimated take to actual simulated take, the strata-level delta-lognormal method, although the most accurate estimation method analyzed, was still slightly biased low (Figure 2.8). This slight bias may be leading to systematic underestimation of bycatch. However, the bias would be rather small. Given how much uncertainty already exists in bycatch estimates, a bias of 20 turtles is not notable. Nevertheless, the risk inclusion scalars may produce more accurate risk-adjusted bycatch estimates.

However, the risk inclusion scalars are dependent on the assumptions of the simulation model. Further analysis is needed to fully investigate the results' sensitivity to model parameters and identify an appropriate method for incorporating uncertainty and risk. I will discuss model assumptions and their implications in the next section.

Regardless of the method for adjusting estimates, the concept of the bycatch estimate risk distribution has great potential. Rather than providing managers with a 95% lower bound, a point estimate, and a 95% upper bound, the bycatch estimate risk distribution gives managers a more comprehensive understanding of bycatch estimates. They have access to the entire estimate distribution and can select what they consider to be an acceptable level of risk. Managers can select any level of risk and find the corresponding bycatch estimate.

D.3 MODEL ASSUMPTIONS AND THEIR IMPLICATIONS

While a simulation model is imperfect by definition, it is important to consider the effects of these imperfections on model results. Here I will focus on a number of assumptions that I consider most important, but additional model assumptions are described in Appendix A.

I attempted to make reasonable assumptions both when incorporating known sea turtle – pelagic longline fishery relationships and when modeling unknown aspects. However, there are many ways in which each component of the simulation model could be designed. I consider the most influential assumptions to include (1) the spatial constraints, (2) the algorithm for selecting GLM explanatory variable values, and (3) the simplified effort-based observer distribution.

First, the spatial configuration of sea turtles, the spatial characteristics of fishing, and their interactions had to be explicitly defined in the model. I modeled five combinations of sea turtle and fishing set distributions with assumptions regarding the number of turtles, the size of clumps, the number of clumps, how turtles or sets should be placed in clumps, how clumps could overlap, and the size of the ocean. Although five different spatial configurations were modeled and clump placement, the number of turtles per cell, a set's initial cell, and the direction of fishing had stochastic elements, the spatial models were still rather rigid. Model results could be

influenced by constraints on the dimensions and spatial co-occurrence of turtles and sets distributions.

To test the influence of these assumptions on model results, I would vary the overall dimensions from 100-by-100 cells, number of clumps, clump dimensions from 9-by-9 cells, degree clumps can overlap, and density of turtles within clumps. Varying these conditions would lead to different bycatch rates and would affect the variance of bycatch rates, which should be especially important for estimating bycatch with the delta-lognormal method. Also, the (Turtles_{clump}, Sets_{clump-sets}) model was uninformative because there were so few takes, despite theoretically appearing to be a realistic spatial model. If the spatial constraints were altered so the turtle clumps and set clumps encountered each other more frequently, this could be an illuminating spatial model.

Second, the GLM is based on the premise that environmental or fishing conditions can be used to predict the number of turtles caught. Therefore, how explanatory variable values are assigned to sets has a significant effect on GLM performance. I selected variable values from sets observed by NMFS from 2005 through 2007 while attempting to account for the sets' spatial distribution and strata characteristics. However, there are many ways variable values could be assigned, and different procedures could influence how well the GLM estimates bycatch.

To test the influence of the algorithm for selecting explanatory variable values on GLM performance, I could select NMFS sets from the same stratum instead of using a distance value. However, with only three years of observer data, there may be more modeled sets than NMFS observed sets in a stratum. Either NMFS sets must be selected more than once or a distance value must be used. The variable selection algorithm could also be tested by using a distance value to assign sets to a clump rather than selecting sets from the same trip.

Violation of GLM model assumptions may still be an issue even though other algorithms for selecting explanatory variable values may be more realistic or may result in better GLM estimation. The GLM-P assumes that counts are randomly distributed in space and are independent (McCracken 2000, Sileshi 2006). Since some degree of set and/or turtle clumping seems apparent and counts are at least dependent within a trip, violations of GLM-P assumptions are likely even with an improved algorithm for selecting explanatory variable values.

Perhaps GLM-NB performance would be improved under a more suitable algorithm for selecting explanatory variable values. However, the GLM-NB is typically used to address overdispersion (Welsh et al 1996, Thurston et al 2000, Lindsey 2004, Venables and Dichmont 2004), and little overdispersion was detected in the simulation model. I do not expect the performance of the GLM-P to change relative to the delta-lognormal methods. Also, the performance of the strata-based delta-lognormal method relative to the delta-lognormal method with all sets pooled is likely quite robust. However, the GLM-NB could improve its performance relative to the other estimation methods if a clearer functional relationship between the explanatory variables and the level of bycatch was captured.

Third, I modeled a simplified effort-based observer distribution to collect observer data for making bycatch estimates. If there are different patterns in SEFSC observer data and modeled observer data, estimation method performance in the model may not accurately reflect how estimation methods would perform when applied to actual fishery data. The SEFSC currently selects vessels for each quarter and area based on how many sets a vessel fished in that stratum in the previous year (Beerkircher et al 2004, Fairfield and Garrison 2008). Vessels that fished more sets in the previous year have a greater chance of being observed this year, and a vessel may be observed up to four times a year (Beerkircher et al 2004). However, the

simulation model did not cover multiple years, so the previous year's time-area effort data were not available for distributing observers. Instead, I selected a cell at random to serve as an area of high effort and placed observers on the two sets closest to that cell out of the twenty-five simulated sets (see Appendix A, section A1.5.1). Each stratum had 8% observer coverage so there were more observers in strata with more effort, and the observer distribution was independent of turtle presence.

To test the influence of the simplified effort-based observer distribution on model results, I would make the observer placement more flexible and add some of the complexities associated with NMFS longline observer data. I would attempt to better reflect patterns in the SEFSC's observer data by applying probabilities of observation to the sets. The publicly available SEFSC logbook records do not have a vessel or trip code, nor do they indicate the number of sets in a trip. The observer data include a trip code and a haul number, but the observer dataset is too small to use exclusively. However, I could use the observer data as a basis for assigning number of sets per trip and number of trips per vessel, which I would then use to calculate probabilities of observation in a stratum. Also, I would not require two sets out of the twenty-five in a spatial replicate to be observed. Rather, I would consider all sets within a stratum when placing observers.

Model results indicated that the effort-based observer distribution was more appropriate than the bycatch-based observer distribution, but the robustness of the model to the method of distributing observers relative to effort should be tested. A more realistic method of effort-based observer distribution may also be achieved so that model results will be more applicable to the fishery.

These three assumptions and others discussed in the appendices could also be investigated through a sensitivity analysis. A sensitivity analysis would help determine which parameters were most influential and how robust the results are to model assumptions (Saltelli et al 2008).

D.4 MANAGEMENT RECOMMENDATIONS

I recommend estimating bycatch with the strata-based delta-lognormal method, and I recommend that observers be distributed based on fishing effort. This is consistent with the SEFSC's current procedure. I encourage the use of a bycatch estimate risk distribution in year to year management so that managers have access to the entire distribution of bycatch estimates, may select the level of risk they deem acceptable, and then can identify the corresponding bycatch estimate. This enables managers to more explicitly incorporate uncertainty in bycatch estimates, as opposed to only having the upper- and lower bounds of a confidence interval that are considered under Section 7 Consultation. I also believe that NMFS should further investigate post-interaction mortality. Ultimately, bycatch is estimated in order to control the fishery's impact on the survival of the protected species. This impact can only truly be assessed if post-interaction mortality is understood. Estimates of post-interaction mortality are the informative estimates for fishery management and protected species conservation; estimates of the number of protected species caught are only a proxy.

D.5 ADDITIONAL RESEARCH

The simulation model was designed to be flexible so that new questions could be examined. Three possible model extensions are (1) varying the observer coverage, (2) including

stochasticity in the probability of take, and (3) including a spatial model that has different sea turtle and fishing set distributions in different strata. Increased levels of observer coverage should improve bycatch estimation. Modeling different levels of observer coverage will help managers determine an optimal balance between observer expenditure and improved data. Also, the goal of 8% coverage is not always reached. The simulation model can be used to assess the effect of lower coverage on bycatch estimation. Realism may be added to the model by including a stochastic error term to the probability of take. In the current model, probabilities of take varied across strata but were deterministic within a stratum. The model may also be made more realistic by including different turtle and set distributions in one simulation. Fishing set and turtle distributions in the Gulf of Mexico probably vary from the distributions in the Caribbean or along the eastern coastal shelf. Being able to model different spatial distributions within one simulation would address this.

Three possible model additions are (1) analyzing marine mammal bycatch, (2) including post-interaction mortality, and (3) testing additional estimation methods. The results from the model of sea turtle interactions are generally applicable to marine mammal interactions, but a few parameters could easily be changed to make the model more specific to marine mammal bycatch. While estimating the number of sea turtles or marine mammals caught by the longline fishery is important, the affect of fishery interactions on populations of protected species is actually the biologically important measure. Modeling the population-level effects of different levels of post-interaction mortality would be beneficial for fishery and protected species management. Finally, there are a number of other estimation methods that could be explored. Among the commonly used methods, I would next investigate the zero-inflated Poisson and zero-inflated negative binomial (Minami et al 2007, Gardner et al 2008a). Other novel

estimation methods could also be explored. For example, perhaps the GLM and delta-lognormal could be used to make estimates in different strata which are then combined in an annual estimate. If a GLM outperformed the delta-lognormal method in heavily fished strata, the GLM could be used to estimate bycatch in the strata without GLM convergence problems. Then the delta-lognormal method could be used in strata lacking sufficient data for the GLM. Another option is to incorporate weighting to strata estimates. Strata estimates would be made as usual, but they would be weighted relative to the fishing effort or size of the stratum to generate an annual estimate (Syrjala 2000, Walters 2003).

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TABLE 1.1

Incidental take statement for sea turtles in the U.S. Atlantic pelagic longline fishery. From NMFS 2004a (public domain).

Species	Number Captured from 2004-2006	Number Captured each Subsequent 3-Year Period
Leatherback turtle	1981	1764
Loggerhead turtle	1869	1905
Green, Hawksbill, Kemp's ridley, and Olive ridley turtle, in combination	105	105

TABLE 1.2

Bycatch estimation methods used by the SEFSC and PIFSC from 1991 to 2007. The year refers to the fishing year, not the year in which the estimate was made. CART stands for Classification and Regression Tree Analysis. When multiple methods are listed for one year, the methods are listed in the order in which they were used. For example, the SEFSC first used a GLM to estimate bycatch from 1992 but used the delta log-normal method in a later report to estimate bycatch from 1992.

	SEFSC	PIFSC
1991	-	CART ¹³
1992	GLM ¹ delta-lognormal ³	CART ¹³
1993	GLM ¹ delta-lognormal ³	CART ¹³
1994	delta-lognormal ^{2,3}	survey sampling ¹² CART ¹³ GLM ^{14,15} GAM ¹⁵
1995	delta-lognormal ^{2,3}	survey sampling ¹² CART ¹³ GLM ^{14,15} GAM ¹⁵
1996	delta-lognormal ³	CART ^{12,13} GLM ^{14,15} GAM ¹⁵
1997	delta-lognormal ³	CART ¹³ GLM ^{14,15} GAM ¹⁵
1998	delta-lognormal ⁴	GLM ^{14,15} GAM ¹⁵
1999	delta-lognormal ⁵	GLM ^{14,15} GAM ¹⁵
2000	delta-lognormal ⁵	(closed)
2001	delta-lognormal ⁶	(closed)
2002	delta-lognormal ⁶	(closed)
2003	delta-lognormal ⁷	(closed)
2004	delta-lognormal ⁸	Horvitz-Thompson ¹⁵
2005	delta-lognormal ⁹	Horvitz-Thompson ¹⁵
2006	delta-lognormal ¹⁰	Horvitz-Thompson ¹⁵
2007	delta-lognormal ¹¹	Horvitz-Thompson ¹⁵

1 = Witzell and Cramer 1995

2 = Scott and Brown 1997

3 = Johnson et al 1999

4 = Yeung 1999

5 = Yeung 2001

6 = Garrison 2003

7 = Garrison and Richards 2004

8 = Garrison 2005

9 = Walsh and Garrison 2006

10 = Fairfield-Walsh and Garrison 2007

11 = Fairfield and Garrison 2008

12 = Skillman and Kleiber 1998

13 = Kleiber 1998

14 = McCracken 2000

15 = McCracken 2004

TABLE 1.3

Mortality estimates for post-longline interaction. The percent of turtles with the given injury category and release condition that are expected to die are shown for hard shelled turtles followed by percentages for leatherbacks in parentheses. It is assumed that a resuscitated turtle will always have the line cut to a length less than half the length of the carapace, even if the hook remains. From Ryder et al 2004 (public domain).

INJURY CATEGORY	RELEASE CONDITION			
	Released with hook and with trailing line \geq half the length of the carapace (turtle not entangled)	Released with hook and with trailing line < half the length of the carapace (turtle not entangled)	Released with hook and entangled	Released with all gear removed
Hooked externally with or without entanglement	20 (30)	10 (15)	55 (65)	5 (10)
Hooked in upper or lower jaw, including ramphotheca with or without entanglement	30 (40)	20 (30)	65 (75)	10 (15)
Hooked in cervical esophagus, glottis, jaw joint, soft palate, tongue, and/or other jaw/mouth tissue parts with or without entanglement. Includes all events where the insertion point of the hook is visible when viewed through the mouth.	45 (55)	35 (45)	75 (85)	25 (35)
Hooked in esophagus at or below level of the heart with or without entanglement. Includes all events where the insertion point of the hook is not visible when viewed through the mouth.	60 (70)	50 (60)	85 (95)	n/a
Entangled no hook involved	Released entangled 50 (60)			Fully disentangled 1 (2)
Comatose / resuscitated	n/a	70 (80)	n/a	60 (70)

TABLE 2.1

The five spatial models, each with one of two sea turtle distributions and one of three fishing set distributions. A visual example of each spatial model is also given.






		SEA TURTLE DISTRIBUTION		FISHING SET DISTRIBUTION		
		uniformly random	clumped	uniformly random	clumped independent of turtles	clumped in same area as turtles
	TURTLE _{clump} .SET _{clump-turtle}		X			X
	TURTLE _{clump} .SET _{clump-vol}		X		X	
	TURTLE _{random} .SET _{clump-vol}	X			X	
	TURTLE _{clump} .SET _{random}		X	X		
	TURTLE _{random} .SET _{random}	X		X		

TABLE 2.2

The number of simulations with no observed bycatch out of the 1,000 simulations of each spatial model. The first three models are in bold because they are believed to be the most realistic with sets clumped in some configuration.

NUMBER OF SIMULATIONS WITH ZERO OBSERVED TAKE	
	OBSERVERS _{effort}
Turtles_{clump}, Sets_{clump-turtles}	0
Turtles_{clump}, Sets_{clump-sets}	90
Turtle_{random}, Sets_{clump-sets}	0
Turtles _{clump} , Sets _{random}	107
Turtle _{random} , Sets _{random}	0

TABLE 2.3

Confidence interval widths from two methods are compared. (A) The mean width of the 95% CI from the strata-based delta-lognormal estimate is compared to the mean width of the 95% CI from the delta-lognormal estimate of all sets pooled. The models in bold are believed to be the most realistic. (B) To facilitate the comparison, the mean widths of the two 95% CIs are shown as percents of the point estimates.

(A)

MEAN CI WIDTH (OBSERVERS_{effort})

	all sets	strata
Turtles_{clump}, Sets_{clump-turtles}	405.2	670.0
Turtles_{clump}, Sets_{clump-sets}	96.8	140.9
Turtle_{random}, Sets_{clump-sets}	358.9	573.0
Turtles _{clump} , Sets _{random}	85.9	136.2
Turtle _{random} , Sets _{random}	335.5	529.9

(B)

CI WIDTH RELATIVE TO BYCATCH ESTIMATE (OBSERVERS_{effort})

	all sets	strata
Turtles_{clump}, Sets_{clump-turtles}	55.5%	87.1%
Turtles_{clump}, Sets_{clump-sets}	319.8%	316.4%
Turtle_{random}, Sets_{clump-sets}	61.3%	93.3%
Turtles _{clump} , Sets _{random}	335.7%	336.1%
Turtle _{random} , Sets _{random}	60.3%	91.2%

TABLE 2.4

Extreme underestimation and overestimation of the two 95% confidence intervals. The number of times the actual amount of bycatch falls above or below (A) the strata-based CI or (B) the CI of all sets pooled is presented.

(A)

NUMBER OF SIMULATIONS WITH ACTUAL TAKE OUTSIDE CI (OBSERVERS_{effort}) - STRATA

	Underestimate	Overestimate
Turtles_{clump}, Sets_{clump-turtles}	2	0
Turtles_{clump}, Sets_{clump-sets}	0	45
Turtle_{random}, Sets_{clump-sets}	1	4
Turtles _{clump} , Sets _{random}	0	25
Turtle _{random} , Sets _{random}	4	1

(B)

NUMBER OF SIMULATIONS WITH ACTUAL TAKE OUTSIDE CI (OBSERVERS_{effort}) - ALL SETS

	Underestimate	Overestimate
Turtles_{clump}, Sets_{clump-turtles}	82	1
Turtles_{clump}, Sets_{clump-sets}	1	27
Turtle_{random}, Sets_{clump-sets}	27	7
Turtles _{clump} , Sets _{random}	0	16
Turtle _{random} , Sets _{random}	73	0

FIGURE 1.1

Typical configuration of pelagic longline gear. From NMFS-OSF 2007 (public domain).

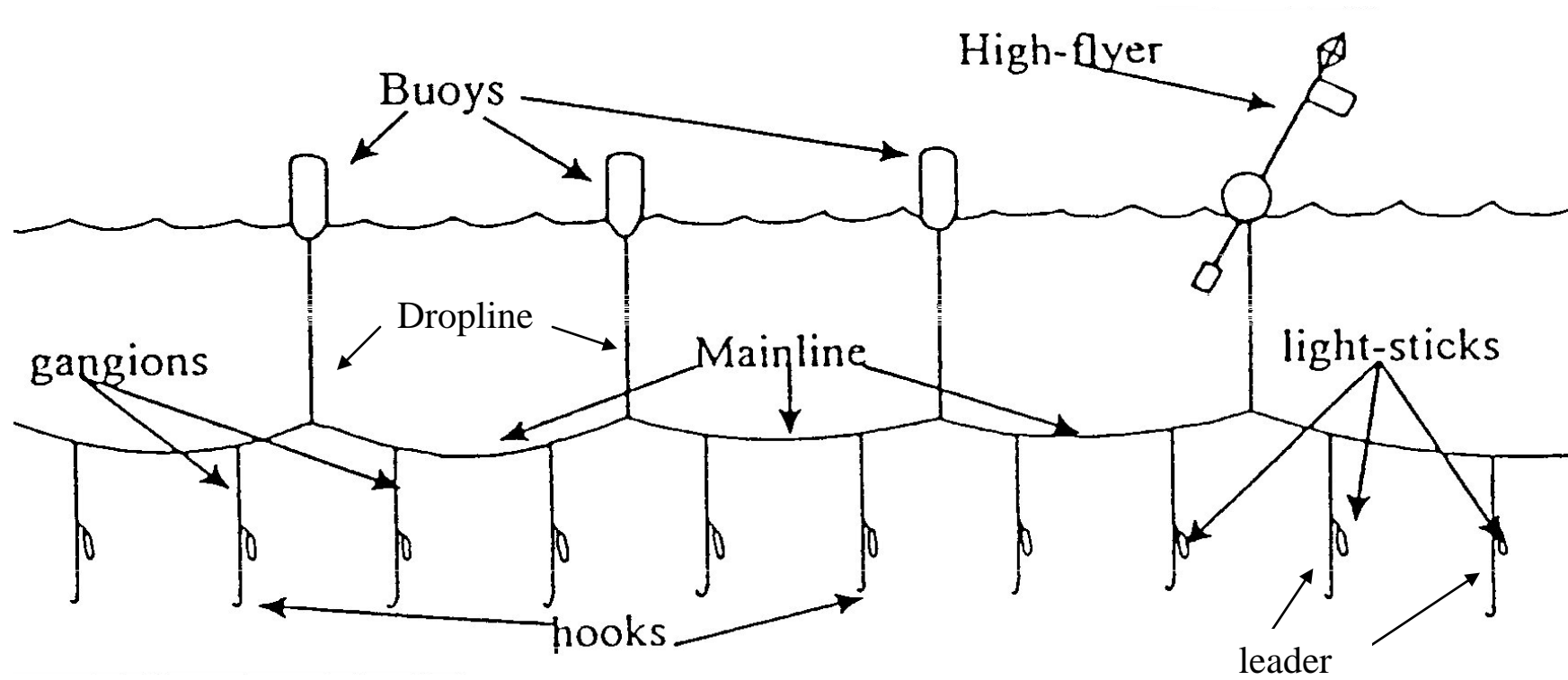


FIGURE 1.2

Observed catch composition for 1992-2002. Swordfish and tuna, the main target species, composed 30% and 18% of the catch respectively, where tuna includes yellowfin, bigeye, and bluefin. Less than 1% of the catch was incidental take (INCD TAKE) of marine mammals, sea turtles, and sea birds. The subdivisions of the UNKNOWN category result from the observer only being able to classify fish into a general category – unknown tuna, unknown billfish, unknown shark. From Beerkircher et al 2004 (public domain).

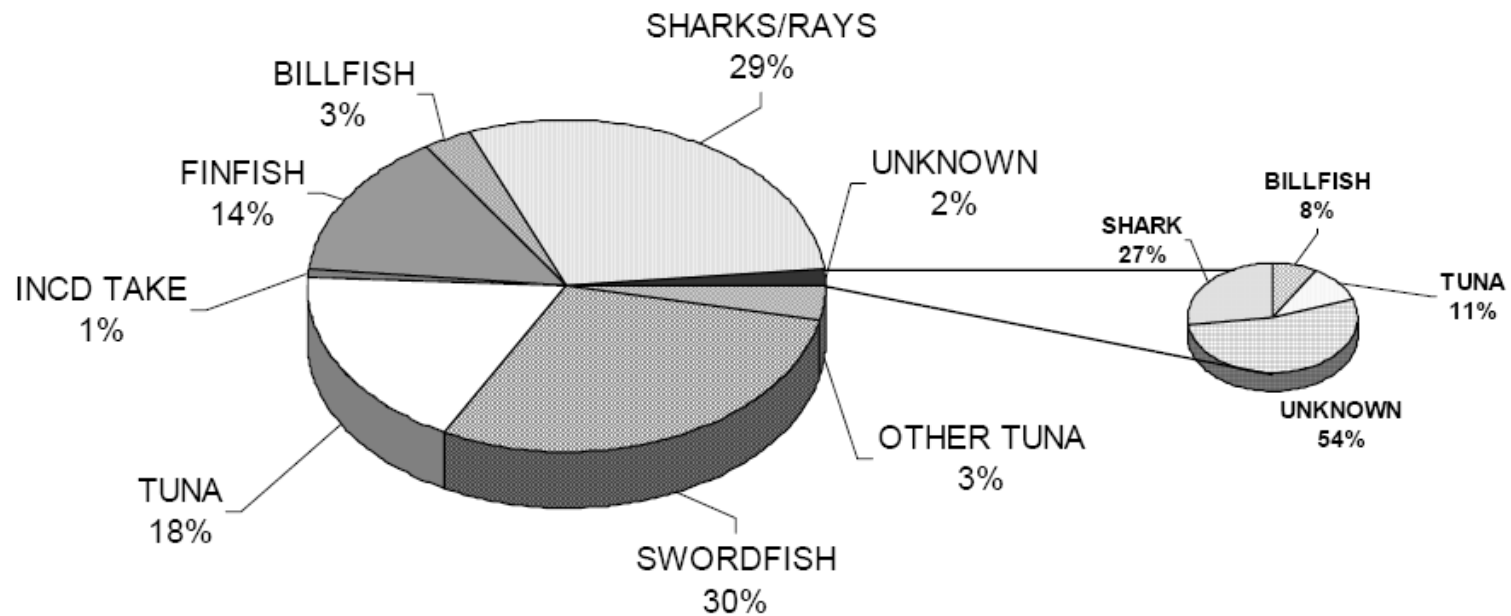


FIGURE 1.3

Fishing areas used in SEFSC bycatch estimation. From Yeung 2001 (public domain).

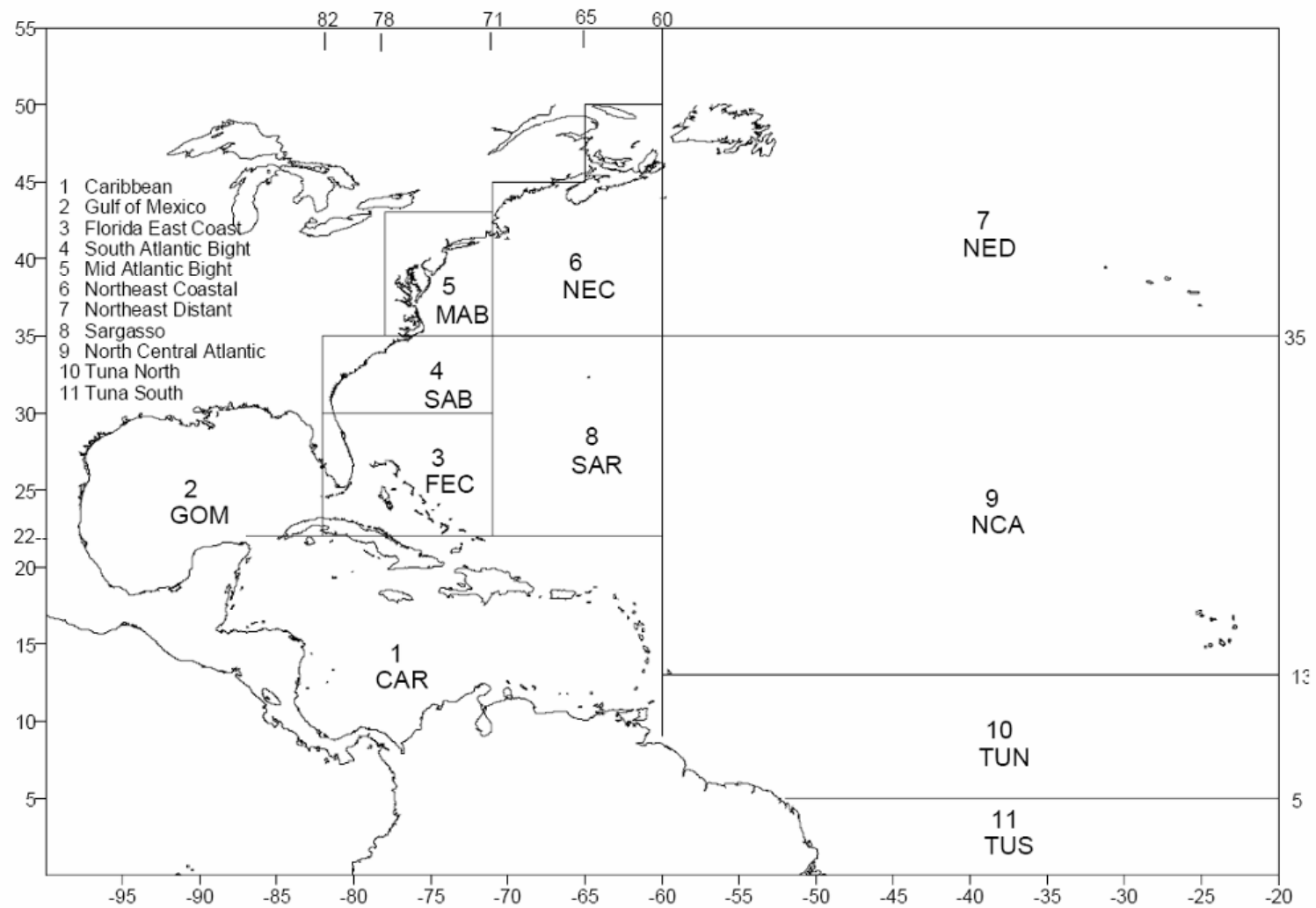
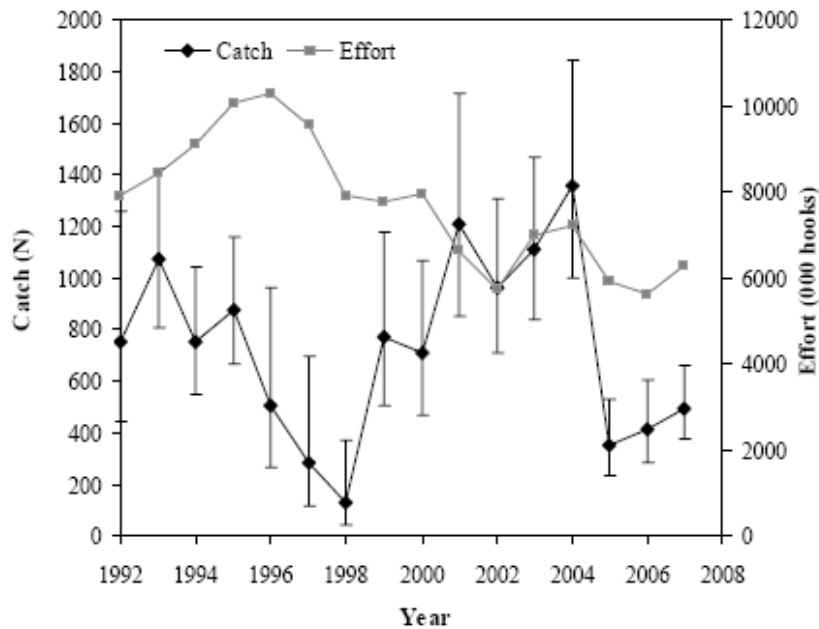


FIGURE 1.4

Leatherback (A) and loggerhead (B) takes estimated by the NMFS SEFSC and total reported effort from 1992 to 2005. Estimated takes include 95% confidence interval bars. From Fairfield and Garrison 2008 (public domain).

A. Leatherback Turtles



B. Loggerhead Turtles

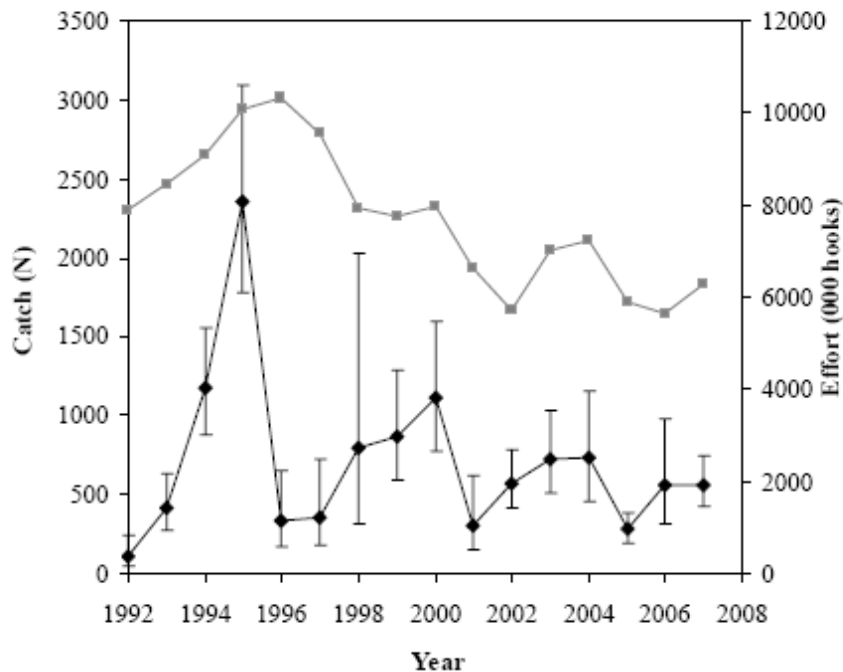


FIGURE 2.1

Estimated loggerhead sea turtle bycatch in the pelagic longline fishery from 1992 through 2007 as calculated by the NMFS SEFSC. The black dots are annual bycatch point estimates, and the black bars extending above and below each black dot are the 95% confidence intervals. From Fairfield and Garrison 2008 (public domain).

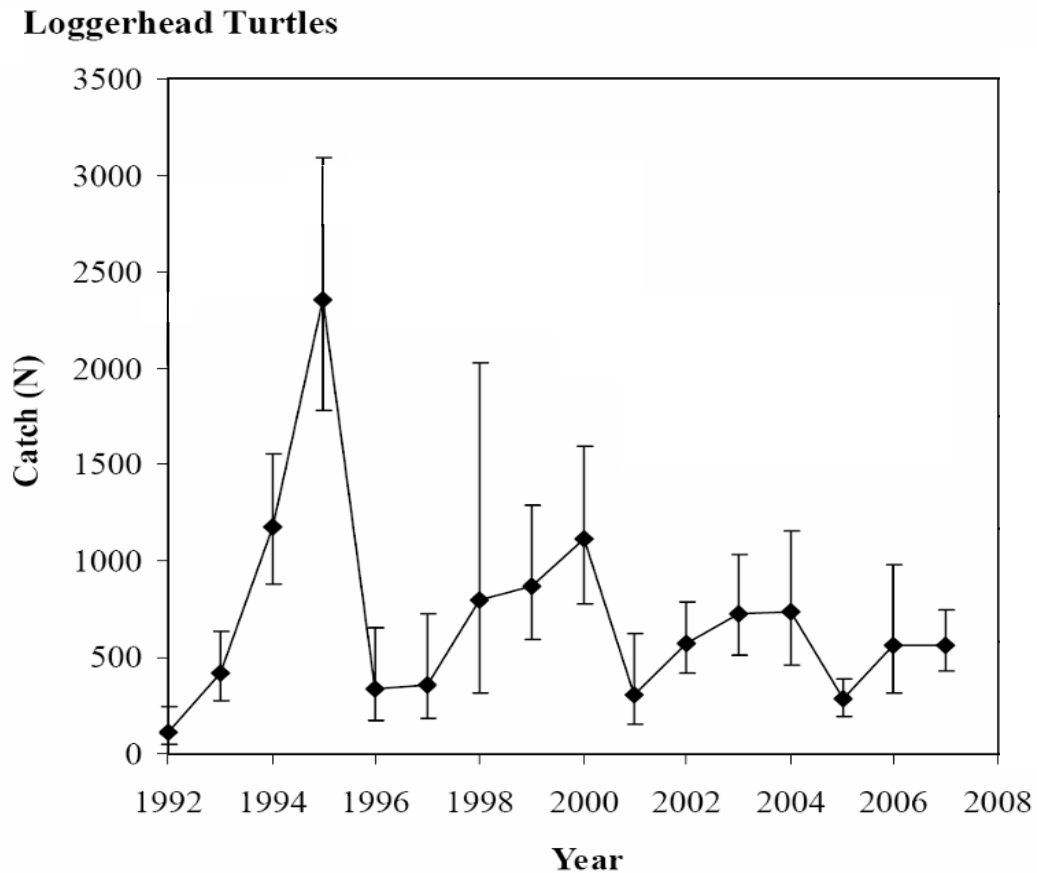
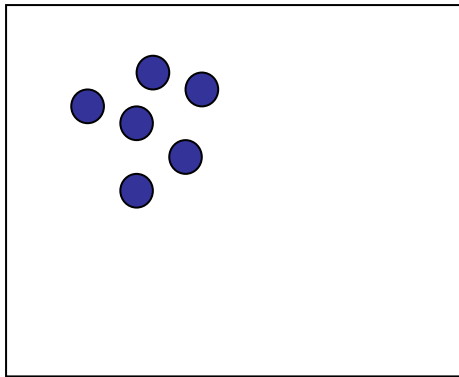
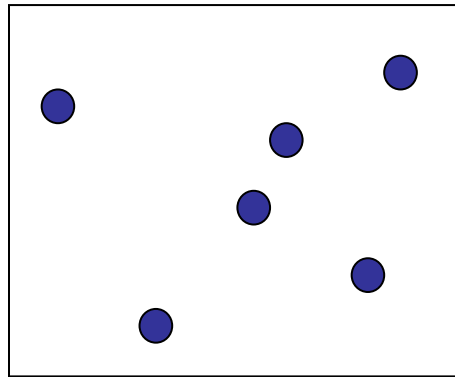


FIGURE 2.2

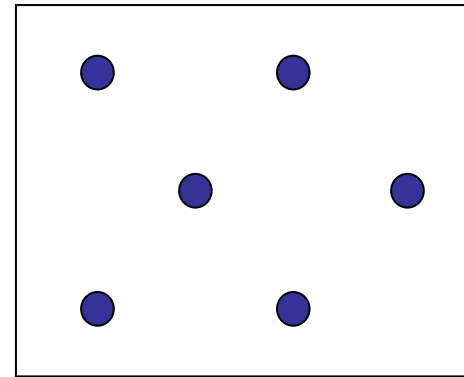
Potential spatial distributions. The evenly spaced distribution was not modeled.



clumped



uniformly random



evenly spaced

FIGURE 2.3

NMFS observed and logbook reported sets in 2005 through 2007. The fishing areas are demarcated by the grey rectangles. The grey hashed areas indicate fishery closures. (A) is from Fairfield and Garrison 2008 (public domain), (B) is from Fairfield-Walsh and Garrison 2007 (public domain), and (C) is from Walsh and Garrison 2006 (public domain). The experimental fishery sets in 2005, marked by the grey boxes, were not included in my study.

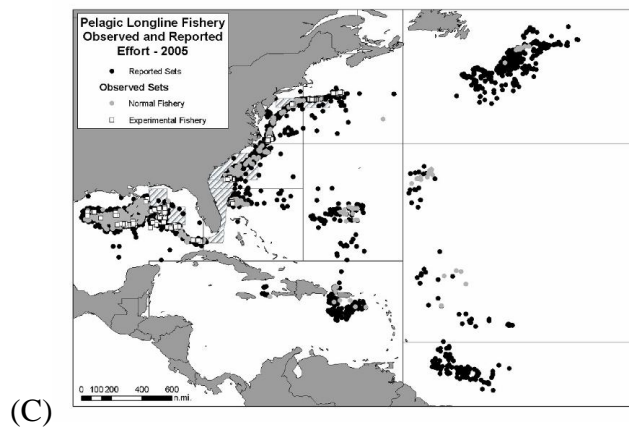
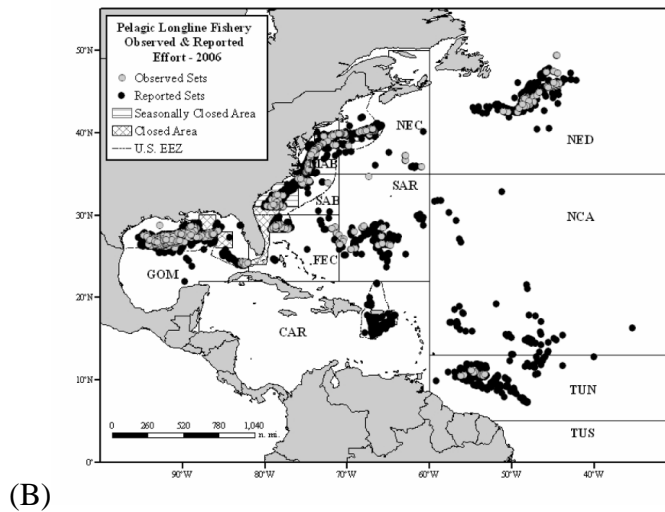
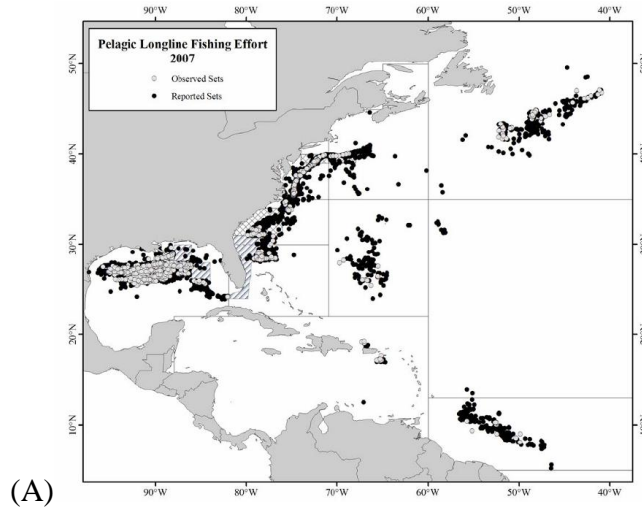


FIGURE 2.4

Diagram representing the conditions of the thirty models. For a model, one turtle distribution, set distribution, estimation method, and spatial scale of estimation are selected. All combinations are modeled except those with turtles uniformly random and sets clumped in the same area as turtles since that is not possible.

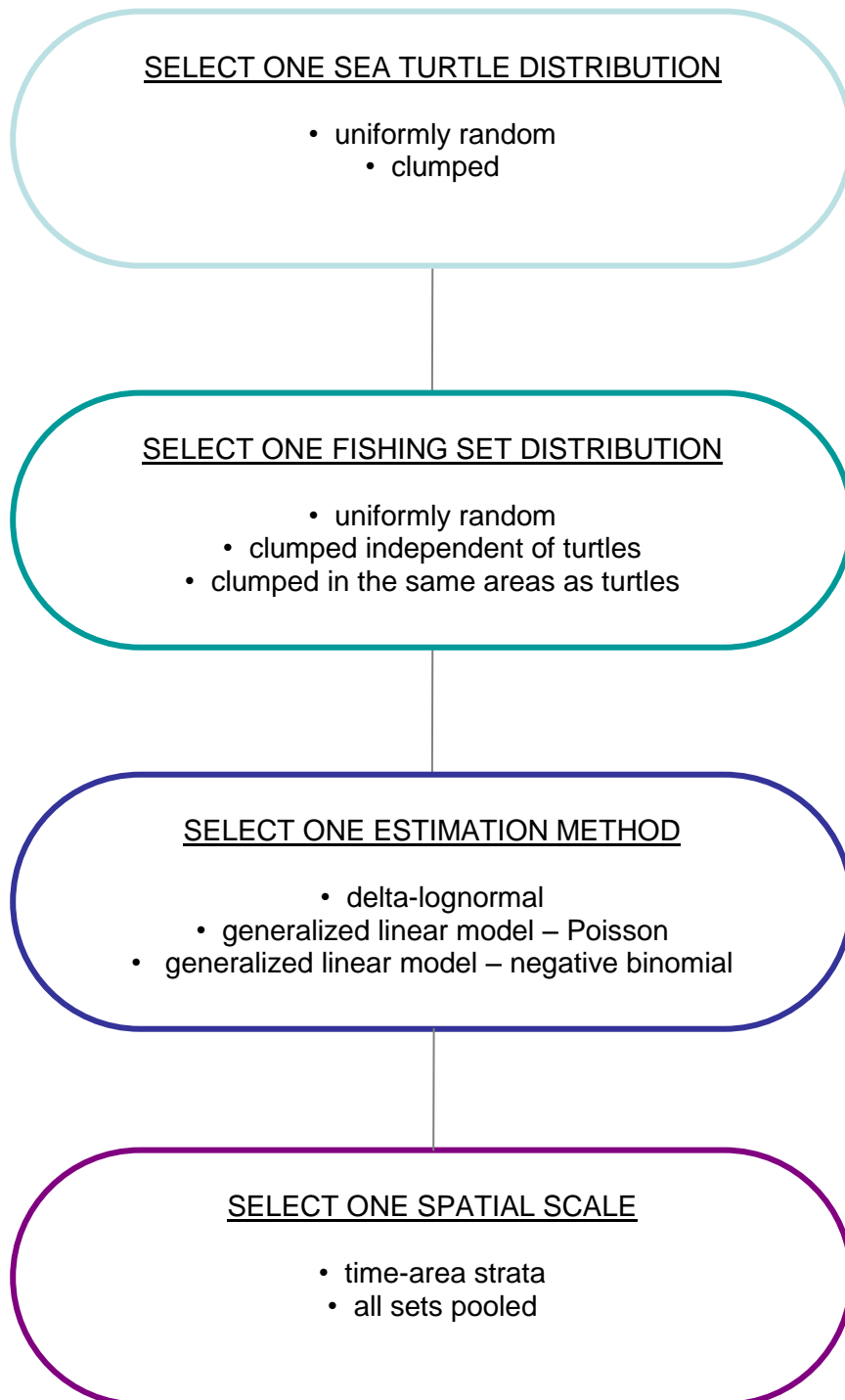


FIGURE 2.5

Diagram representing the use of risk inclusion scalars to make risk-adjusted bycatch estimates. Risk inclusion scalars can be multiplied by a bycatch point estimate to obtain a bycatch estimate with a specific amount of risk incorporated. The selected level of risk corresponds to a probability that the actual amount of bycatch will be greater than the estimate.

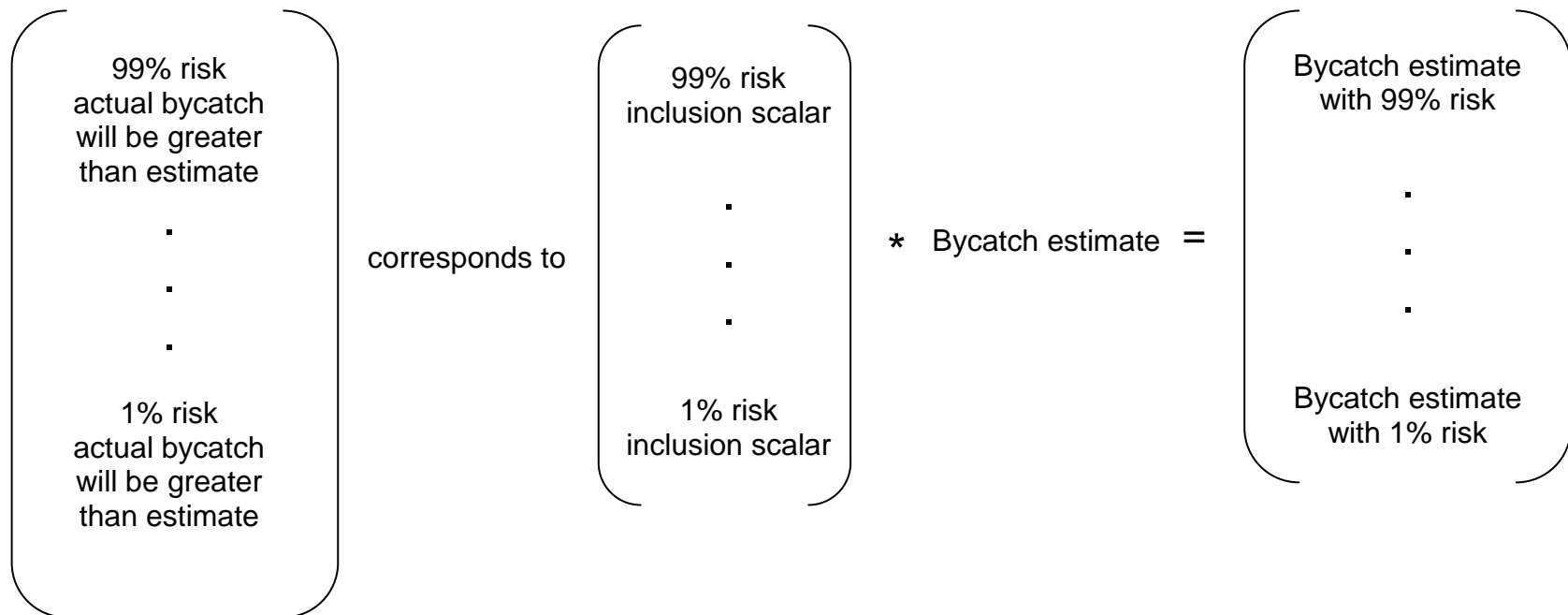


FIGURE 2.6

An example of a risk inclusion scalar CDF, marked by the blue line. As an example, the red dashed line shows a 95% probability that take is no greater, a 5% risk. The corresponding risk inclusion scalar is 1.29. Multiplying a bycatch point estimate by the risk inclusion scalar provides an estimate with a 5% level of risk.

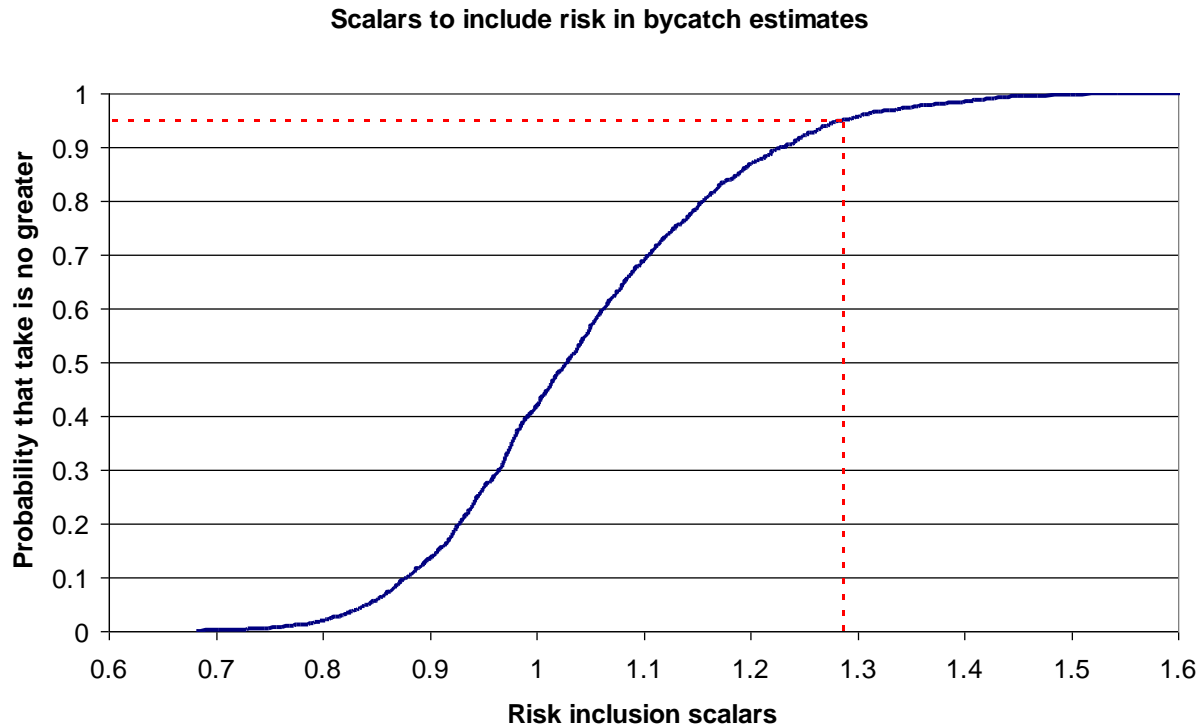


FIGURE 2.7

An example of a bycatch estimate risk curve calculated from a risk inclusion scalar CDF. This example was calculated by multiplying a bycatch point estimate of 500 by each of the risk inclusion scalars plotted in Figure 7.

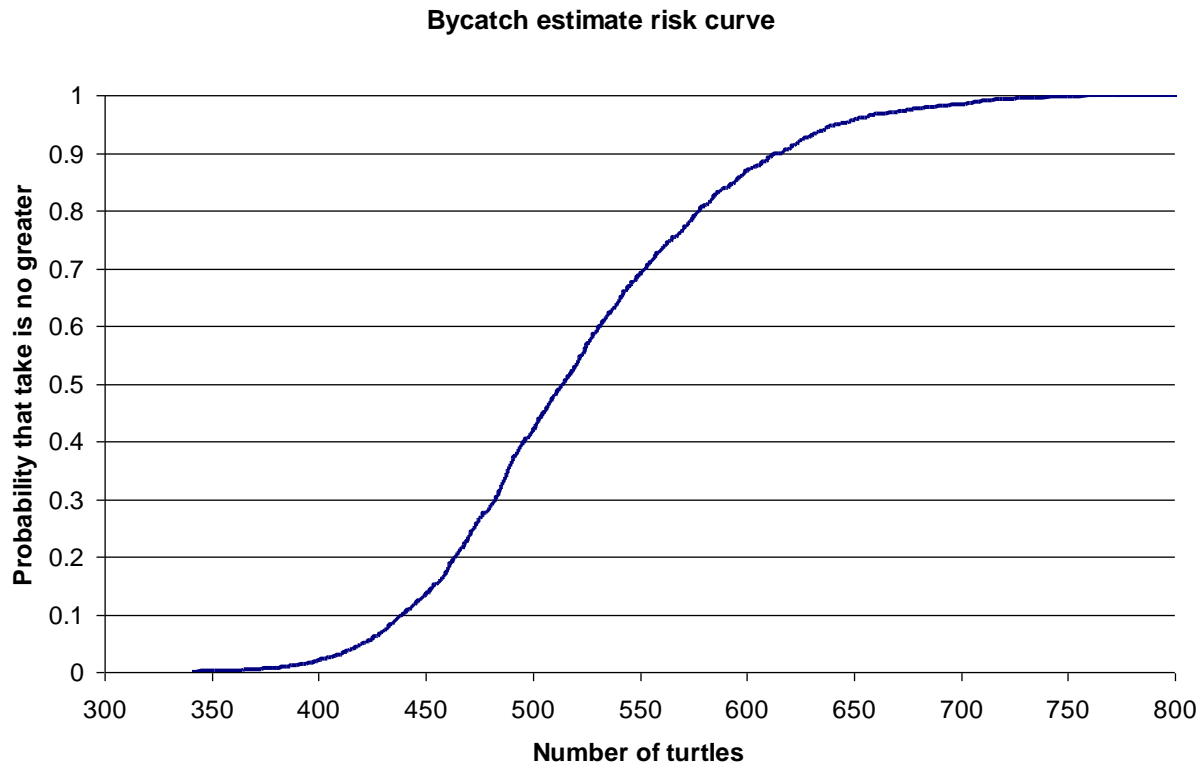


FIGURE 2.8

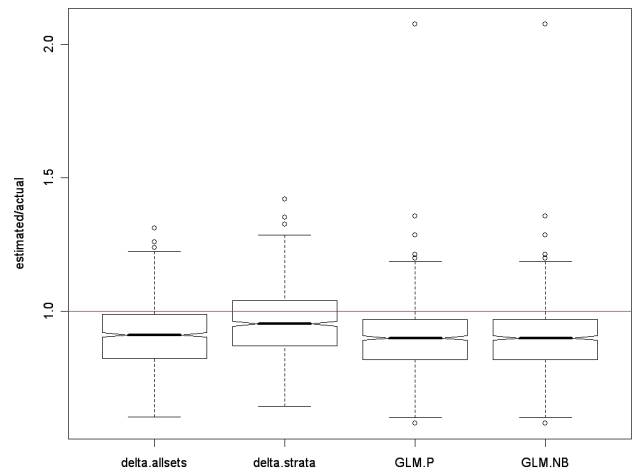
Comparing bycatch estimates to the simulated amount of bycatch to evaluate method performance when observers were placed according to fishing effort.

Each of the five figures corresponds to one of the five spatial models, and the results of the four estimation methods are shown in the box plots.

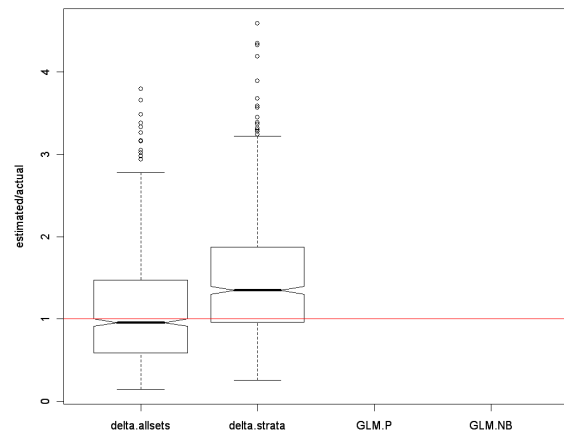
The red line at a value of one marks where the median of an unbiased estimation method should fall. There are notches around the medians, and if the notches of two plots do not overlap, there is strong evidence that the two medians differ (Chambers et al 1983). The box includes the first through third quartile. Whiskers extend to the most extreme data point which is no more than 1.5 times the interquartile range from the box. Dots represent outliers.

In the (Turtle_{random}, Sets_{random}) model, two outliers were removed from the GLM-P box plot and two outliers were removed from the GLM-NB box plot. If these outliers were included, the boxplots would be too compressed to determine method performance.

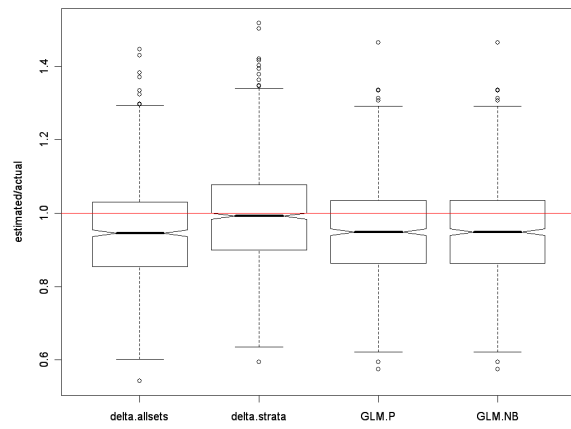
Comparison of estimated bycatch to total simulated bycatch - Turt_c, Set_c-turt, Obs_e



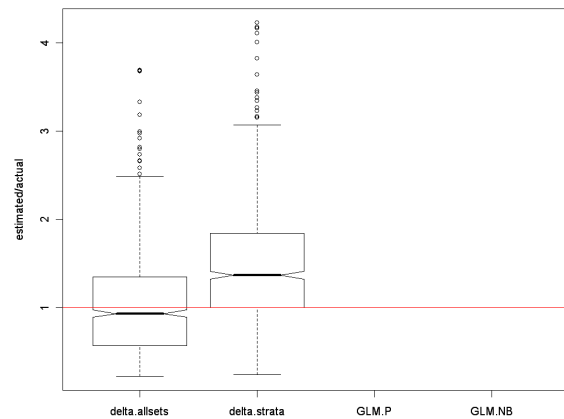
Comparison of estimated bycatch to total simulated bycatch - Turt_c, Set_c-set, Obs_e



Comparison of estimated bycatch to total simulated bycatch - Turt_rand, Set_c-set, Obs_e



Comparison of estimated bycatch to total simulated bycatch - Turt_c, Set_rand, Obs_e



Comparison of estimated bycatch to total simulated bycatch - Turt_rand, Set_rand, Obs_e

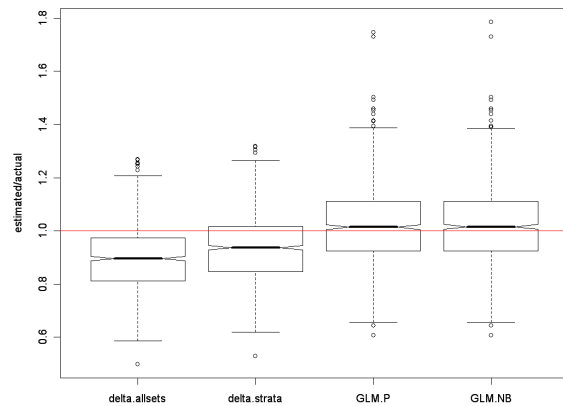


FIGURE 2.9

Observed bycatch rates from the SEFSC in 2005 through 2007 compared to the average observed bycatch rates in the five models with observers placed in proportion to fishing effort. Observed bycatch rates were calculated by dividing the number of observed takes by the number of observed sets. To obtain an observed bycatch rate for a model, the observed bycatch rate was calculated for each simulation then averaged across all 1,000 simulations.

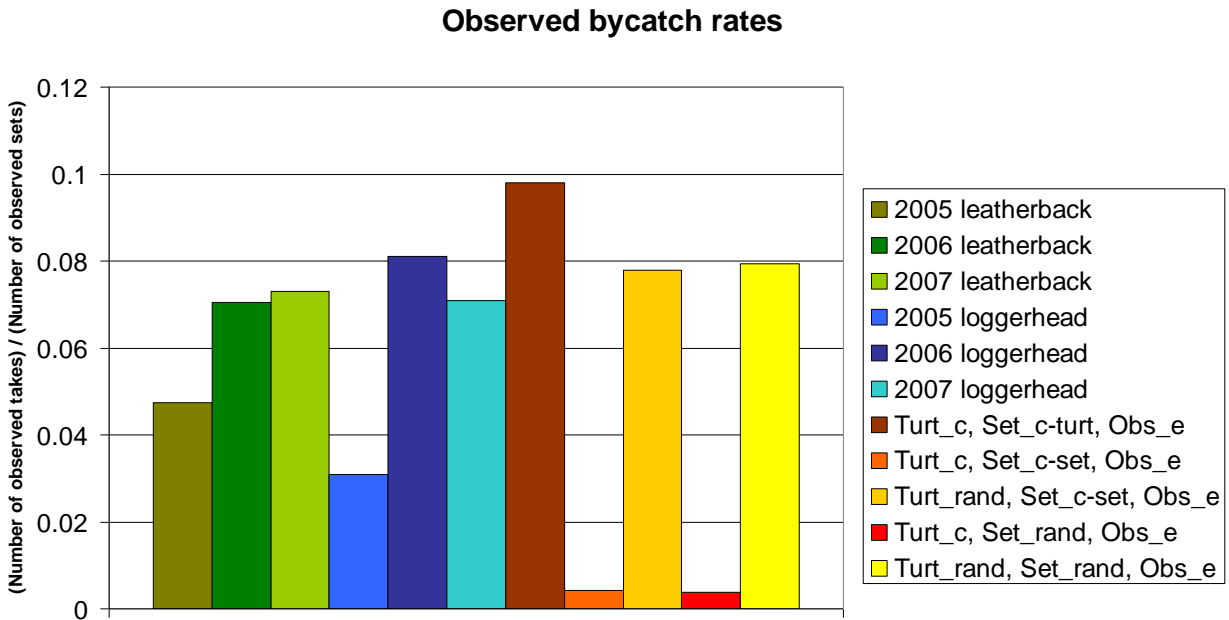


FIGURE 2.10

The estimation method determined to be most suitable in each of the spatial models when observers were based on fishing effort. The estimation methods in bold were determined to be most suitable overall based on estimation accuracy, estimation precision, spatial model realism, and realistic levels of simulated observed bycatch.

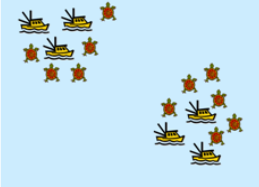
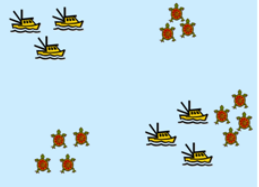
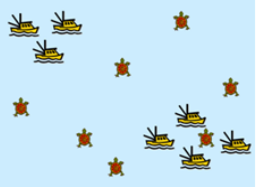
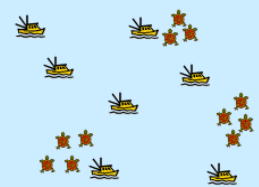
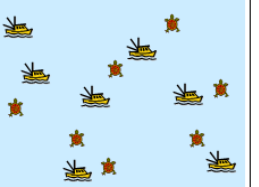
SPATIAL MODEL	TURTLE _{clump} , SET _{clump-turtle}	TURTLE _{clump} , SET _{clump-sets}	TURTLE _{random} , SET _{clump-sets}	TURTLE _{clump} , SET _{random}	TURTLE _{random} , SET _{random}
MOST SUITABLE ESTIMATION METHOD					
	delta-lognormal, strata	delta-lognormal, all sets	delta-lognormal, strata	delta-lognormal, all sets	GLM

FIGURE 2.11

Comparing bycatch estimates to the simulated amount of bycatch to evaluate method performance when observers were placed in bycatch hotspots.

Each of the five figures corresponds to one of the five spatial models, and the results of the four estimation methods are shown in the box plots.

The red line at one marks where the median of an unbiased estimation method should fall. There are notches around the medians, and if the notches of two plots do not overlap, there is strong evidence that the two medians differ (Chambers et al 1983). The box includes the first through third quartile. Whiskers extend to the most extreme data point which is no more than 1.5 times the interquartile range from the box. Dots represent outliers.

In the $(Turtles_{clump}, Sets_{clump-sets})$ model, ten outliers were removed from the GLM-P box plot and ten outliers were removed from the GLM-NB box plot. In the $(Turtles_{clump}, Sets_{random})$ model, eleven outliers were removed from the GLM-P box plot and ten outliers were removed from the GLM-NB box plot. If these outliers were included, the boxplots would be too compressed to determine method performance.

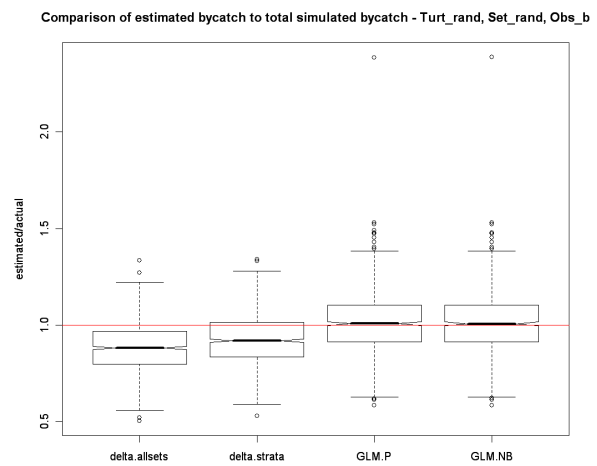
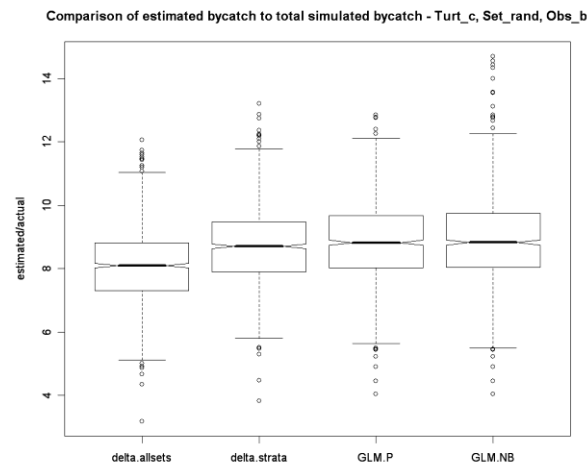
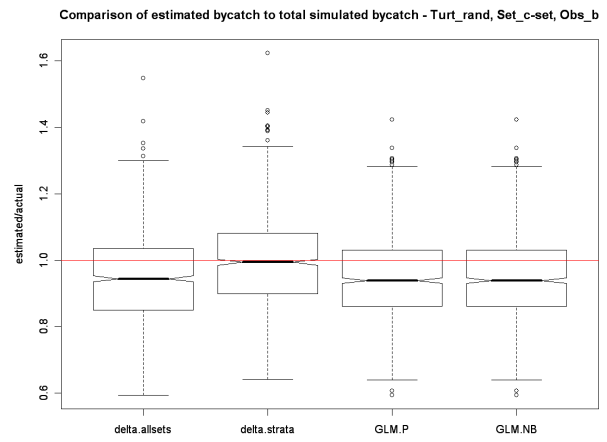
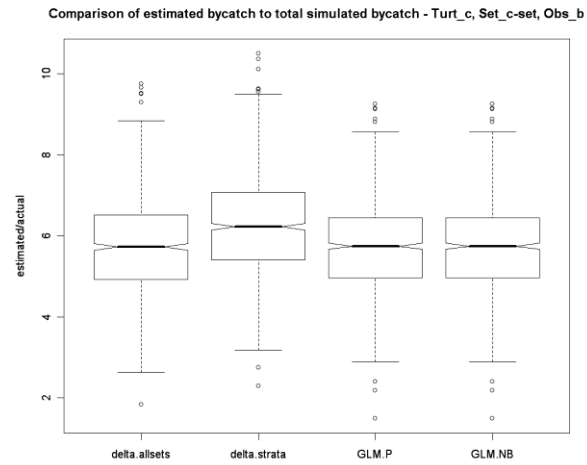
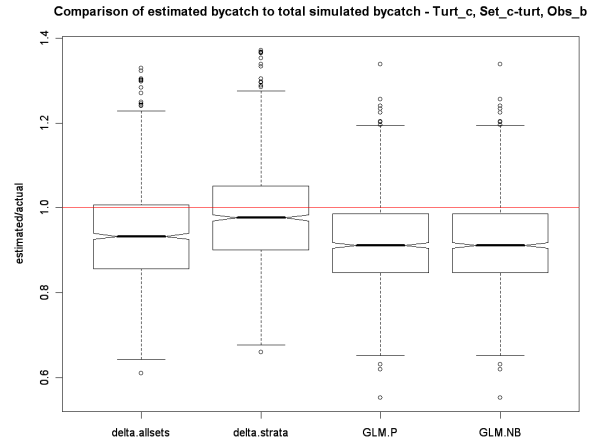


FIGURE 2.12

Observed bycatch rates from the SEFSC in 2005 through 2007 compared to the average observed bycatch rates in the five models with observers placed in bycatch hotspots. Observed bycatch rates were calculated by dividing the number of observed takes by the number of observed sets. To obtain an observed bycatch rate for a model, the observed bycatch rate was calculated for each simulation then averaged across all 1,000 simulations.

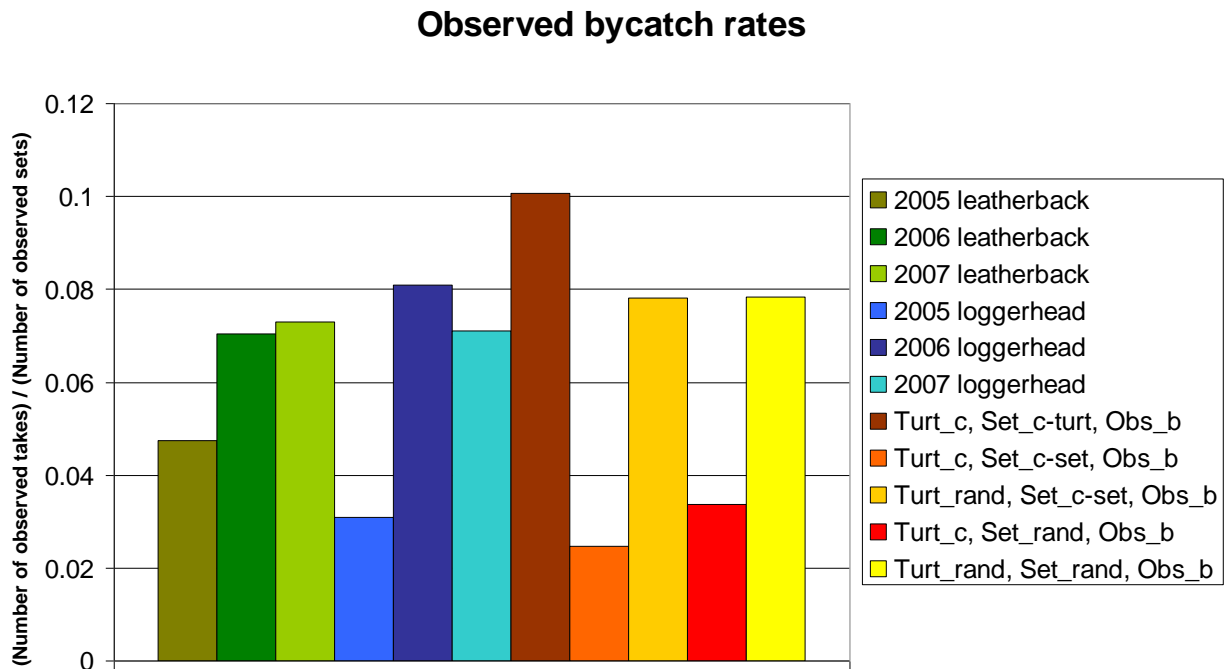


FIGURE 2.13

The estimation method determined to be most suitable in each of the spatial models when observers were based on bycatch hotspots. The estimation method in bold was determined to be most suitable overall based on estimation accuracy, estimation precision, spatial model realism, and realistic levels of simulated observed bycatch. The estimation methods in italic were most suitable in models with observers placed randomly because there were no bycatch hotspots. When “NA” is listed as the most suitable estimation method, none of the methods analyzed performed adequately.

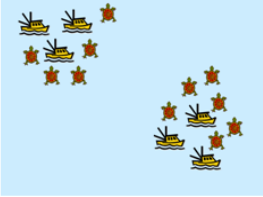
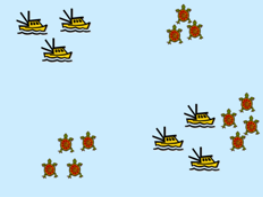
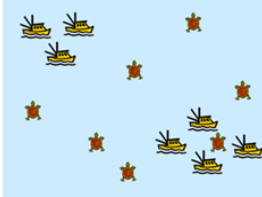
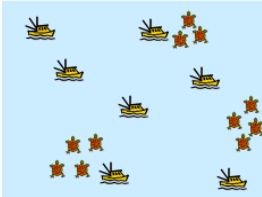
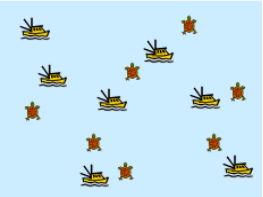
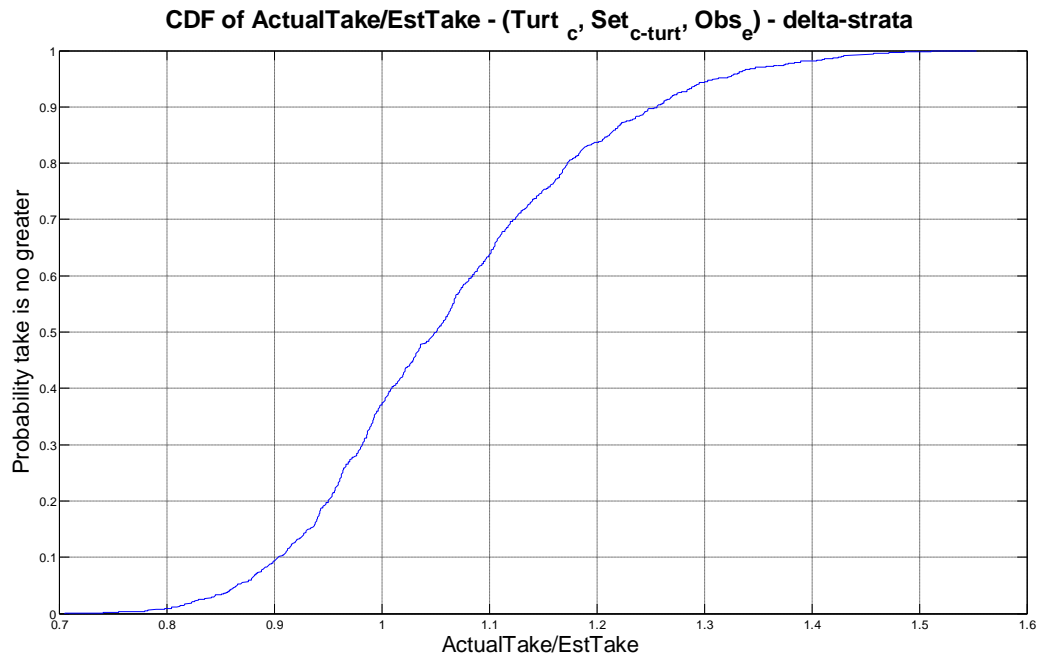
SPATIAL MODEL	TURTLE _{clump} , SET _{clump-turtle}	TURTLE _{clump} , SET _{clump-sets}	TURTLE _{random} , SET _{clump-sets}	TURTLE _{clump} , SET _{random}	TURTLE _{random} , SET _{random}
					
MOST SUITABLE ESTIMATION METHOD	delta-lognormal, strata	NA	<i>delta-lognormal, strata</i>	NA	<i>GLM</i>

FIGURE 2.14

Cumulative distribution function of the ratio of actual take to estimated take for (A) the $(\text{Turtles}_{\text{clump}}, \text{Sets}_{\text{clump-turtles}}, \text{Observer}_{\text{effort}})$ model and (B) the $(\text{Turtle}_{\text{random}}, \text{Sets}_{\text{clump-sets}}, \text{Observer}_{\text{effort}})$ model with estimates made with the strata-based delta-lognormal method. The risk inclusion scalars are on the X axis, and the probability that take is no greater is on the Y axis.

(A)



(B)

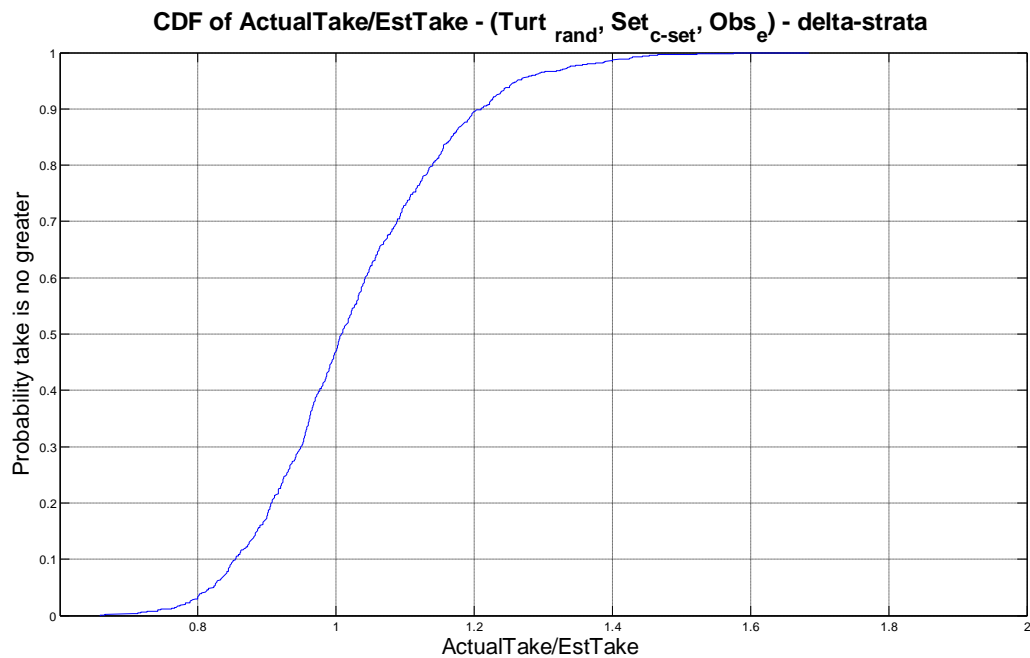


FIGURE 2.15

Average of the ($Turtles_{clump}$, $Sets_{clump-turtles}$, $Observer_{effort}$) model CDF and the ($Turtle_{random}$, $Sets_{clump-sets}$, $Observer_{effort}$) model CDF. The averaged risk inclusion scalars are on the X axis, and the probability that take is no greater is on the Y axis.

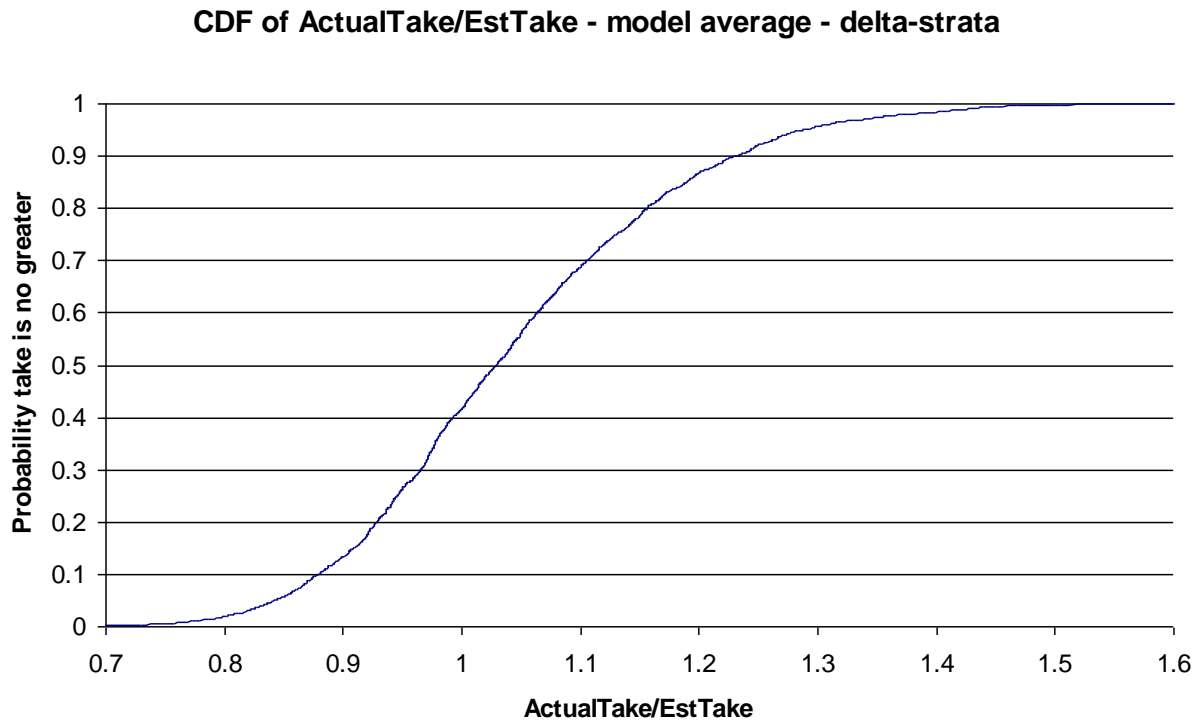
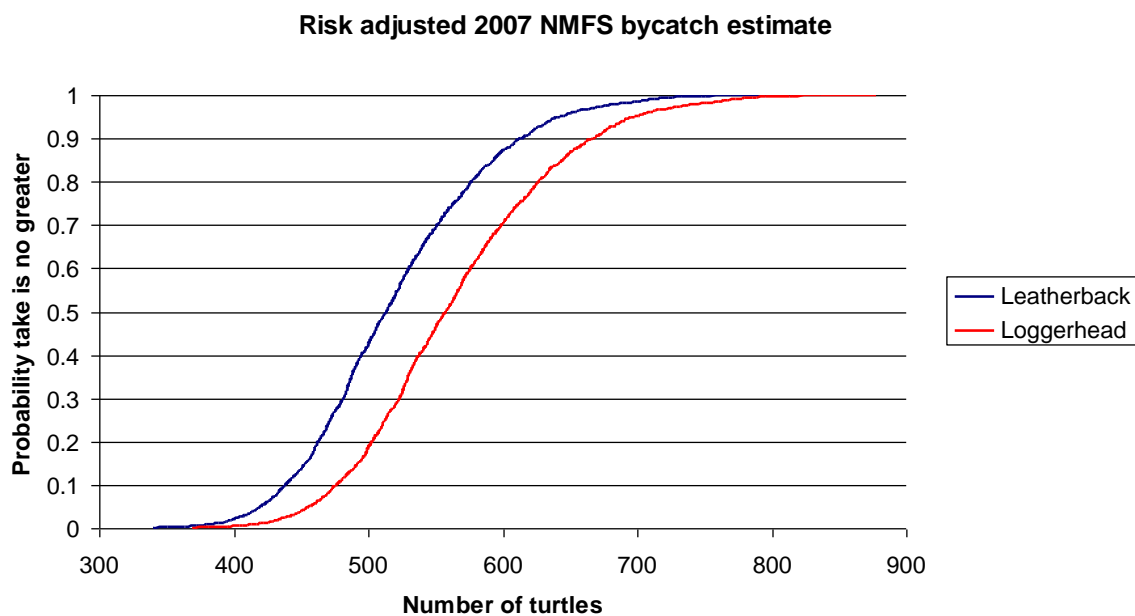


FIGURE 2.16

Bycatch estimate risk curves. (A) Risk inclusion scalars from Figure 2.15 were applied to the SEFSC's 2007 estimate of sea turtle bycatch and plotted. (B) The SEFSC's 2007 estimates of sea turtle bycatch are plotted on the bycatch estimate risk curve. The risk curve indicates that these point estimates correspond to 58% risk.

(A)



(B)

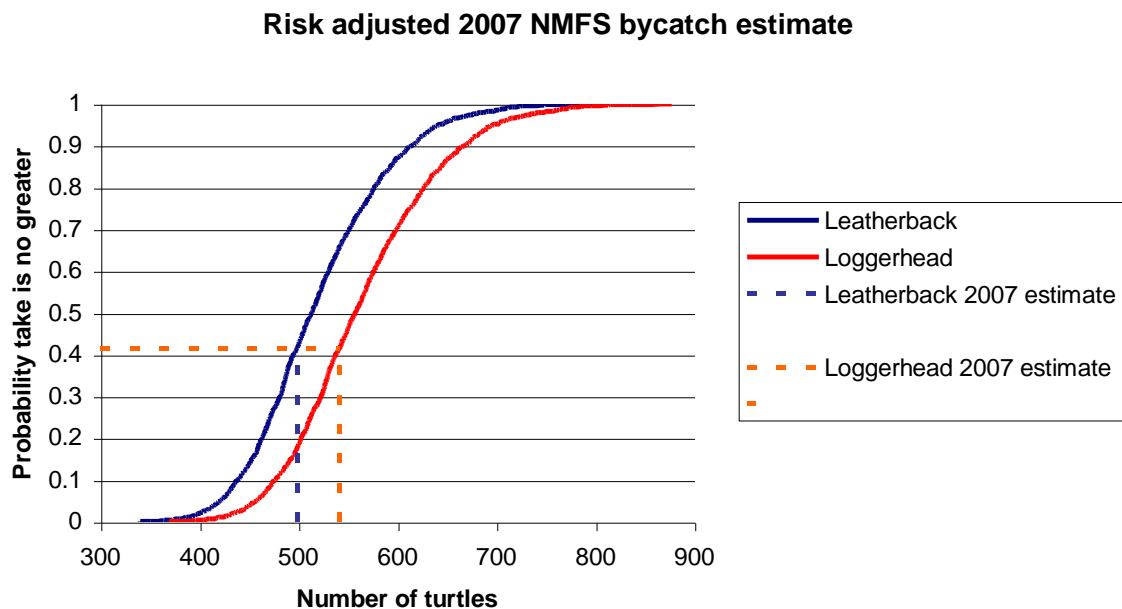
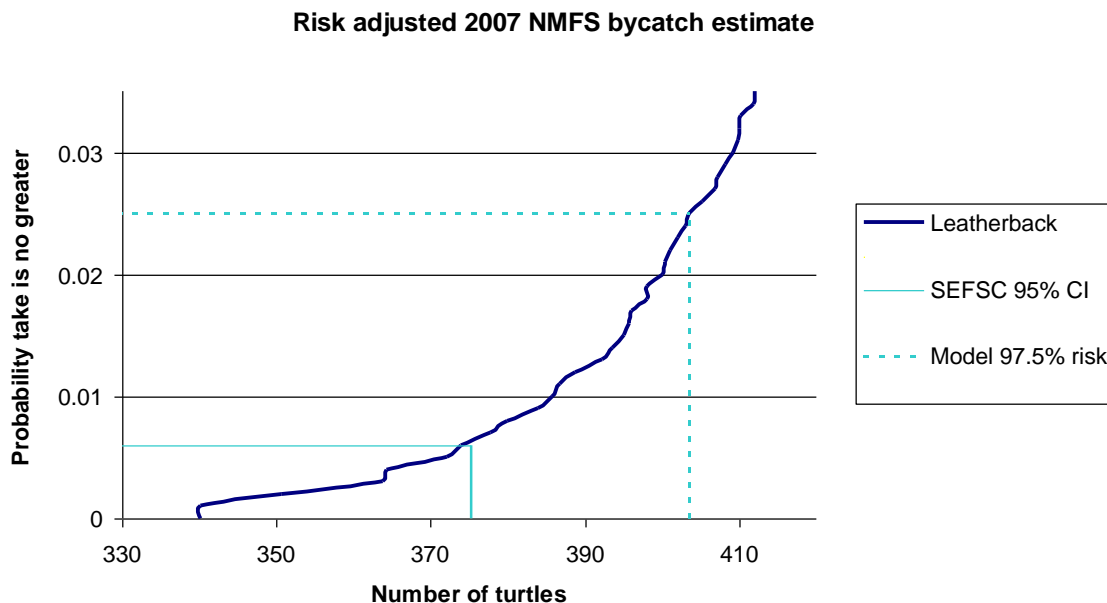


FIGURE 2.17

(A) The solid light blue line marks where the lower bound of the SEFSC's 95% CI fell in relation to the scalar-based bycatch estimate risk distribution. The hatched light blue line indicates a 2.5% probability that take is no greater on the scalar-based bycatch estimate risk distribution, which corresponds with the probability associated with the lower bound of a 95% CI.



(B) The solid light blue line marks where the upper bound of the SEFSC's 95% CI fell in relation to the scalar-based bycatch estimate risk distribution. The hatched light blue line indicates a 97.5% probability that take is no greater on the scalar-based bycatch estimate risk distribution, which corresponds with the probability associated with the upper bound of a 95% CI.

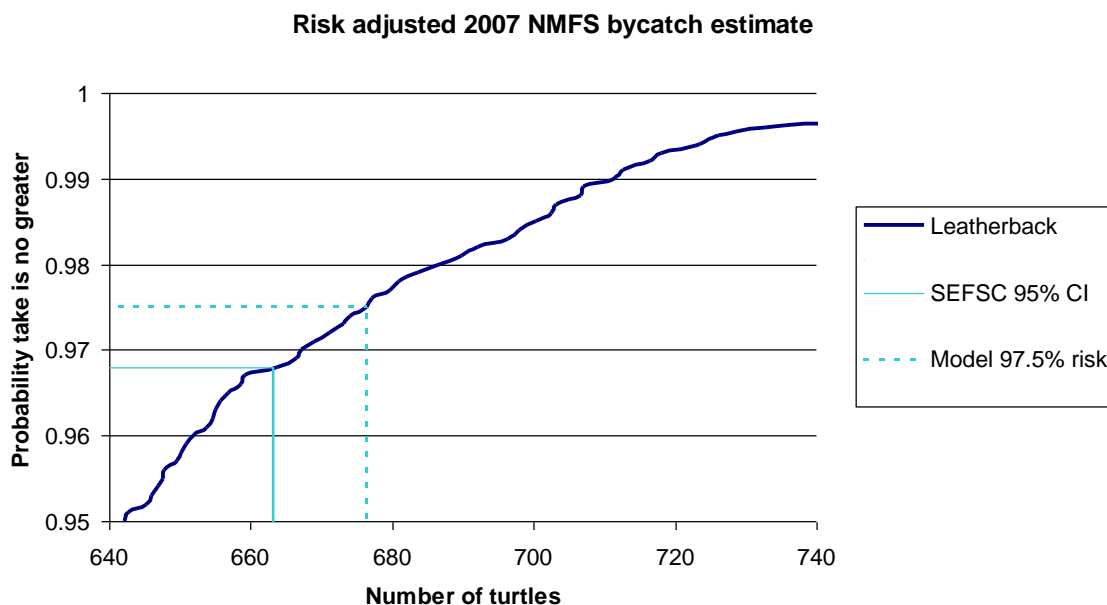
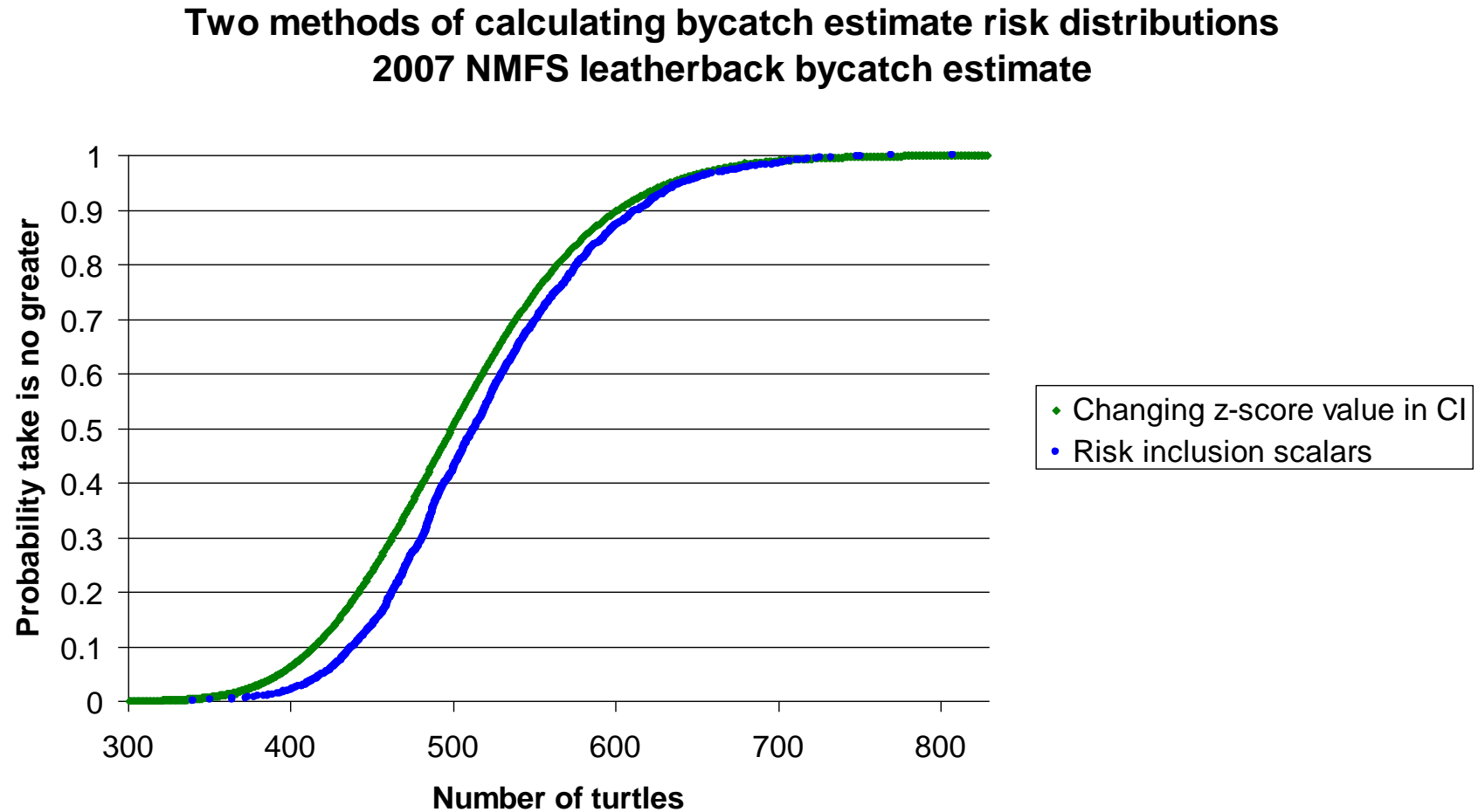


FIGURE 2.18

Leatherback bycatch estimate risk curves calculated by varying the z-score in the confidence interval and by using risk inclusion scalars.



APPENDIX A:

SPATIAL DISTRIBUTIONS FOR SIMULATION MODEL

This appendix provides details about the spatial simulation models not included in the methods section. While the purpose of the methods section was to give a general description of the simulation model, this appendix gives a specific account of how the model was constructed.

A1.1 STRUCTURAL ASSUMPTIONS

First, some basic assumptions were required to construct the model, including the structural framework, dimensions, and number of simulations.

A1.1.1 OCEAN AS COORDINATE GRID

In order to create a simulation model of sea turtle interactions with the U.S. Atlantic pelagic longline fishery, I conceptualized the model as a square grid with X and Y coordinates for each cell. One of my objectives was to model different spatial configurations, so the (X,Y) coordinate system was a logical way to structure the spatial model. Sea turtles and fishing sets were assigned (X,Y) coordinates probabilistically to mimic various spatial fishing scenarios.

A1.1.2 LENGTH OF FISHING SETS

The average fishing set covers about 50km (average 47km, minimum 32km, maximum 64km) (Witzell 1999, Beerkircher et al 2004, Gilman et al 2006, NMFS 2007). I assigned dimensions to the model cells so they would be 10km by 10km and a set would cover five cells. This simplified model computations for placing fishing sets within the (X,Y) grid.

A1.1.3 NUMBER OF SETS

I modeled 8,000 sets per simulation, as this is approximately the average number of sets fished per year in the U.S. Atlantic pelagic longline fishery from 2005 through 2007, the period after the regulated change from J hooks to circle hooks (Table A1.1).

TABLE A1.1

Number of sets fished annually since the switch from J hooks to circle hooks and the average annual number of sets. The annual numbers of sets were obtained from Walsh and Garrison 2006, Fairfield-Walsh and Garrison 2007, and Fairfield and Garrison 2008.

	Number of sets
2005	7645
2006	7551
2007	8795
Average	7997

A1.1.4 SPATIAL REPLICATES

Modeling 8,000 sets at once would be unwieldy, so I decided to divide the annual fishing into smaller components that could be replicated as many times as necessary to model all 8,000 sets. Since 2002, NMFS's target observer coverage has been 8% (Beerkircher et al 2004). To have one observer present at 8% coverage, there had to be 12.5 sets per replicate. Obviously, it is impossible to have half of a set, so it was necessary to have more than one observed set per spatial replicate. To have two observers present at 8% coverage, there had to be twenty-five sets. I decided to model twenty-five sets, with one observer on each of two sets, then replicate this 320 times to model 8,000 sets per simulated year.

A1.1.5 TIME-AREA STRATA

The SEFSC deploys observers based on effort in time-area strata and estimates bycatch in time-area strata. To mimic this procedure, I calculated the average number of sets fished per time-area stratum from the 2005 through 2007 SEFSC observer data to determine how many spatial replicates to simulate per stratum (Table A1.2).

TABLE A1.2

Determining the number of sets to model in each time-area stratum. The “STRATUM” column numbers the strata. There are 44 NMFS strata (4 quarters and 11 areas), but there were insufficient data in 10 strata (the grey cells) so 32 strata were modeled. The “AVG NMFS EFFORT” column shows the average number of sets fished in a NMFS time-area stratum from 2005 through 2007. This number was divided by 25 (the number of sets in a modeled spatial replicate) to get the value in the “NUM SPATIAL REPLICATES” column. Then that value was rounded to a whole number to obtain the value in the last column.

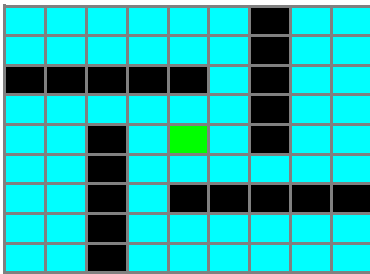
STRATUM	AVG NMFS EFFORT (SETS)	NUM SPATIAL REPLICATES	NUM SPATIAL REPLICATES (ROUNDED)
1	85.67	3.43	3
2	204.67	8.19	8
3	977.33	39.09	39
4	154.67	6.19	6
5	20.00	0.80	1
6	119.33	4.77	5
7	88.00	3.52	4
8	35.00	1.40	1
9	18.33	0.73	1
10	180.00	7.20	7
11	991.67	39.67	40
12	251.00	10.04	10
13	29.33	1.17	1
14	59.33	2.37	2
15	30.33	1.21	1
16	472.33	18.89	19
17	54.00	2.16	2
18	152.33	6.09	6
19	957.33	38.29	38
20	604.67	24.19	24
21	300.00	12.00	12
22	290.67	11.63	12
23	116.67	4.67	5
24	41.33	1.65	2
25	84.33	3.37	3
26	762.67	30.51	31
27	562.33	22.49	23
28	58.00	2.32	2
29	77.67	3.11	3
30	135.33	5.41	5
31	37.67	1.51	2
32	40.00	1.60	2

A1.1.6 CLUMPING

A set fished in five cells (A1.1.2), so I modeled nine-by-nine cells clumps so that a set could fish entirely inside a clump (Figure A1.1). A set could begin in the center-most cell of the clump and move four cells up, right, down, or left and remain inside the clump. Having a nine-by-nine cell clump also allowed the construction of a turtle density gradient within the clump.

FIGURE A1.1

A fishing set clump. The green cell indicates the center of the nine-by-nine cell fishing set clump. The black cells represent the fished cells. In this example there are four sets that fish five cells each. Notice that a set that begins in the middle of the clump can fish five cells in any of the four directions and remain inside the clump.



I made cells 10km by 10km; therefore, clumps were 90km by 90km or 8100km². This seems reasonable as Gardner et al (2008) found turtle catch distributions spanning 30 to 200km.

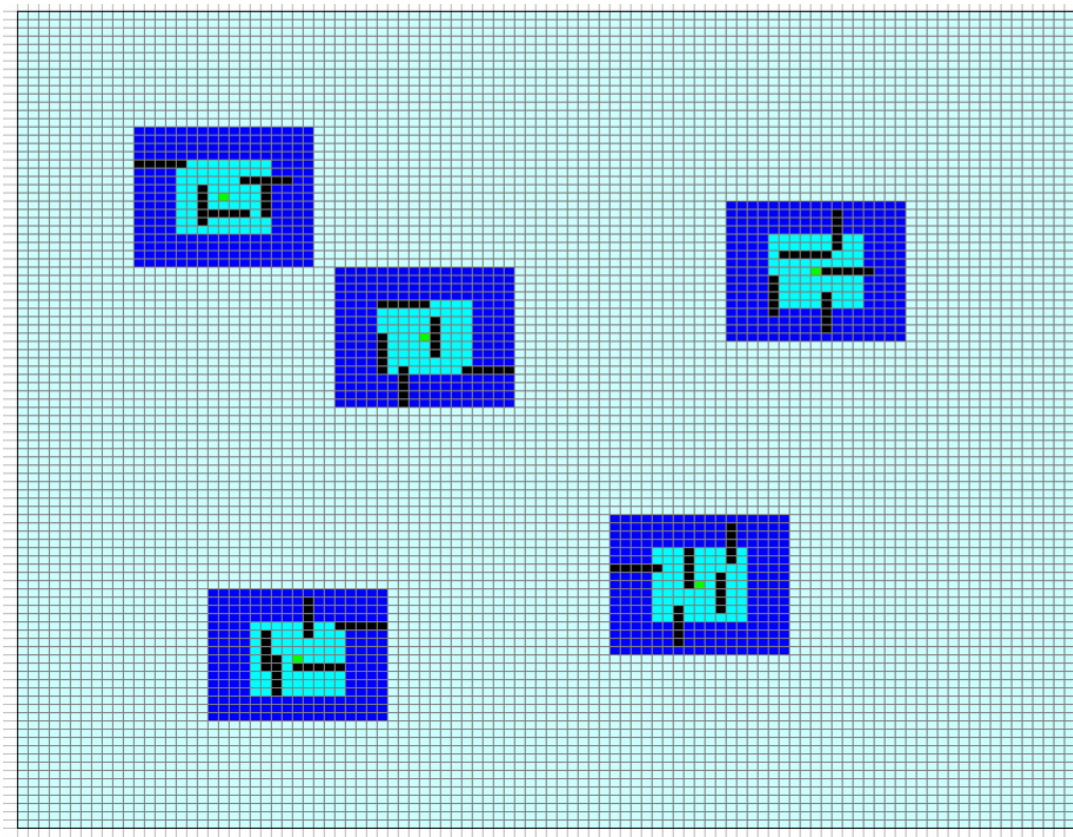
I programmed spatial models with clumped turtle distributions and clumped fishing set distributions. To maintain consistency between spatial models, the number of turtle clumps in spatial models with clumped turtles was set equal to the number of fishing set clumps in spatial models with clumped sets. To determine the number of clumps to model per spatial replicate, I considered the number of fishing sets per spatial replicate, twenty-five. The smallest number, besides one, that divides evenly into twenty-five is five, so I modeled five clumps with five sets

in each clump in spatial replicates with clumped sets. Likewise, I modeled five turtle clumps per spatial replicate with clumped turtles to maintain consistency between spatial models.

So in spatial models with clumping, there were five nine-by-nine cell clumps. I programmed rules for how these clumps could overlap, which I discuss in the specific spatial models below, but to follow these rules and have a reasonable computation time, a spatial replicate was set at 100-by-100 cells. Five clumps of nine-by-nine cells could be placed in a 100-by-100 cell grid in a reasonable amount of time (Figure A1.2).

FIGURE A1.2

A spatial replicate with clumped sets. The grid of light blue is 100-by-100 cells. There are five fishing set clumps that are nine-by-nine cells each. The fishing set clumps are consistent with the clump presented in Figure A1.1, except there is now a dark blue border around each clump. The border is four cells wide. It represents the area that could be fished by a set beginning at the edge of the clump.



A1.2 TURTLE DISTRIBUTIONS

After configuring the fundamental dimensions and number of replications, I placed sea turtles in the spatial model according to one of two spatial distributions.

A1.2.1 UNIFORMLY RANDOM

A random number generator, the Rnd() function in Visual Basic, was used to select an X and a Y coordinate independently for each turtle. The possible X and Y coordinates ranged from 0 to 99, thus including all cells in the spatial replicate.

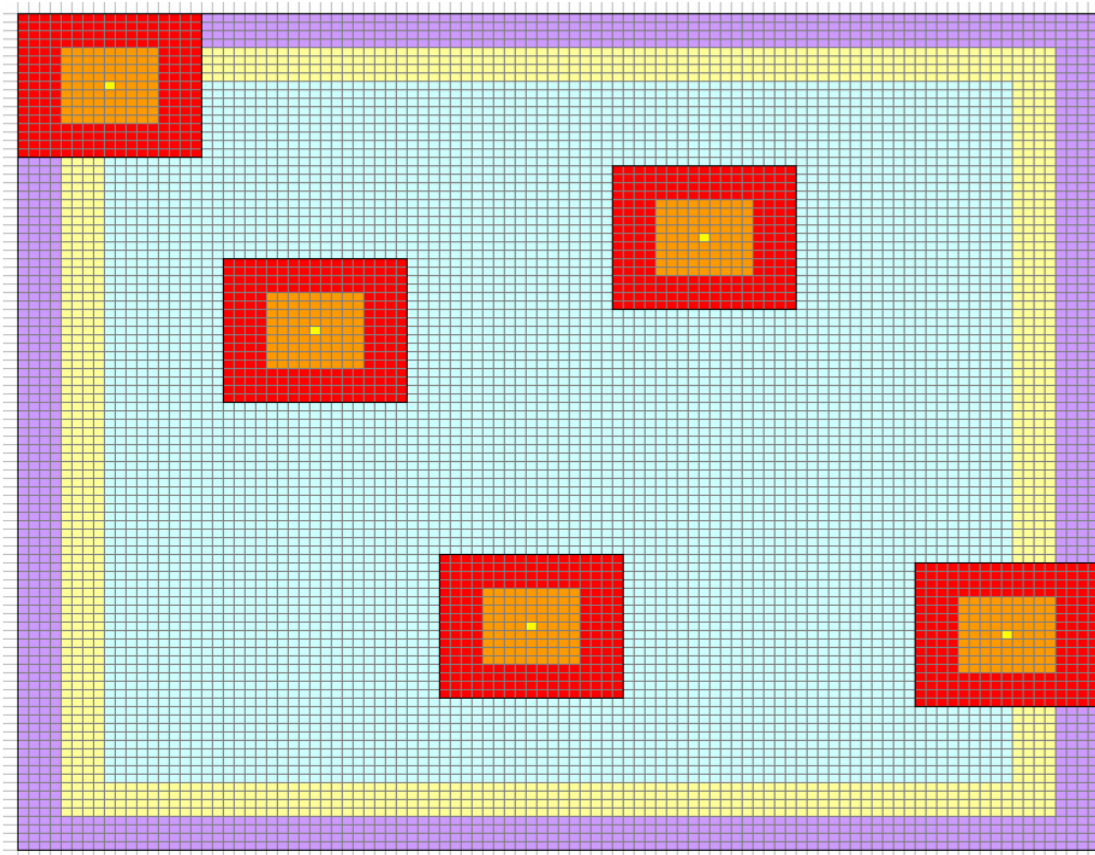
A1.2.2 CLUMPED

A1.2.2.1 Placing a sea turtle clump

A random number generator was employed to select an X and a Y coordinate independently that served as the seed of the first turtle clump. So that sets could start on the edge of a turtle clump and fish all five cells in any direction, the possible X and Y coordinates ranged from eight to ninety-one, allowing four coordinates on each side of the seed for the rest of the clump and four more coordinates for set movement (Figure A1.3).

FIGURE A1.3

A spatial replicate with clumped turtles. The grid is 100-by-100 cells. There are five turtle clumps that are nine-by-nine cells each. The dark yellow cell indicates the center of the clump. The medium orange cells compose the turtle clump. The dark orange cells around the turtle clump are a fishing set border. The border is four cells wide and indicates the cells that could be fished by a set that begins at the edge of the turtle clump. The light blue cells extend from cell number eight to ninety-one. The center of the turtle clump, the dark yellow cell, can be placed anywhere within the light blue cells. The light yellow cells bordering the light blue cells represent the extent of the turtle clump if the center of the clump is placed on the edge of the light blue cells. The light purple cells bordering the light yellow cells indicate where a set could fish if it started fishing at the edge of a turtle clump centered on the edge of the light blue cells.



A1.2.2.2 Placing turtles within a clump

A random number generator was used to assign each turtle in the clump an X coordinate $[(X_{\text{seed}} - 4) \leq X \leq (X_{\text{seed}} + 4)]$ and a Y coordinate $[(Y_{\text{seed}} - 4) \leq Y \leq (Y_{\text{seed}} + 4)]$. The coordinates closer to the seed had a greater probability to accentuate the clumping. The turtles were not just

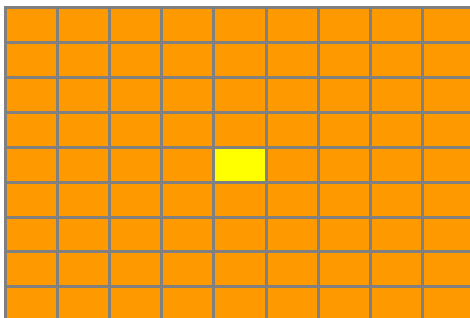
distributed evenly over a 9 by 9 block of cells but were placed densely in the center with a declining probability with distance from the center.

$$\begin{aligned}
 P(\text{Seed}) &= 5a = 0.2 \\
 P(\text{Seed} \pm 1) &= 4a = 0.16 \\
 P(\text{Seed} \pm 2) &= 3a = 0.12 \\
 P(\text{Seed} \pm 3) &= 2a = 0.08 \\
 P(\text{Seed} \pm 4) &= a = 0.04 \\
 1 &= 25a = 5a + 2(4a) + 2(3a) + 2(2a) + 2(2a) + 2a \\
 a &= 0.04
 \end{aligned}$$

The probabilities assigned to the clump coordinates were used to construct ranges of random numbers for each coordinate (Figure A1.4). So if the random number generator selected 0.852 for the X coordinate and 0.124 for the Y coordinate, the turtle would be placed in (Seed + 2, Seed - 2).

FIGURE A1.4

Probabilities for placing turtles within a clump. Probabilities are assigned to X coordinates and Y coordinates independently so the center cell has the highest probability and probabilities decline with distance from the center. The range of random numbers that would be assigned to a coordinate are shown.



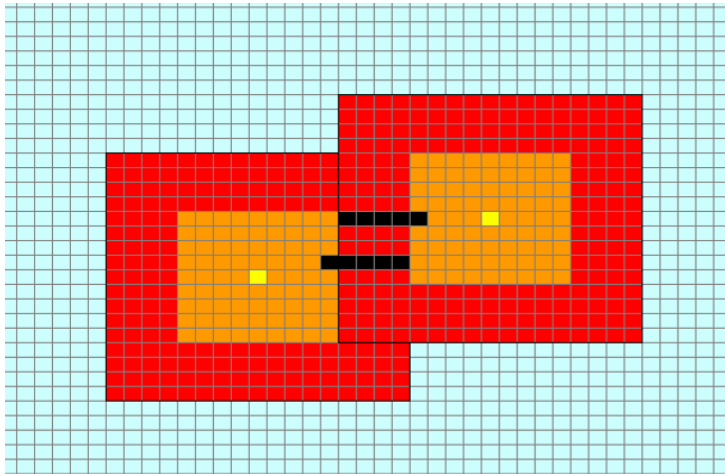
$P(Y = \text{Seed}-4) = 0.04$	[0, 0.04)
$P(Y = \text{Seed}-3) = 0.08$	[0.04, 0.12)
$P(Y = \text{Seed}-2) = 0.12$	[0.12, 0.24)
$P(Y = \text{Seed}-1) = 0.16$	[0.24, 0.4)
$P(Y = \text{Seed}) = 0.2$	[0.4, 0.6)
$P(Y = \text{Seed}+1) = 0.16$	[0.6, 0.76)
$P(Y = \text{Seed}+2) = 0.12$	[0.76, 0.88)
$P(Y = \text{Seed}+3) = 0.08$	[0.88, 0.96)
$P(Y = \text{Seed}+4) = 0.04$	[0.96, 1)

A1.2.2.3 Place clumps relative to each other

After all turtles were placed in the first clump, the second clump's seed coordinates were selected with a random number generator so that a set could not fish in multiple turtle clumps (Figure A1.5). There had to be enough room between clump seeds to accommodate the 4 clump cells around each clump's seed and four cells between the two clumps for set movement; the four cells for set movement could overlap in the clumped turtle distribution. Therefore, at least one coordinate (X or Y) had to be less than or equal to (Seed – 13) or greater than or equal to (Seed + 13).

FIGURE A1.5

The maximum amount of overlap allowed between two turtle clumps. This configuration prohibits a set from fishing in multiple turtle clumps.



Once the second clump's seed coordinates were determined, turtles were placed as above. The next clump's seed coordinates were then chosen so that the clump would fit around the pre-existing clumps. This process continued until all five clumps were placed and turtles were assigned to each clump.

A1.2.3 NUMBER OF TURTLES TO DISTRIBUTE

To maintain consistency between the two spatial distributions, clumped or uniformly random, I distributed the same number of turtles in the five clumps as across the entire grid in the random model. This resulted in different turtle densities, but different probabilities of interaction were applied in the clumped and random models to account for greater densities in clumped models.

Assuming a density of 0.5 turtles/km², as discussed in the main methods section, there was an average of 50 turtles per cell or 4,050 turtles per clump.

$$\frac{0.5 \text{ turtles}}{1 \text{ km}^2} * \frac{100 \text{ km}^2}{1 \text{ cell}} = 50 \text{ turtles/cell} \quad (20)$$

$$\frac{50 \text{ turtles}}{1 \text{ cell}} * \frac{81 \text{ cells}}{1 \text{ clump}} = 4,050 \text{ turtles/clump} \quad (21)$$

Since there were a total of five clumps per replication, there were 20,250 turtles in the entire grid. When non-clumped models were run, the 20,250 turtles were distributed uniformly random across the grid. This averaged to 2.025 turtles/cell and 0.0203 turtles/km².

$$\frac{20,250 \text{ turtles}}{1 \text{ grid}} * \frac{1 \text{ grid}}{10,000 \text{ cells}} = 2.025 \text{ turtles/cell} \quad (22)$$

$$\frac{20,250 \text{ turtles}}{1 \text{ grid}} * \frac{1 \text{ grid}}{10,000 \text{ cells}} * \frac{1 \text{ cell}}{100 \text{ km}^2} = 0.0203 \text{ turtles/km}^2 \quad (23)$$

A1.3 FISHING SET DISTRIBUTIONS

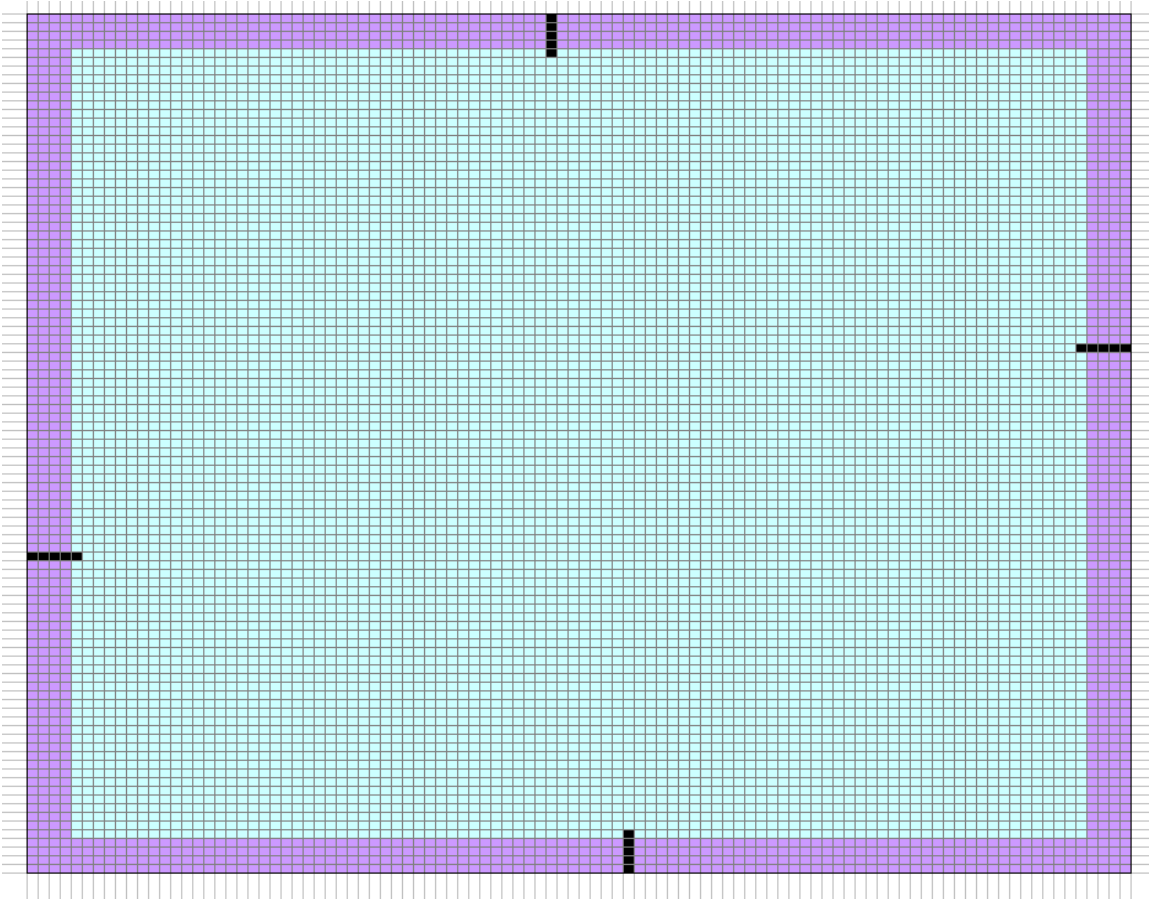
Fishing sets were placed in one of three distributions: uniformly random, clumped independent of turtle presence, and clumped in the same areas as turtles.

A1.3.1 UNIFORMLY RANDOM

A random number generator was used to select an X and a Y coordinate independently for each of the twenty-five sets. The selected coordinates provided the location of the beginning of the set. To ensure that a set covered five cells, the potential beginning coordinates ranged from four to ninety-five (Figure A1.6). A set fished a total of five cells either right, left, up, or down from the starting cell. A random number generator was used to choose an integer between 0 and 3, inclusive, to decide the direction the set moved (0 = right, 1 = up, 2 = left, 3 = down).

FIGURE A1.6

Border placement of uniformly random sets. A set could begin in any of the light blue cells, which range from coordinate four to ninety-five. This ensured that sets could cover five cells within the 100-by-100 cell grid. The purple border four cells wide demarcates where a set can fish if it begins on the edge of the light blue cells.

**A1.3.2 CLUMPED INDEPENDENT OF TURTLES**

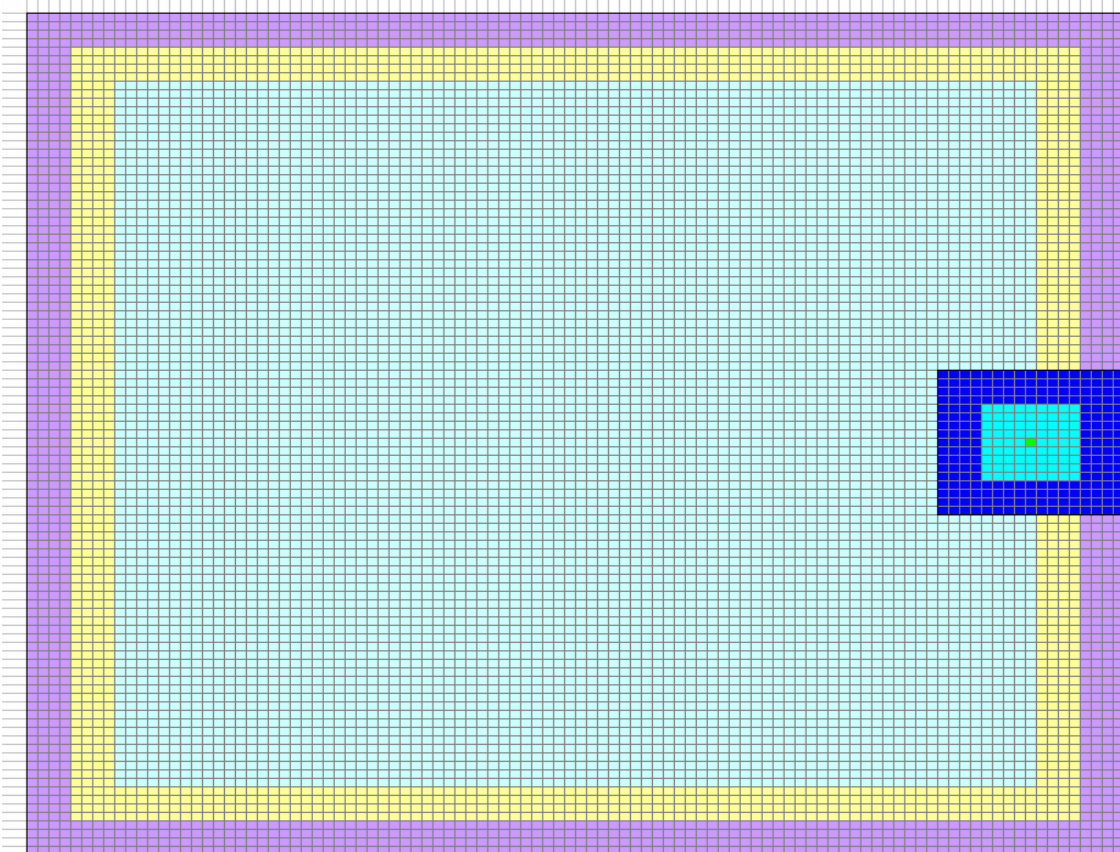
I characterized this clumping by assuming that the five sets began fishing within the clump and that there was a positive relationship between the probability a set would fish in a particular direction and the number of sets in that direction.

A1.3.2.1 Place clump

A random number generator was used to select an X and a Y coordinate independently to serve as the seed of the first clump. The X and Y coordinates ranged from eight to ninety-one, allowing four coordinates on each side of the seed for the rest of the clump and four more coordinates for set movement away from the edge of the clump (Figure A1.7).

FIGURE A1.7

A spatial replicate with a set clump. The grid is 100-by-100 cells. The green cell indicates the center of the clump. The medium blue cells compose the set clump. The dark blue cells around the set clump are a fishing set border. The border is four cells wide and indicates the cells that could be fished by a set that begins at the edge of the set clump. The light blue cells extend from cell number eight to ninety-one. The center of the set clump, the dark green cell, can be placed anywhere within the light blue cells. The light yellow cells bordering the light blue cells represent the extent of the set clump if the center of the clump is placed on the edge of the light blue cells. The light purple cells bordering the light yellow cells indicate where a set could fish if it started fishing at the edge of a set clump centered on the edge of the light blue cells.

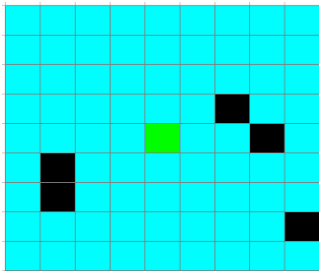


A1.3.2.2 Place sets within clump

A random number generator was used to select an X coordinate $[(X_{\text{seed}} - 4) \leq X \leq (X_{\text{seed}} + 4)]$ and a Y coordinate $[(Y_{\text{seed}} - 4) \leq Y \leq (Y_{\text{seed}} + 4)]$ for each of the five sets in a clump. These coordinates served as the starting positions of each set. This assumes that each set begins inside the nine-by-nine cell clump (Figure A1.8).

FIGURE A1.8

A fishing set clump. The green cell is the center of the clump. The black cells are the beginning cells of five fishing sets.



A1.3.2.3 Determine direction of fishing

An algorithm was needed to determine each set's direction of movement so that a set was more likely to move in the direction where there were more sets. I first considered $\text{Set}_0\text{Cell}_0$, the first cell in the first set. I calculated the distances, using the Pythagorean theorem, from $\text{Set}_0\text{Cell}_0$ to $\text{Set}_i\text{Cell}_0$ where $i = 1$ to 4. Then I sum these distances. I moved $\text{Set}_0\text{Cell}_0$ one cell to the right, and calculated the distances from $\text{Set}_0\text{Cell}_{1R}$ to $\text{Set}_i\text{Cell}_0$. I added these distances to the distances from $\text{Set}_0\text{Cell}_0$ to $\text{Set}_i\text{Cell}_0$, and I continued to move Set_0 one cell to the right, calculating the distances to $\text{Set}_i\text{Cell}_0$, and summing the distances until Set_0 has moved all 4 cells to the right. This gave the distance from Set_0 to $\text{Set}_i\text{Cell}_0$ if Set_0 moves right. Next I moved Set_0 to the left one cell at a time calculating and summing distances from $\text{Set}_i\text{Cell}_0$. I did the same

moving up and moving down. Then I had 4 distances for Set₀, one each for moving right, left, up, and down. I wanted the direction with the smallest distance between sets to have the greatest probability, so I transformed the distances. I found the smallest of the 4 distances, and divided each of the 4 distances by this distance. I summed the four transformed distances and divided each of the 4 transformed distances by this sum to obtain a probability of Set₀ moving in each direction. Next I used a random number generator to draw a number between 0 and 1. The set moved in the direction which had that number in its range (Figure A1.9). I did this for each of the sets.

1). I calculated the distance from set₀ to all other sets' cell₀ for set *i* and cell *j*:

$$\sum_{i=1}^4 \sum_{j=0}^4 \sqrt{(X_{\text{Set0Cell}j} - X_{\text{Set}i\text{Cell}0})^2 + (Y_{\text{Set0Cell}j} - Y_{\text{Set}i\text{Cell}0})^2} \quad (24)$$

2). I calculated the distance from Set₀ to Set_iCell₀ if Set₀ moves right, left, up, down.

Distance_{Set0R}
Distance_{Set0L}
Distance_{Set0U}
Distance_{Set0D}

3). I found the smallest of the four distances. Then I standardized the distances by dividing each by the smallest of the four. For this example, suppose Distance_{Set0R} was the smallest.

$$\begin{aligned}
\text{StandDistance}_{\text{Set0R}} &= \text{Distance}_{\text{Set0R}} / \text{Distance}_{\text{Set0R}} \\
\text{StandDistance}_{\text{Set0L}} &= \text{Distance}_{\text{Set0L}} / \text{Distance}_{\text{Set0R}} \\
\text{StandDistance}_{\text{Set0U}} &= \text{Distance}_{\text{Set0U}} / \text{Distance}_{\text{Set0R}} \\
\text{StandDistance}_{\text{Set0D}} &= \text{Distance}_{\text{Set0D}} / \text{Distance}_{\text{Set0R}}
\end{aligned} \tag{25}$$

4). Next, I summed the standardized distances.

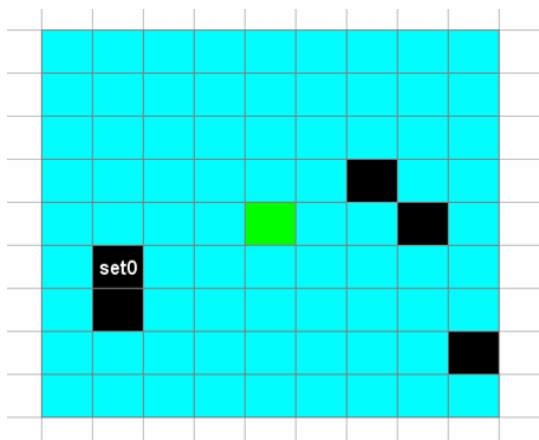
$$\begin{aligned}
\text{TotalDistance} &= \text{StandDistance}_{\text{Set0R}} + \text{StandDistance}_{\text{Set0L}} + \\
&\text{StandDistance}_{\text{Set0U}} + \text{StandDistance}_{\text{Set0D}}
\end{aligned} \tag{26}$$

5). Finally, I calculated the probabilities of moving in each of the four directions by dividing the distance in that direction by the total distance.

$$\begin{aligned}
P(\text{Right}) &= \text{StandDistance}_{\text{Set0R}} / \text{TotalDistance} \\
P(\text{Left}) &= \text{StandDistance}_{\text{Set0L}} / \text{TotalDistance} \\
P(\text{Up}) &= \text{StandDistance}_{\text{Set0U}} / \text{TotalDistance} \\
P(\text{Down}) &= \text{StandDistance}_{\text{Set0D}} / \text{TotalDistance}
\end{aligned} \tag{27}$$

FIGURE A1.9

A fishing set clump. The black cells are the beginning cells of five fishing sets. Based on the algorithm described above, $\text{Distance}_{\text{Set0R}} = 81.93$, $\text{Distance}_{\text{Set0L}} = 136.67$, $\text{Distance}_{\text{Set0U}} = 102.86$, and $\text{Distance}_{\text{Set0D}} = 123.30$. So $P(\text{Right}) = 0.327$, $P(\text{Left}) = 0.196$, $P(\text{Up}) = 0.260$, and $P(\text{Down}) = 0.217$.

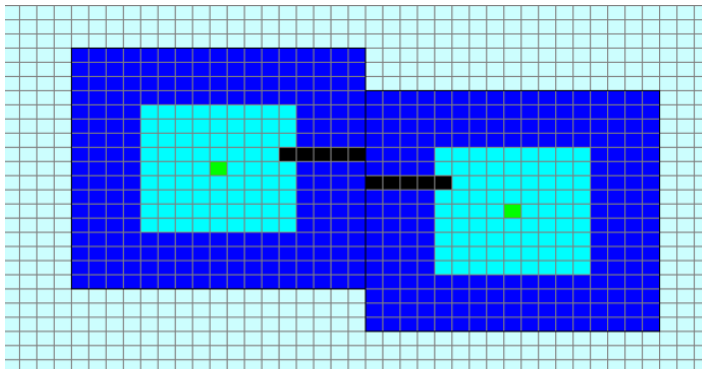


A1.3.2.4 Place clumps relative to each other

After finishing with the first clump, I moved to the second clump. I drew random numbers for X and Y coordinates. There had to be enough room between clump seeds to accommodate each clump's four cells around the seed and the four cells outside each clump for set movement (Figure A1.10). This gave each clump its own fishing area and prevented the overlapping of sets from different clumps. Therefore, at least one coordinate (X or Y) had to be less than or equal to (Seed - 17) or greater than or equal to (Seed + 17).

FIGURE A1.10

The maximum amount of overlap allowed between two fishing set clumps. This configuration prohibits the overlap of sets from multiple set clumps.



Once I had coordinates for the next clump, I proceeded through the sequence above to place sets and determine their direction of movement. Next, I selected the coordinates for the third clump making sure that they did not result in a clump that overlapped at all with either of the pre-existing clumps. I continued through this process until all five clumps and five sets per clump were placed.

A1.3.3 CLUMPED IN THE SAME AREA AS TURTLES

A1.3.3.1 Place sets within turtle clumps

I assumed that five sets began in each of the five turtle clumps. To determine the sets' initial coordinates, the numbers of turtles in each X coordinate of the clump were tallied.

For example, consider this placement of turtles:

$$(X_{\text{Seed}} - 4) = 161$$

$$(X_{\text{Seed}} - 3) = 292$$

$$(X_{\text{Seed}} - 2) = 527$$

$$(X_{\text{Seed}} - 1) = 639$$

$$(X_{\text{Seed}}) = 801$$

$$(X_{\text{Seed}} + 1) = 618$$

$$(X_{\text{Seed}} + 2) = 523$$

$$(X_{\text{Seed}} + 3) = 293$$

$$(X_{\text{Seed}} + 4) = 196$$

This tally was used to construct a probability for set placement by dividing the number of turtles in an X coordinate by the total number of turtles.

$$P(X_{\text{Seed}} - 4) = 0.0398$$

$$P(X_{\text{Seed}} - 3) = 0.0721$$

$$P(X_{\text{Seed}} - 2) = 0.130$$

$$P(X_{\text{Seed}} - 1) = 0.158$$

$$P(X_{\text{Seed}}) = 0.198$$

$$P(X_{\text{Seed}} + 1) = 0.153$$

$$P(X_{\text{Seed}} + 2) = 0.129$$

$$P(X_{\text{Seed}} + 3) = 0.0723$$

$$P(X_{\text{Seed}} + 4) = 0.0484$$

The same was done for the Y coordinates. An X and a Y coordinate were selected with a random number generator and these ranges for each of the five sets per clump (Figure A1.11).

FIGURE A1.11

Algorithm for placing sets within a turtle clump. The number of turtles with each X and Y coordinate are tallied. The fraction of turtles with a given coordinate is used to determine the probability a set will begin in that coordinate. In this example, the orange cells are the nine-by-nine cell turtle clump. The yellow cell is the center of the clump. The black cells are the starting positions of five sets.

		Number of turtles	154	284	502	630	775	714	469	346	176
		P(X=x)	0.038	0.07	0.124	0.156	0.191	0.176	0.116	0.085	0.043
Number of turtles	P(Y=y)										
165	0.041										
357	0.088										
502	0.124										
670	0.165										
756	0.187										
620	0.153										
479	0.118										
343	0.085										
158	0.039										

A1.3.3.2 Determine direction of fishing

To determine the direction of set fishing, the number of turtles that would be encountered by a set moving right, left, up, and down were tallied (Figure A1.12). While each set began in the turtle clump, it could leave the clump during fishing. These four counts were summed, and the number encountered in each direction was divided by the total to obtain a probability of moving in each direction. The ranges of random numbers corresponding to each direction were determined and used with a random number generator to decide the direction of fishing. This was done for each of the five sets in a clump.

$$\text{TotalAnimals} = \text{Animals}_R + \text{Animals}_L + \text{Animals}_U + \text{Animals}_D \quad (28)$$

$$\begin{aligned} P(\text{Right}) &= \text{Animals}_R / \text{TotalAnimals} \\ P(\text{Left}) &= \text{Animals}_L / \text{TotalAnimals} \\ P(\text{Up}) &= \text{Animals}_U / \text{TotalAnimals} \\ P(\text{Down}) &= \text{Animals}_D / \text{TotalAnimals} \end{aligned} \quad (29)$$

FIGURE A1.12

Algorithm for determining the direction a set fishes in a turtle clump. The numbers in the cells indicate the number of turtles present. Consider the black cell in the top right portion of the clump. The grey cells show the possible fishing routes. The numbers of turtles that would be encountered in each direction are used to calculate the probability of fishing in that direction. In this example, $\text{Animals}_R = 20$, $\text{Animals}_L = 222$, $\text{Animals}_U = 11$, and $\text{Animals}_D = 212$. So $P(\text{Right}) = 0.043$, $P(\text{Left}) = 0.477$, $P(\text{Up}) = 0.024$, and $P(\text{Down}) = 0.456$.

	6	12	25	27	30	31	18	11	5
	13	29	34	61	64	55	42	39	20
	19	29	68	71	112	87	48	46	22
	27	54	81	94	132	114	89	44	35
	33	58	92	116	142	140	80	62	33
	27	40	82	84	118	109	66	60	34
	20	30	69	82	86	89	54	36	13
	6	23	29	68	60	63	46	35	13
	3	9	22	27	31	26	26	13	1

A1.4 DIAGRAMS OF POSSIBLE SPATIAL MODELS

A visual example of one possible simulation is presented for each of the five spatial models. I also discuss some assumptions controlling model construction.

FIGURE A1.13

Turtles uniformly random and sets uniformly random

- Turtles could be placed in any cell, purple or light blue.
- To ensure that sets fished entirely within the grid, sets could start in any light blue cell and could move into the purple cells. The black cells indicate fished cells in one scenario.

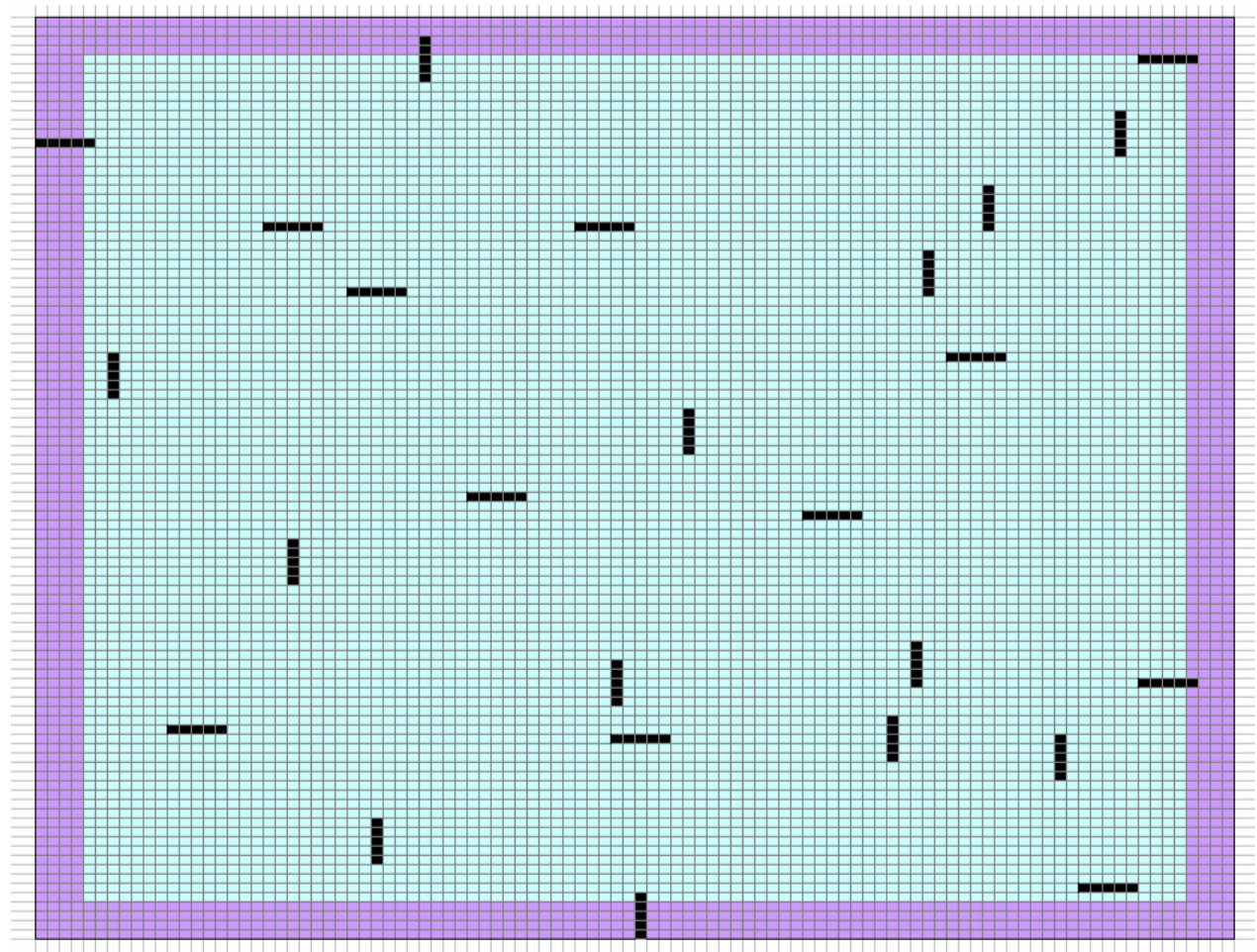


FIGURE A1.14

Turtles uniformly random and sets clumped

- Turtles could be placed in any cell, purple, yellow, or light blue.
- Fishing set clumps were placed so that sets fished entirely within the grid. The middle cell of set clumps could occur in any light blue cell. If the middle cell occurred on the border of the light blue cells, the clump extended into yellow cells. Sets could begin in any medium blue cell of the clump. Fishing could extend into the dark blue cells around the clump.
- No part of clumps could overlap so sets from multiple clumps did not overlap. The black cells indicate fished cells in one scenario.

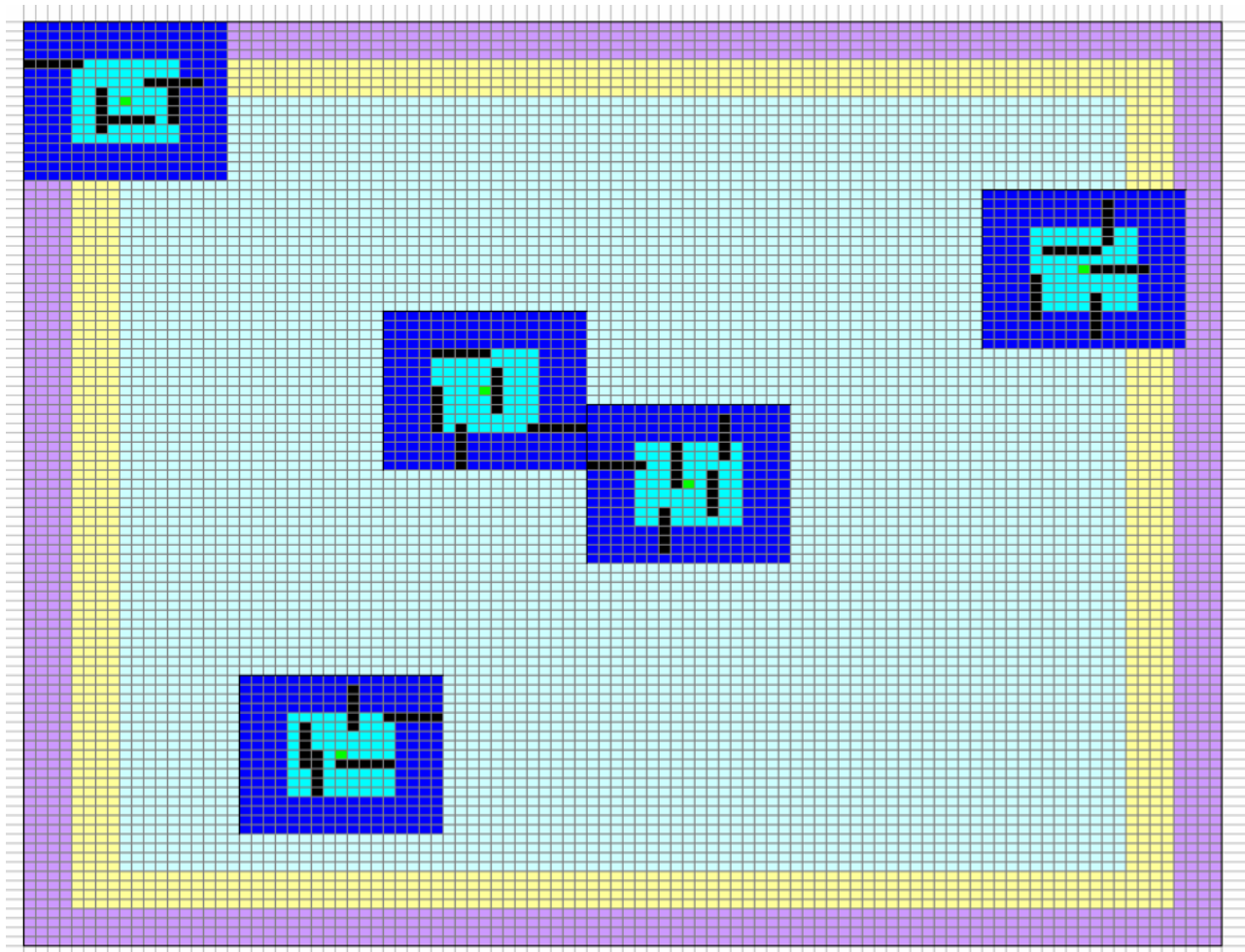


FIGURE A1.15

Turtles clumped and sets uniformly random

- Turtle clumps were placed so that the entire clump could fit within the grid. The middle cell of turtle clumps could occur in any light blue cell. If the middle cell occurred on the border of the light blue cells, the clump extended into yellow cells. Turtles could occur in any medium orange cell of the clump. The dark orange cells around the turtle clump indicate the fishing border.
- Sets could start in any cell except purple cells. Sets that began in the turtle clump could extend into the dark orange cells. The black cells indicate fished cells in one scenario.
- The dark orange cells of multiple clumps could overlap but the medium orange could not, so sets could not fish in multiple turtle clumps.

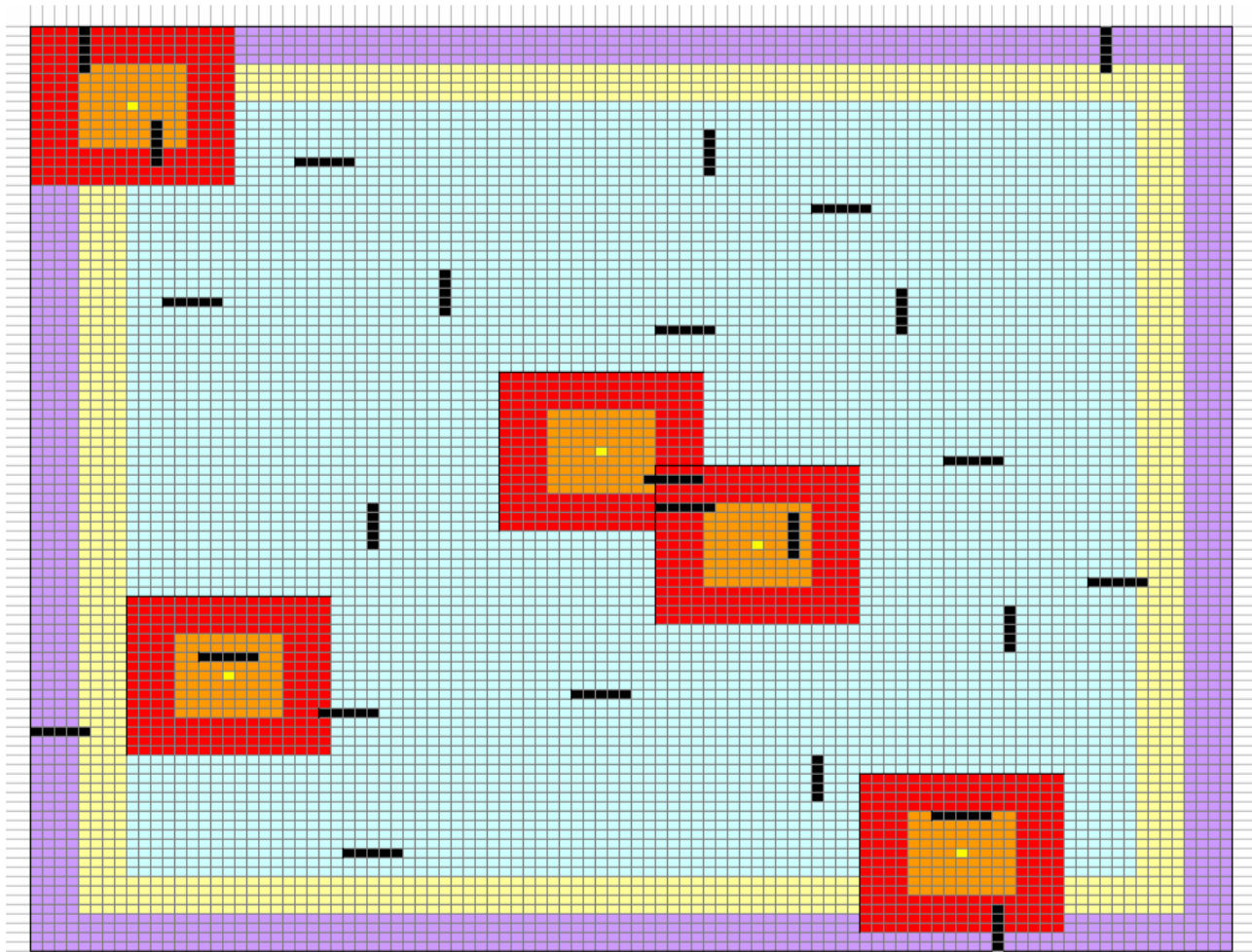


FIGURE A1.16

Turtles clumped and sets clumped independently

- Turtle clumps were placed so that the entire clump could fit within the grid. The middle cell of turtle clumps could occur in any light blue cell. If the middle cell occurred on the border of the light blue cells, the clump extended into yellow cells. Turtles could occur in any medium orange cell of the clump. The dark orange cells around the turtle clump indicate the fishing border. Sets that began in the turtle clump could extend into the dark orange cells. The dark orange cells of multiple clumps could overlap but the medium orange could not, so sets could not fish in multiple turtle clumps.
- Fishing set clumps were placed so that sets fished entirely within the grid. The middle cell of set clumps could occur in any light blue cell. If the middle cell occurred on the border of the light blue cells, the clump extended into yellow cells. Sets could begin in any medium blue cell of the clump. Fishing could extend into the dark blue cells around the clump. No part of set clumps could overlap so that sets from multiple clumps did not overlap. The black cells indicate fished cells in one scenario.
- There was no restriction on how turtle clumps and set clumps could overlap.

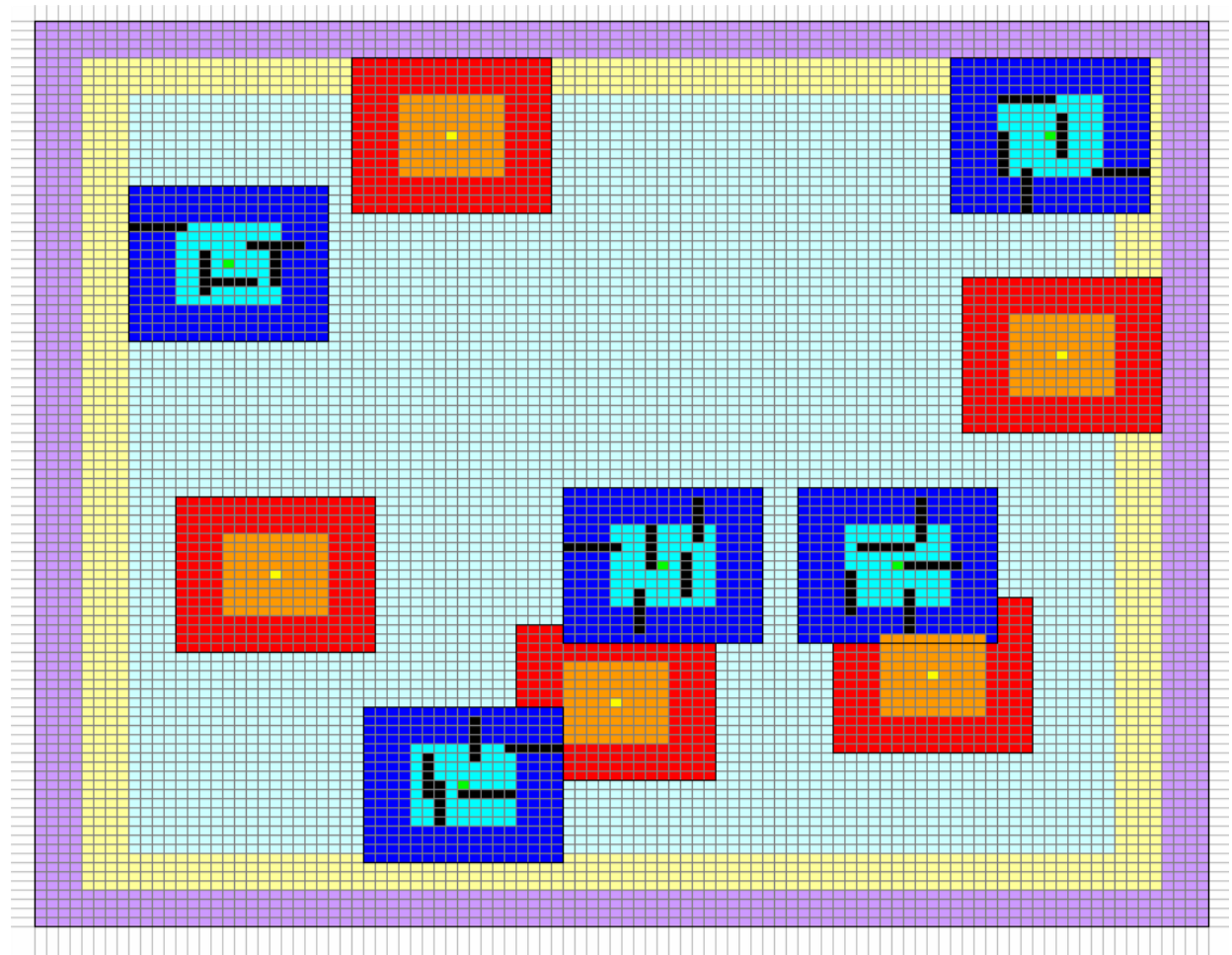
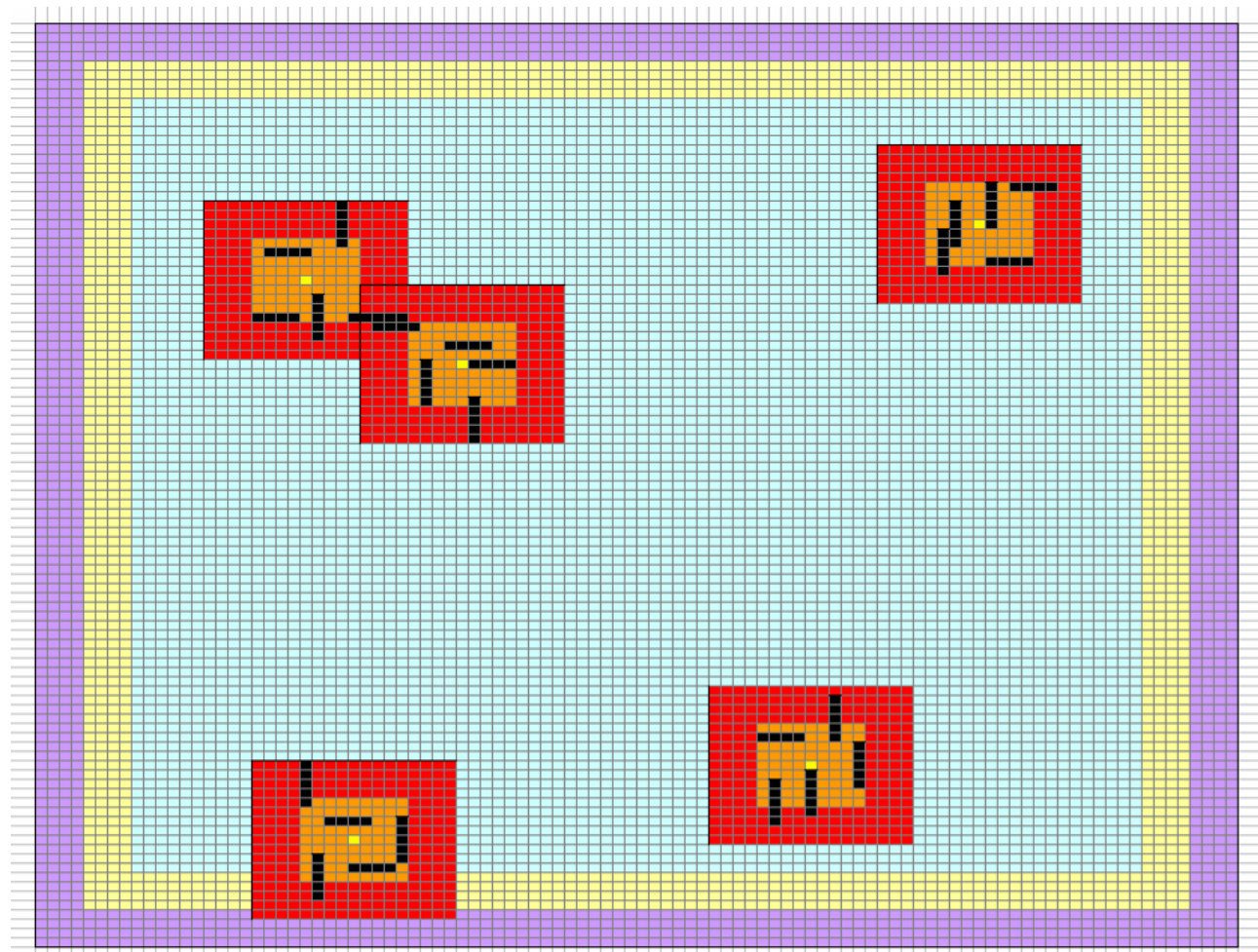


FIGURE A1.17

Turtles clumped and sets clumped in the same area

- Turtle clumps were placed so that the entire clump could fit within the grid. The middle cell of turtle clumps could occur in any light blue cell. If the middle cell occurred on the border of the light blue cells, the clump extended into yellow cells. Turtles could occur in any medium orange cell of the clump. The dark orange cells around the turtle clump indicate the fishing border. Sets that began in the turtle clump could extend into the dark orange cells. The dark orange cells of multiple clumps could overlap but the medium orange could not, so sets could not fish in multiple turtle clumps.
- Sets began inside the medium orange turtle clump. They could extend into the dark orange cells. The black cells indicate fished cells in one scenario.



A1.5 OBSERVER DISTRIBUTIONS

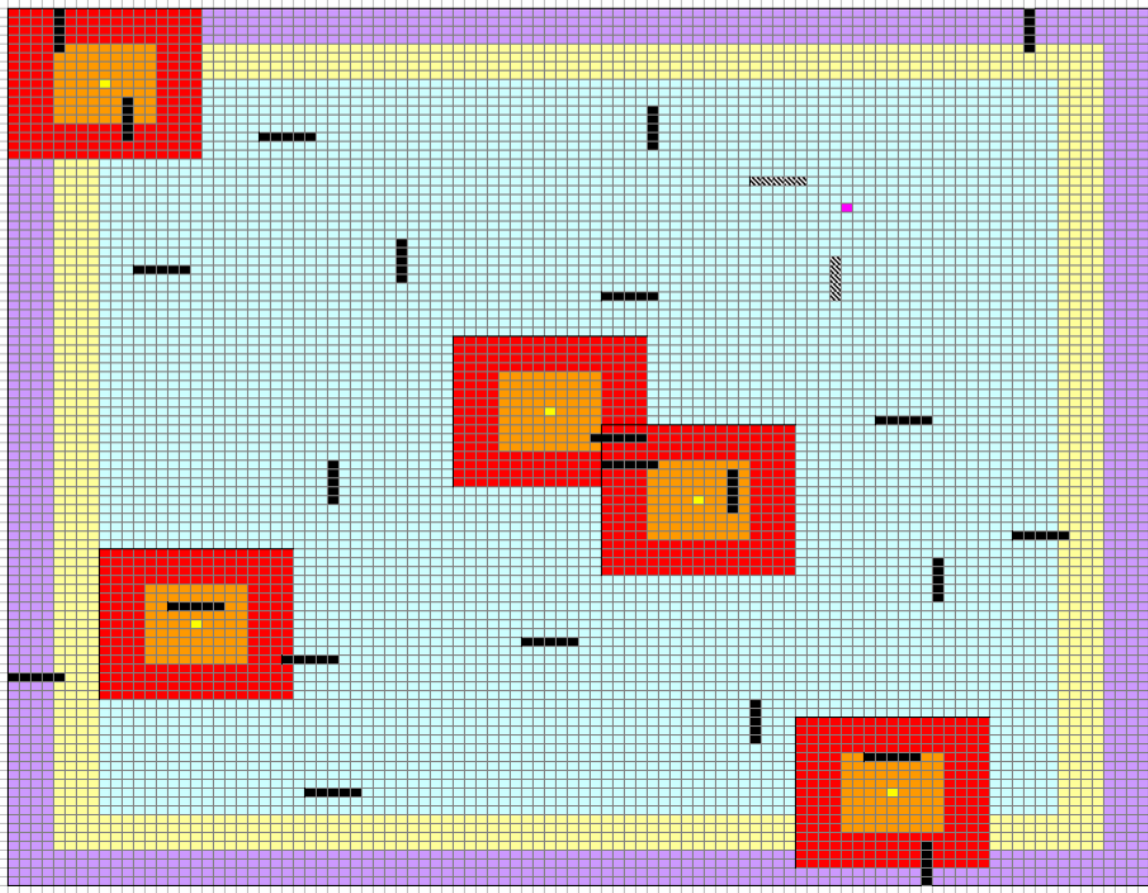
Once sea turtles and fishing sets were placed, two sets were selected for observation. Observers were distributed either based on fishing effort or bycatch rates. NMFS currently uses an effort-based observer distribution, so I modeled this procedure as well, but I also evaluated whether placing observers in bycatch hotspots would improve bycatch estimation.

A1.5.1 BASED ON FISHING EFFORT

In this simulation model there was no effort in a previous year-calendar quarter-fishing area upon which to distribute observers. Rather, an (X, Y) coordinate, with X and Y each ranging from zero to ninety-nine, was chosen at random to represent an area of high fishing effort. The Pythagorean theorem was used to calculate the distance from the high-effort cell to every fished cell, all five cells of all twenty-five sets. Observers were placed on the two sets with cells closest to the cell of high fishing effort (Figure A1.18). For this distribution, the most important criterion was that observers were distributed relative to something independent of bycatch.

FIGURE A1.18

Effort-based observer distribution. Suppose the pink cell was randomly selected to be the cell of high fishing effort. Then the two closest sets, marked with black and white hatches, were selected for observation.



A1.5.2 BASED ON BYCATCH

When turtles had a random uniform distribution there was, on average, no area of high bycatch, so observers were placed on two sets at random.

When turtles had a clumped distribution, the number of sets that fished in the turtle clumps were tallied. If that number was greater than two, two of the sets were chosen at random to have observers. If there were two sets that fished in the turtle clumps, both received observers. If there was one set in the turtle clumps, it received an observer and the number of sets that fished in the four cells of the set movement buffers around the turtle clumps but did not

enter the turtle clumps were tallied. The remaining observers were placed on sets that fished in the set movement buffers according to the procedure discussed above – chose sets at random if there were an excess, placed observers on the available sets if there were the required number of sets. If both observers had not been placed after this point, set(s) were chosen at random among those that fished in the medium around turtle clumps.

A1.6 STRATUM-SPECIFIC PROBABILITY OF TAKE

Sea turtles, fishing sets, and observers were placed in the simulation model. Next interactions between fishing sets and sea turtles were simulated. This was done by tallying all the times a fishing set encountered a turtle then applying a probability of capture to determine whether the set caught the encountered turtle. Probabilities of capture varied across time-area strata.

The NMFS SEFSC currently estimates bycatch for each of the calendar quarter-spatial area stratum, leading to forty potential estimates per year. I calculated the strata bycatch rates for leatherbacks and loggerheads for each year from 2005 through 2007 by dividing the number of observed takes by the number of observed sets (Tables A1.3 and A1.5). Then I averaged the strata bycatch rates across the three years (Tables A1.4 and A1.6). I decided to use the leatherback rates because they are more of a conservation concern than loggerheads and the average number of observed sets per year without take was smaller for leatherbacks (100 sets) than for loggerheads (179 sets).

TABLE A1.3

Leatherback time-area strata bycatch rates (number of observed leatherback takes divided by number of observed sets) calculated from 2005 through 2007 NMFS observer data. Q1 represents quarter 1. The three letter abbreviations represent the fishing areas: CAR = Caribbean, GOM = Gulf of Mexico, FEC = Florida East Coast, SAB = South Atlantic Bight, MAB = Mid Atlantic Bight, NEC = Northeast Coastal, NED = Northeast Distant, SAR = Sargasso, NCA = North Central Atlantic, TUN = Tuna North, TUS = Tuna South. If there is a hyphen, there was either no fishing effort or no observer coverage. If there is a 0, no bycatch was observed.

2005

LEATHERBACK RATE	CAR	FEC	GOM	MAB	NCA	NEC	NED	SAB	SAR	TUN	TUS
Q1	0	0.1875	0.053097	0	0	-	-	0	-	-	-
Q2	-	0	0.045977	0	0	0	-	0	-	-	-
Q3	-	-	0	0.02381	-	-	0.142857	0	-	-	-
Q4	-	0	0.111111	0	-	0	-	-	0.238095	-	-

2006

LEATHERBACK RATE	CAR	FEC	GOM	MAB	NCA	NEC	NED	SAB	SAR	TUN	TUS
Q1	-	0.111111	0.018519	0	-	-	-	0.272727	0.0625	0	-
Q2	-	0.083333	0.050505	0	-	0.266667	-	0	-	-	-
Q3	-	0	0.018519	0	-	0.153846	0.333333	0	-	-	-
Q4	-	-	0.048387	0.066667	-	0.125	0.242424	-	-	-	-

2007

LEATHERBACK RATE	CAR	FEC	GOM	MAB	NCA	NEC	NED	SAB	SAR	TUN	TUS
Q1	0	0.05	0	0	-	-	-	0	0	-	-
Q2	0.0625	0	0.072639	0	-	-	-	0	-	-	-
Q3	-	0	0.014085	0.071429	-	0.25	0.2	0	-	0	-
Q4	-	0	0.150685	0.153846	-	-	0.357143	0	-	-	-

TABLE A1.4

Leatherback time-area strata bycatch rates averaged across 2005 through 2007.

AVG LEATHERBACK RATE	CAR	FEC	GOM	MAB	NCA	NEC	NED	SAB	SAR	TUN	TUS
Q1	0	0.116204	0.023872	0	0	-	-	0.090909	0.03125	0	-
Q2	0.0625	0.027778	0.056374	0	0	0.133333	-	0	-	-	-
Q3	-	0	0.010868	0.031746	-	0.201923	0.225397	0	-	0	-
Q4	-	0	0.103394	0.073504	-	0.0625	0.299784	0	0.238095	-	-

TABLE A1.5

Loggerhead time-area strata bycatch rates (number of observed loggerhead takes divided by number of observed sets) calculated from 2005 through 2007 NMFS observer data. Q1 represents quarter 1. The three letter abbreviations represent the fishing areas: CAR = Caribbean, GOM = Gulf of Mexico, FEC = Florida East Coast, SAB = South Atlantic Bight, MAB = Mid Atlantic Bight, NEC = Northeast Coastal, NED = Northeast Distant, SAR = Sargasso, NCA = North Central Atlantic, TUN = Tuna North, TUS = Tuna South. If there is a hyphen, there was either no fishing effort or no observer coverage. If there is a 0, no bycatch was observed.

2005

LOGGERHEAD RATE	CAR	FEC	GOM	MAB	NCA	NEC	NED	SAB	SAR	TUN	TUS
Q1	0.2	0	0.017699	0.047619	0	-	-	0.153846	-	-	-
Q2	-	0	0	0	0.090909	0	-	0	-	-	-
Q3	-	-	0	0.071429	-	-	0	0.066667	-	-	-
Q4	-	0	0	0.037037	-	0	-	-	0	-	-

2006

LOGGERHEAD RATE	CAR	FEC	GOM	MAB	NCA	NEC	NED	SAB	SAR	TUN	TUS
Q1	-	0.111111	0	0	-	-	-	0	0.125	0	-
Q2	-	0.083333	0.020202	0	-	0.133333	-	0	-	-	-
Q3	-	0	0	0.09375	-	0.5	0.8	0	-	-	-
Q4	-	-	0	0.033333	-	0	0.272727	-	-	-	-

2007

LOGGERHEAD RATE	CAR	FEC	GOM	MAB	NCA	NEC	NED	SAB	SAR	TUN	TUS
Q1	0.333333	0.1	0	0	-	-	-	0.214286	0	-	-
Q2	0	0.125	0.014528	0	-	-	-	0	-	-	-
Q3	-	0.115385	0	0.238095	-	0.166667	1.033333	0.055556	-	0	-
Q4	-	0.285714	0	0.076923	-	-	0	0	-	-	-

TABLE A1.6

Loggerhead time-area strata bycatch rates averaged across 2005 through 2007.

AVG LOGGERHEAD RATE	CAR	FEC	GOM	MAB	NCA	NEC	NED	SAB	SAR	TUN	TUS
Q1	0.266667	0.07037	0.0059	0.015873	0	-	-	0.122711	0.0625	0	-
Q2	0	0.069444	0.011577	0	0.090909	0.066667	-	0	-	-	-
Q3	-	0.057692	0	0.134425	-	0.333333	0.611111	0.040741	-	0	-
Q4	-	0.142857	0	0.049098	-	0	0.136364	0	0	-	-

Some of the forty NMFS time-area strata had no observer coverage and others had no observed bycatch from 2005 through 2007. The strata without effort or observer coverage were eliminated from the model. The zeros in observed strata probably did not arise because it was impossible for turtles to interact with the fishery. Therefore, I did not want to program a zero probability of take for those strata. Instead I estimated probabilities of interaction based on bycatch rates in those strata at different quarters, when possible, or used a median bycatch rate across the time-area strata (Table A1.7). This was consistent with the NMFS SEFSC's pooling method in which there was pooling across quarters before pooling across spatial areas (Garrison 2003).

TABLE A1.7

Determining average time-area strata leatherback bycatch rates for the simulation model. Grey cells indicate strata that were eliminated because either there was no NMFS fishing effort or no observer coverage. Yellow cells indicate bycatch rates that were calculated from NMFS observer data. Purple cells indicate bycatch rates that could not be directly calculated but were estimated from other NMFS strata or quarters. The method of adjustment is described.

QUARTER	FISHING AREA	CALCULATED BYCATCH RATE	TREATMENT TO ESTIMATE BYCATCH RATE	ESTIMATED BYCATCH RATE
1	CAR	0	Take CAR rate from Q2	0.0625
1	FEC	0.116203704		0.116203704
1	GOM	0.023871955		0.023871955
1	MAB	0	Average of MAB from Q3 and Q4	0.052625153
1	NCA	0	No observed leatherback take in NCA. In Q3 and Q4 no fishing at all. Use median leather bycatch 0.0277	0.027777778
1	NEC	-	deleted	
1	NED	-	deleted	
1	SAB	0.090909091		0.090909091
1	SAR	0.03125		0.03125
1	TUN	0	No observed leatherback take in TUN. In Q2 and Q4 no fishing at all. Use median leather bycatch 0.0277	0.027777778
1	TUS	-	deleted	
2	CAR	0.0625		0.0625
2	FEC	0.027777778		0.027777778
2	GOM	0.056373762		0.056373762
2	MAB	0	Average of MAB from Q3 and Q4	0.052625153
2	NCA	0	No observed leatherback take in NCA. In Q3 and Q4 no fishing at all. Use median leather bycatch 0.0277	0.027777778
2	NEC	0.133333333		0.133333333
2	NED	-	Average of NED from Q3 and Q4	0.262590188
2	SAB	0	Take SAB from Q1	0.090909091
2	SAR	-	deleted	
2	TUN	-	No observed leatherback take in TUN. In Q2 and Q4 no fishing at all. Use median leather bycatch 0.0277	0.027777778
2	TUS	-	deleted	
3	CAR	-	deleted	
3	FEC	0	Average of FEC from Q1 and Q2	0.071990741
3	GOM	0.010867675		0.010867675
3	MAB	0.031746032		0.031746032
3	NCA	-	deleted	
3	NEC	0.201923077		0.201923077
3	NED	0.225396825		0.225396825
3	SAB	0	Take SAB from Q1	0.090909091
3	SAR	-	deleted	
3	TUN	0	No observed leatherback take in TUN. In Q2 and Q4 no fishing at all. Use median leather bycatch 0.0277	0.027777778
3	TUS	-	deleted	
4	CAR	-	deleted	
4	FEC	0	Average of FEC from Q1 and Q2	0.071990741
4	GOM	0.10339438		0.10339438
4	MAB	0.073504274		0.073504274
4	NCA	-		0.0625
4	NEC	0.0625		0.29978355
4	NED	0.29978355	Take SAB from Q1	0.090909091
4	SAB	0		0.238095238
4	SAR	0.238095238	No observed leatherback take in TUN. In Q2 and Q4 no fishing at all. Use median leather bycatch 0.0277	0.027777778
4	TUN	-	deleted	
4	TUS	-	deleted	

For each turtle sharing a cell with a fishing set, a random number between zero and one was selected. If that number was less than or equal to that stratum's probability of being caught, that turtle was taken by the set.

The probabilities calculated from the observer data needed to be adjusted so they could be applied to each turtle in a fished cell. For example, the first stratum bycatch rate was 0.0625 turtles/set. If this set encountered 100 turtles and this probability was applied to each turtle to determine whether or not it was caught, I could end up with (0.0625 turtles/set * 100 turtles = 6.25 turtles/set). Instead, I divided the probability by the average number of turtles to be encountered:

$$\frac{0.0625 \text{ turtles}}{\text{set}} / 100 \text{ turtles} = 0.000625 \quad (30)$$

Then this probability could be applied to each turtle encountered to determine whether it was caught, and the average bycatch rate would be the intended 0.0625 turtles/set.

A set fishing among uniformly random turtles would on average encounter 10.125 turtles. On average, a set fishing among clumped turtles would encounter 250 turtles (Table A1.8).

$$\frac{20,250 \text{ turtles}}{10,000 \text{ cells}} * \frac{5 \text{ cells}}{1 \text{ set}} = 10.125 \text{ turtles/set} \quad (31)$$

$$\frac{4,050 \text{ turtles}}{81 \text{ cells}} * \frac{5 \text{ cells}}{1 \text{ set}} = 250 \text{ turtles/set} \quad (32)$$

TABLE A1.8

Time-area strata bycatch rates adjusted for application to each encountered turtle. The estimated bycatch rate is divided by the average number of turtles encountered by a set when turtles are uniformly random and when turtles are clumped.

ESTIMATED BYCATCH RATE	TURTLES RANDOM	TURTLES CLUMPED
0.0625	0.006173	0.00025
0.116203704	0.011477	0.0004648
0.023871955	0.002358	9.549E-05
0.052625153	0.005198	0.0002105
0.027777778	0.002743	0.0001111
0.090909091	0.008979	0.0003636
0.03125	0.003086	0.000125
0.027777778	0.002743	0.0001111
0.0625	0.006173	0.00025
0.027777778	0.002743	0.0001111
0.056373762	0.005568	0.0002255
0.052625153	0.005198	0.0002105
0.027777778	0.002743	0.0001111
0.133333333	0.013169	0.0005333
0.262590188	0.025935	0.0010504
0.090909091	0.008979	0.0003636
0.027777778	0.002743	0.0001111
0.071990741	0.00711	0.000288
0.010867675	0.001073	4.347E-05
0.031746032	0.003135	0.000127
0.201923077	0.019943	0.0008077
0.225396825	0.022261	0.0009016
0.090909091	0.008979	0.0003636
0.027777778	0.002743	0.0001111
0.071990741	0.00711	0.000288
0.10339438	0.010212	0.0004136
0.073504274	0.00726	0.000294
0.0625	0.006173	0.00025
0.29978355	0.029608	0.0011991
0.090909091	0.008979	0.0003636
0.238095238	0.023516	0.0009524
0.027777778	0.002743	0.0001111

APPENDIX B:

BYCATCH ESTIMATION METHODS

This appendix provides details about the bycatch estimation methods. They were introduced in the methods section, but in this appendix, I describe the theory behind the delta-lognormal method and the generalized linear model (GLM) as well as how they were applied in the simulation model.

The delta-lognormal method is a sample-based estimator, and the generalized linear model (GLM) is a model-based estimator. A sample-based estimator assumes sampling probabilities so that observed takes can be raised to make fishery-level estimates (McCracken 2000). A mean bycatch rate is calculated from the observed bycatch and effort. It is used to estimate bycatch on unobserved sets by extrapolating the bycatch rate to the amount of unobserved effort reported in logbooks. While sample-based estimators are essentially free of assumptions about the population structure and estimated characteristics, sample-based estimators are generally less efficient than model-based predictors (McCracken 2000).

However, model-based predictors assume a statistical model of turtle takes. The assumed statistical model should represent the process generating the response variable (Y) from explanatory variables (x) (McCracken 2000, McCracken 2004). For example, mainline length and sea surface temperature could be explanatory variables for the number of turtles caught on a set, the response variable. Parameters (β) would be estimated for the observed explanatory variables to relate the explanatory variable values to the observed response variable values. Then explanatory variable values from logbooks could be used in this function to predict bycatch on unobserved sets.

A2.1 GENERALIZED LINEAR MODEL (GLM)

A2.1.1 THEORY

Generalized linear models (GLMs) are extensions of classical linear models. In the classical linear model, systematic effects are additive and a normal error distribution is assumed. The GLM extends the classical linear model by using distributions from an exponential family other than the normal distribution and using any monotonic differentiable link function. In the log-linear model, the GLM most commonly used with count data such as the number of turtles caught, systematic effects are multiplicative and a Poisson error distribution is assumed (McCullagh and Nelder 1989).

The classical linear model can be described by three components, and these three components will be compared to the components of the GLM (McCullagh and Nelder 1989).

1. The **random component**:

The components of the random response variable Y have independent Normal distributions with $E(Y) = \mu$ and constant variance σ^2

2. The **systematic component**:

The covariates x_1, x_2, \dots, x_p produce a linear predictor η

$$\eta = \sum_{j=1}^p x_j \beta_j \tag{33}$$

where:

p = the number of covariates

β = an unknown parameter to be estimated

3. The **link** between the random and systematic components; $g()$ is called the link function:

$$\eta_i = g(\mu_i) \quad (34)$$

where:

μ_i = the expected value of the i th datum y

η_i = the linear predictor for the i th datum

The link function relates the mean of the response variable (μ) to the linear predictor (Lindsey 1997, Venables and Dichmont 2004).

In the GLM for count data, the random component has a Poisson distribution, and a log-link function is used. In the classical linear model, the mean and linear predictor are identical. However, when modeling count data with a Poisson distribution, μ must be positive. In this case, a log-link is more appropriate. Under the log-link, η rather than μ follows a linear model. This guarantees that μ is positive for all η and thus all parameter and covariate combinations.

$$\eta_i = \log(\mu_i) \quad (35)$$

Besides the Normal and Poisson distributions, the exponential family also includes the gamma and binomial distributions. Other distributions, such as the negative binomial, beta, and inverse Gaussian, can be included if the extra variance parameter, Φ , is known (Venables and Dichmont 2004).

A2.1.1.1 Poisson distribution

The Poisson distribution is a common distribution for counts of rare events, and the GLM known as the log linear model is suitable for Poisson count and frequency data (Lindsey 1997,

McCracken 2000). Under this model it is assumed that the counts are randomly distributed in space and are independent (McCracken 2000, Sileshi 2006).

When the response variables exhibit a Poisson distribution (Hogg and Tanis 2001):

$$f(x; \lambda) = \frac{\lambda^x e^{-\lambda}}{x!}, \quad x = 0, 1, 2 \quad (36)$$

where:

$$\mu = \lambda$$

$$\sigma^2 = \lambda$$

the log-link is the natural link function between the $E(Y_i)$ and a linear combination of parameters (McCullagh and Nelder 1989, Dobson 1999, Venables and Ripley 2002):

$$\eta_i = \log(\mu_i) = \beta^T X_i \quad (37)$$

where:

η = the linear predictor

$\mu_i = E(Y_i)$

β^T = the transposed parameter vector

X = the covariate vector

A2.1.1.2 Negative binomial distribution

In a Poisson model, the mean and variance are assumed equal. However, bycatch data do not always show this relationship. Often the variance is larger than the mean, a case known as overdispersion (McCracken 2000, McCracken 2004, Potts and Elith 2006). Patchy distributions, hierarchical data, the observation of a rare event, or lack of independence can lead to the

presence of excess zeros, variance heterogeneity, and in turn, overdispersion (McCracken 2000, McCracken 2004, Lindsey 2004, Fahrmeir and Echavarría 2006).

The Poisson model is the most commonly used and most straightforward model for count data, but neither zero-inflation nor overdispersion is accounted for with the Poisson distribution. If overdispersion is not addressed, standard errors can be seriously underestimated and the form of the linear predictor can be misinterpreted (McCracken 2000, Rideout et al 2001, Potts and Elith 2006). Modeling responses as a negative binomial random variable may be more appropriate if data are overdispersed (Welsh et al 1996, Thurston et al 2000, Lindsey 2004, Venables and Dichmont 2004).

Under the negative binomial distribution, the mean is estimated from the data, and the variance is defined as a multiple of the mean (Potts and Elith 2006). In both the Poisson and the negative binomial models, variance is dependent on the mean, but the negative binomial distribution is appropriate for modeling overdispersed data because its variance is always greater than the Poisson variance with the same mean (White and Bennetts 1996, Potts and Elith 2006, Sileshi 2006). There are two parameters in the negative binomial distribution: the mean and a dispersion parameter (White and Bennetts 1996). The dispersion parameter can be understood as a measure of the degree of clumping in the population. The negative binomial distribution approaches a Poisson distribution as the dispersion parameter approaches infinity, which is consistent with the spatial independence assumption in the Poisson distribution. This assumption is relaxed in the negative binomial distribution (White and Bennetts 1996).

A2.1.2 APPLICATION IN SIMULATION MODEL

I used a GLM to estimate bycatch in the simulation model. Here I describe in detail how I programmed the GLM. I address explanatory variable selection when sets were uniformly random and when sets were clumped. I also explain the model selection functions.

A2.1.2.1 Potential explanatory variable values

I selected values from SEFSC observer data from 2005 through 2007 to be explanatory variables in the simulation model. To be considered for inclusion in the model, the variables must be recorded both by observers and in the logbooks so that the SEFSC could fit the GLM with observer data and predictions could be made with logbook data. SEFSC observers record the date, time, latitude, longitude, and sea surface temperature (SST) for beginning a set, ending a set, beginning a haul, and ending a haul. SEFSC observers also record the landing date. However, only the date, latitude, longitude, and SST at the beginning of a set are present in NMFS logbooks.

Therefore, I used the date, latitude, longitude, and sea surface temperature (SST) from the beginning of a set. The latitude and longitude were modeled as “*degrees.minutes*”. The fishing area was determined from the reported latitude and longitude (Table A2.1). I modeled target species, light stick presence, and fishing area as categorical variables.

TABLE A2.1

Latitude and longitude used to assign sets to fishing areas. CAR = Caribbean, GOM = Gulf of Mexico, FEC = Florida East Coast, SAB = South Atlantic Bight, MAB = Mid Atlantic Bight, NEC = Northeast Coastal, NED = Northeast Distant, SAR = Sargasso, NCA = North Central Atlantic, TUN = Tuna North, TUS = Tuna South

Fishing area	Min lat (\geq)	Max lat ($<$)	Min long (\geq)	Max long ($<$)
CAR	8	22	60	87
GOM	22	31	82	87
GOM	18	31	87	99
FEC	22	30	71	82
SAB	30	35	71	82
MAB	35	43	71	78
NEC	35	45	65	71
NEC	35	50	60	65
NED	35	55	20	60
SAR	22	35	60	71
NCA	13	35	20	60
TUN	5	13	20	60
TUS	0	5	20	60

NMFS SEFSC observer data from 2005 through 2007 were used to provide explanatory variable values for simulated sets according to the following procedures.

○ **Sets uniformly random**

As discussed in Appendix A, sections A1.1.4 and A1.1.5, there were twenty-five sets per spatial replicate, and the number of spatial replicates varied across strata. Variable values were assigned for the first simulated set in a stratum based on whether there was bycatch on that set. If the simulated set had bycatch, a set from the SEFSC observer data with bycatch was chosen at random, and its variable values were assigned to the simulated set, likewise for sets without bycatch. A distance value was calculated from the chosen SEFSC set to all other SEFSC observed sets. Since closer SEFSC sets should have a greater probability of selection, the reciprocal of the distance formula was used.

$$D_s = \frac{1}{\sqrt{(\text{Date} - \text{Date}_s)^2 + (\text{Lat} - \text{Lat}_s)^2 + (\text{Long} - \text{Long}_s)^2}} \quad (38)$$

where:

D_s = distance value for SEFSC observed set s

Date = the date from a randomly selected SEFSC observed set and assigned to the first simulated set in a strata

Date_s = the date for SEFSC observed set s

Lat = the latitude from a randomly selected SEFSC observed set and assigned to the first simulated set in a strata

Lat_s = the latitude for SEFSC observed set s

Long = the longitude from a randomly selected SEFSC observed set and assigned to the first simulated set in a strata

Long_s = the longitude for SEFSC observed set s

After distance values were calculated for each SEFSC observed set, these values were used to apply probabilities of selection to each SEFSC observed set.

$$P(S) = \frac{D_s}{\sum_s D_s} \quad (39)$$

where:

$P(S)$ = the probability of SEFSC observed set S being selected

D_s = distance value for SEFSC observed set s

These probabilities were used to select twenty-four other SEFSC observed sets, and their variable values were applied to the twenty-four remaining simulated sets. The SEFSC observed

sets were divided into two groups: those with take and those without take. Variable values for a simulated set were selected from the appropriate SEFSC observed take group according to the calculated probabilities.

If there were multiple spatial replicates per simulated stratum, the SEFSC observed set probabilities remained the same. Also, the same set could not be selected multiple times within the same stratum. The probabilities of selection were recalculated relative to the first set in the next stratum.

- **Sets clumped**

As covered in Appendix A, section A1.1.6, models with clumped sets had five sets per clump. In an attempt to reflect the spatial clumping in the variable values, I assigned the five simulated sets in a clump with variable values from SEFSC observed sets within one trip. Therefore, SEFSC observed trips with fewer than five sets were eliminated from consideration. The remaining trips were sorted into trips with zero sets with take, at least one set with take and four sets without take, at least two sets with take and three sets without take, at least three sets with take and two sets without take, at least four sets with take and one set without take, and at least five sets with take.

The number of positive sets out of the five simulated sets per clump was tallied, and the corresponding group of SEFSC observed trips was isolated. One trip out of the potential SEFSC observed trips was selected at random. The required number of sets with take and sets without take were selected at random from the SEFSC trip. If this was the first clump in a stratum, a distance value was calculated from the first set of that clump to all other SEFSC observed sets from trips with at least five sets.

$$D_s = \frac{1}{\sqrt{(\text{Date} - \text{Date}_s)^2 + (\text{Lat} - \text{Lat}_s)^2 + (\text{Long} - \text{Long}_s)^2}} \quad (40)$$

where:

D_s = distance value for SEFSC observed set s

Date = the date from a randomly selected SEFSC observed set assigned to the first simulated set in the first clump in a stratum

Date_s = the date for SEFSC observed set s

Lat = the latitude from a randomly selected SEFSC observed set assigned to the first simulated set in the first clump in a stratum

Lat_s = the latitude for SEFSC observed set s

Long = the longitude from a randomly selected SEFSC observed set assigned to the first simulated set in the first clump in a stratum

Long_s = the longitude for SEFSC observed set s

After all the distance values were calculated, the average distance value per set within a trip was calculated. I assumed trip t consisted of sets i through j ,

$$D_t = \frac{\sum_{s=i}^j D_s}{j - i + 1} \quad (41)$$

where:

D_t = average distance value for SEFSC observed sets within trip t

D_s = distance value for SEFSC observed set s

Next, probabilities were calculated for each SEFSC observed trip.

$$P(t) = \frac{D_t}{\sum D_t} \quad (42)$$

where:

$P(t)$ = the probability of trip t being selected

D_t = average distance value for SEFSC observed sets within trip t

Next, I assigned variable values to the second clump of simulated sets. The number of sets with take was tallied, and a SEFSC trip with the corresponding number of sets with take was selected based on the calculated probabilities. The same trip could not be selected multiple times in the same stratum. Once a SEFSC trip was selected, the required number of sets with take and sets without take were selected randomly from the trip. This continued through all set clumps within all spatial replicates until the next stratum was reached. Then the probabilities were recalculated.

A2.1.2.2 Model selection

The Poisson GLM was fit with the `glm()` function in R, and the negative binomial GLM was fit with the `glm.nb()` function in R. The `step()` function in R was used to select a model based on AIC.

A2.1.2.3 Bycatch estimation

The `predict()` function in R was used to estimate bycatch on an unobserved set with the AIC-selected GLM.

A2.2 DELTA-LOGNORMAL

A2.2.1 THEORY

Delta-lognormal estimates are essentially the product of the proportion of sets with bycatch and the average rate of bycatch for those sets. The variance of the estimator incorporates both the positive bycatch rates and the number of sets with and without bycatch (Yeung 2001). Minimum variance unbiased estimators of means and variances are provided under the delta-lognormal method when data contain many zeros and the non-zero observations are log-normally distributed (Pennington 1983, NFS-SEFSC 2001, Garrison 2003). The delta-lognormal method accommodates a predominant group of zero observations by including a probability of zero catch (Ortiz et al 2000). Fishing area and calendar quarter effects are also considered by making estimates for multiple time-area strata.

In addition to assuming that catch rates are log-normally distributed, the delta-lognormal method assumes that the number of hooks is an appropriate unit of effort. Violations of the log-normal assumption could result in positive or negative biased estimates of catch rate and variance. Not much analysis has been done on the implications of the unit of effort assumption (Garrison 2003). Other possible measures of effort include vessel size, number of vessels in the fleet, number of days fishing per vessel, number of trips per vessel, or number of sets per trip (Crowder and Myers 2001).

Violations of several other model assumptions could result in an underestimation of variance: (a) omission of covariance terms to account for lack of independence, (b) not incorporating variance of proportion of positive sets (m_t/n_t) in $\text{Var}(C_t)$, and (c) treating effort as a

known constant. Sets are used as the primary sampling unit, but they are not independent within a trip. The potential bias and the possibility of using trips as the sampling unit have not been deeply explored, but underestimation of summed region-wide bycatch and variance are possible (Yeung et al 2000). Similarly, bycatch estimates are assumed independent by stratum, so estimated bycatch and variance are summed across strata to construct region-wide annual estimates. The actual variance may be underestimated by this assumption, especially when consecutive sets occur in the same stratum (Yeung 2001). By treating the proportion of positive sets and the reported number of hooks as constants within a stratum, they are assumed to be uncorrelated with the bycatch rate. This should not be a problem for extremely rare taxa, but for other cases, an underestimate of variance will generate narrower confidence intervals with a confidence level that is below that desired (Yeung et al 2000).

Finally, it is assumed that there is a linear relationship between total bycatch and the total number of hooks, but this assumption could be violated if there are saturation effects. Then the relationship between bycatch and number of hooks would not be linear and bycatch estimates could be biased (Garrison 2003).

A2.2.2 APPLICATION IN SIMULATION MODEL

To calculate L (the mean of the \log_e -transformed number of turtles taken by 1,000 hooks when bycatch occurred), the sets with take were identified. The number of hooks per set was determined according to the procedure for assigning potential explanatory variable values to sets for the GLM. The bycatch rate (turtles/1000 hooks) was calculated for a set and was \log_e transformed. The sets' \log_e -transformed bycatch rates (l_i where $i = 1, 2, \dots, m$ and m = the number of sets with observed bycatch) were averaged to obtain L .

I calculated S_L^2 (the sample variance of the \log_e -transformed bycatch rate) by taking the sample variance of the sets' \log_e -transformed bycatch rates.

$$S_L^2 = \frac{\sum_{i=1}^m (l_i - L)^2}{m - 1} \quad (43)$$

where:

S_L^2 = the sample variance of the \log_e -transformed bycatch rate

L = the mean of the \log_e -transformed number of turtles taken by 1,000 hooks when bycatch occurred

l_i = the i th sets' \log_e -transformed bycatch rate

m = the number of sets with observed bycatch

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