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A Spatio-Temporal Analysis of Dolphinfish; *Coryphaena hippurus*, Abundance in the Western Atlantic: Implications for Stock Assessment of a Data-Limited Pelagic Resource.

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UNIVERSITY OF MIAMI

A SPATIO-TEMPORAL ANALYSIS OF DOLPHINFISH, CORYPHAENA
HIPPURUS, ABUNDANCE IN THE WESTERN ATLANTIC: IMPLICATIONS FOR
STOCK ASSESSMENT OF A DATA-LIMITED PELAGIC RESOURCE

By

Kristin M. Kleisner

A DISSERTATION

Submitted to the Faculty
of the University of Miami
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A Spatio-Temporal Analysis of Dolphinfinh; *Coryphaena*
Hippurus, Abundance in the Western Atlantic: Implications
for Stock Assessment of a Data-Limited Pelagic Resource.

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Dolphinfinh (*Coryphaena hippurus*) is a pelagic species that is ecologically and commercially important in the western Atlantic region. This species has been linked to dominant oceanographic features such as sea surface temperature (SST) frontal regions. This work first explored the linkages between the catch rates of dolphinfinh and the oceanography (satellite-derived SST, distance to front calculations, bottom depth and hook depth) using Principal Components Analysis (PCA). It was demonstrated that higher catch rates are found in relation to warmer SST and nearer to frontal regions. This environmental information was then included in standardizations of catch-per-unit-effort (CPUE) indices. It was found that including the satellite-derived SST and distance to front increases the confidence in the index.

The second part of this work focused on addressing spatial variability in the catch rate data for a subsection of the sampling area: the Gulf of Mexico region. This study used geostatistical techniques to model and predict spatial abundances of two pelagic species with different habitat utilization patterns: dolphinfinh (*Coryphaena hippurus*) and swordfish (*Xiphias gladius*). We partitioned catch rates into two components, the probability of encounter, and the abundance, given a positive encounter. We obtained separate variograms and kriged predictions for each component and combined them to

give a single density estimate with corresponding variance. By using this two stage approach we were able to detect patterns of spatial autocorrelation that had distinct differences between the two species, likely due to differences in vertical habitat utilization. The patchy distribution of many living resources necessitates a two-stage variogram modeling and prediction process where the probability of encounter and the positive observations are modeled and predicted separately. Such a “geostatistical delta-lognormal” approach to modeling spatial autocorrelation has distinct advantages in allowing the probability of encounter and the abundance, given an encounter to possess separate patterns of autocorrelation and in modeling of severely non-normally distributed data that is plagued by zeros.

Dedications

This dissertation work is dedicated to my entire family and all the loved ones in my life who have offered me unconditional love and support throughout the course of my research. It is only with their compassion, commiseration, and understanding that I was able to learn that even the greatest task can be accomplished if it is done one step at a time.

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TABLE OF CONTENTS

Page

LIST OF FIGURES	viii
-----------------------	------

LIST OF TABLES.....	xi
---------------------	----

Chapter

1 A SYNOPSIS OF THE FISHERY, ECOLOGY AND HISTORICAL MANAGEMENT OF DOLPHINFISH IN THE WESTERN ATLANTIC.....	1
1.1 Introduction and Current Views of Dolphinfish.....	1
1.2 Oceanography	24
1.3 Estimation of Abundance and Modeling Approach.....	38
1.4 Aims and Objectives of Dissertation.....	42
2 TOWARDS AN UNDERSTANDING OF DOLPHINFISH ABUNDANCE: A MULTIVARIATE ANALYSIS OF THE RELATIONSHIPS BETWEEN ENVIRONMENTAL VARIABLES AND SPECIES ASSOCIATIONS FROM THE U.S. PELAGIC LONGLINE FLEET.....	46
2.1 Challenges of Assessing Dolphinfish	46
2.2 Methodology for Multivariate Analysis.....	53
2.3 Preliminary Analysis.....	57
2.4 Analysis Results.....	64
2.5 Discussion of Multivariate Analysis Results	84
3 MODELING THE SPATIAL AUTOCORRELATION OF CPUE DATA IN THE GULF.	91
3.1 Spatial Patterns in the Environment.....	91
3.2 Data Analysis	94
3.3 Results of Spatial Analysis	110
3.4 Discussion of Spatial Patterns.....	118
4 PREDICTION OF ABUNDANCE BASED ON SPATIALLY AUTOCORRELATED CATCHES	126
4.1 Spatial Variability and Determining Abundance of a Pelagic Species	126
4.2 Methods for Spatial Abundance Predictions from Kriging	131
4.3 Index Calculation Results	146
4.4 Discussion	152
5 ACCOUNTING FOR SPATIAL VARIABILITY IN A STOCK ASSESSMENT MODEL.	160
5.1 Background of Stock Assessment Models and Role of CPUE Indices	160

5.2 Modeling Methodology	164
5.3 Bayesian Surplus Production Model Results	182
5.4 Interpretation of Model Results	207
5.5 Chapter Conclusions	213
GENERAL CONCLUSIONS.....	215
REFERENCES.....	217
APPENDIX A.....	235
APPENDIX B.....	239
APPENDIX C.....	255

LIST OF FIGURES

1.1	Map of the extent of the U.S. and Venezuelan longline observer programs.....	4
1.2	Dolphinfish imports to the U.S. by country from January through December 2005.....	12
1.3	Dolphinfish imports to the U.S. by country for January through November 2006.....	13
1.4	Annual landings of dolphinfish from the east coast of the United States.....	14
1.5	Numbers of recreational saltwater anglers in the U.S. Atlantic and Gulf of Mexico from 1982 to 2005.....	15
1.6	Map of the major basins of the Caribbean Sea.....	25
1.7	Map of SST from the MODIS satellite in March 2001.....	37
2.1	Example weekly SST image for western Atlantic processed with frontal boundaries.....	57
2.2	Fishing areas of the U.S. and Venezuelan longline fleets for GLMs.....	63
2.3	Principle component scores for the first three axes of the eastern species PCA..	67
2.4	Eigenvectors of the principle component 1 for eastern dolphinfish by seasons and for all seasons combined.....	69
2.5	Eigenvectors of the principle component 2 for eastern dolphinfish for all seasons combined and by seasons.....	70
2.6	Eigenvectors of the principle component 3 for eastern dolphinfish by seasons and for all seasons combined.....	71
2.7	Principle component scores for the first three axes of the western species PCA.	73
2.8	Eigenvectors of the principle component 1 for western dolphinfish by seasons and for all seasons combined.....	75
2.9	Eigenvectors of the principle component 2 for western dolphinfish by seasons and for all seasons combined.....	76
2.10	Eigenvectors of the principle component 3 for western dolphinfish by seasons and for all seasons combined.....	77
2.11	Principle components (1-3) from the general eastern PCA plotted against distance from front.....	80
2.12	Principle component 1 from the general eastern PCA against year day.....	81
2.13	The U.S. indices of abundance for dolphinfish in the western Atlantic.....	82
2.14	The Venezuelan indices of abundance. Note the width of the upper confidence interval for the conventional GLM.....	83
2.15	First principle component of the western data against continuous year day.....	85

2.16	First principle component of the western data against continuous year day.....	86
3.1	Seasonal plots of the extent of the longline fleet within the Gulf of Mexico.....	96
3.2	Bathymetry map of the Gulf of Mexico.....	99
3.3	Seasonal log positive variograms for dolphinfish for year 1989.....	111
3.4	Seasonal indicator variograms for dolphinfish for year 2000.....	112
3.5	Distribution of variogram parameters by season and species for indicator and log positive observations.....	113
3.6	Seasonal log positive variograms for swordfish for year 1989.....	116
3.7	Seasonal indicator variograms for swordfish for year 2000.....	117
4.1	An example variogram showing the three parameters defining the shape: the range, the sill, and the nugget.....	133
4.2	The “home range” kernel estimates for each year-season.....	136
4.3	An example of higher abundances along the northern edge of the Loop.....	147
4.4	The geostatistically derived and GLM derived indices for dolphinfish.....	148
4.5	The geostatistically derived and GLM derived indices for swordfish.....	149
4.6	The geostatistically derived and GLM derived indices for dolphinfish with confidence intervals.....	151
4.7	The geostatistically derived and GLM derived indices for swordfish with confidence intervals.....	152
5.1	Trends in abundance indices and catch rate series for swordfish.....	166
5.2	Prior distribution of r parameter for swordfish models.....	179
5.3	Less informative prior distribution of r parameter for dolphinfish models.....	180
5.4	Prior distribution of r parameter for dolphinfish models.....	181
5.5	Posterior distributions of several benchmark parameters for the GLM (in blue) and geostatistical (in red).....	185
5.6	Medians and 80% credibility intervals for relative biomass and relative fishing mortality for the dolphinfish Schaefer BSP models using a less informative prior.....	186
5.7	Graph of the prior and posterior distribution of the r parameter.....	187
5.8	Medians and 80% credibility intervals for relative biomass and relative fishing mortality for models SS1 and SS2.....	190
5.9	Medians and 80% credibility intervals for relative biomass and relative fishing mortality for models SF1 and SF2.....	191
5.10	Posterior distributions of current biomass and the ratio of current biomass over K for the Schaefer and Fletcher models (SS1, SS2, SF1, SF2).....	192

5.11	Medians and 80% credibility intervals for relative biomass and relative fishing mortality for model SS3.....	194
5.12	Medians and 80% credibility intervals for relative biomass and relative fishing mortality for model SF3.....	194
5.13	Medians and 80% credibility intervals for relative biomass and relative fishing mortality for models SS4 and SS5.....	198
5.14	Medians and 80% credibility intervals for relative biomass and relative fishing mortality for models SF4 and SF5.....	199
5.15	Posterior distributions of current biomass and the ratio of current biomass over K for the Schaefer and Fletcher models (SS4, SS5, SF4, SF5).....	200
5.16	Medians and 80% credibility intervals for relative biomass and relative fishing mortality for models SS6 and SS7.....	203
5.17	Medians and 80% credibility intervals for relative biomass and relative fishing mortality for models SF6 and SF7.....	204
5.18	Posterior distributions of current biomass and the ratio of current biomass over K for the Schaefer and Fletcher models (SS6, SS7, SF6, SF7).....	205
5.19	Time series of B/BMSY B and F/FMSY from 1950 to 2005 showing the progression of stock status as the North Atlantic swordfish fisheries evolved and the current year (2005) status for the Schaefer and Fletcher models.....	206
5.20	Prior and posterior distribution of r parameter for the Schaefer and Fletcher models.....	207

LIST OF TABLES

1.1	Status of FMPs in the Caribbean.....	11
1.2	Annual Caribbean catch of dolphinfish by the U.S. and several other Caribbean nations by various effort sources	21
2.1	Correlation matrix for the eastern species PCA.....	60
2.2	Correlation matrix for the western species PCA.....	61
2.3	Eigenvalues of the correlation matrix.....	64
2.4	Eigenvectors of the principal components.....	65
2.5	Correlation matrix of eastern dolphinfish CPUE with environmental variables.....	68
2.6	Correlation matrix of western dolphinfish CPUE with environmental variables.....	74
2.7	Mean and standard deviation of PCA factors for east and west coast data by season	78
5.1	A comparison between the nominal, GLM, and geostatistical indices and approaches used to derive each index.....	163
5.2	A summary of the BSP models and the abundance indices incorporated in each.....	167
5.3	Estimates of MSY , F_{MSY} , r , and K from an ASPIC surplus production model..	171
5.4	Means and CVs of the marginal posterior distributions of management parameters from the BSP model for the Northern stock of Atlantic swordfish.....	173
5.5	Best Linear Unbiased Estimators (BLUEs) from Myers <i>et al.</i> , 1999.....	175
5.6	Expected values of the posterior distribution of the parameters from model D1 and D2.....	183
5.7	Expected values of the posterior distribution of the parameters from the BSP model run with either the U.S. GLM or geostatistical (GEO) index (1987-2005).....	188
5.8	Expected values of the posterior distribution of the parameters from models SS3 and SF3.....	193
5.9	Expected values of the posterior distribution of the parameters from the BSP model run with the truncated Japanese CPUE index (1967-1999) and either the U.S. GLM or geostatistical (GEO) index (1987-2005).....	196
5.10	Expected values of the posterior distribution of the parameters from the BSP model run with the full Japanese CPUE index (1967-2005) and either the U.S. GLM or geostatistical (GEO) index (1987-2005).....	201

5.11	Comparison of MSY , $F_{current}/F_{MSY}$, r , and K from an ASPIC surplus production model and two Bayesian surplus production models that incorporate different indices of abundance (GLM vs. geostatistical).....	210
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CHAPTER 1: A SYNOPSIS OF THE FISHERY, ECOLOGY AND HISTORICAL MANAGEMENT OF DOLPHINFISH IN THE WESTERN ATLANTIC.

1.1 Introduction and Current Views of Dolphinfinh

One of the key areas of fisheries biology that presents a challenge to stock assessment scientists is the ability to quantify the abundance of a species that is moving in space and time over a vast area. Research in this area is crucial because robust indices of abundance are necessary if the goal is the prediction of future abundances and the regulation of catches to ensure sustainability. One of the goals of assessing a pelagic species is to identify and understand the factors that may be contributing to the variability in abundance. This is akin to defining the habitat or range of the species, and logical influences on this parameter are the presence of prey or predators, suitable spawning location, and optimal oceanographic conditions. Dolphinfinh is an example of a pelagic species that is migratory and important commercially, recreationally, and ecologically throughout its range in the western Atlantic. However, this species has not received the attention to the collection of biological data and assessment that has been afforded to the larger tunas and billfish probably due to the fact that there are no large commercial fisheries that primarily target dolphinfinh. This suggests that an assessment of dolphinfinh in the western Atlantic should not only account for removals across fishing sectors and across national boundaries, but also incorporate knowledge of the relationship of this species to the environment in order to create a complete picture of dolphinfinh stock dynamics in the region.

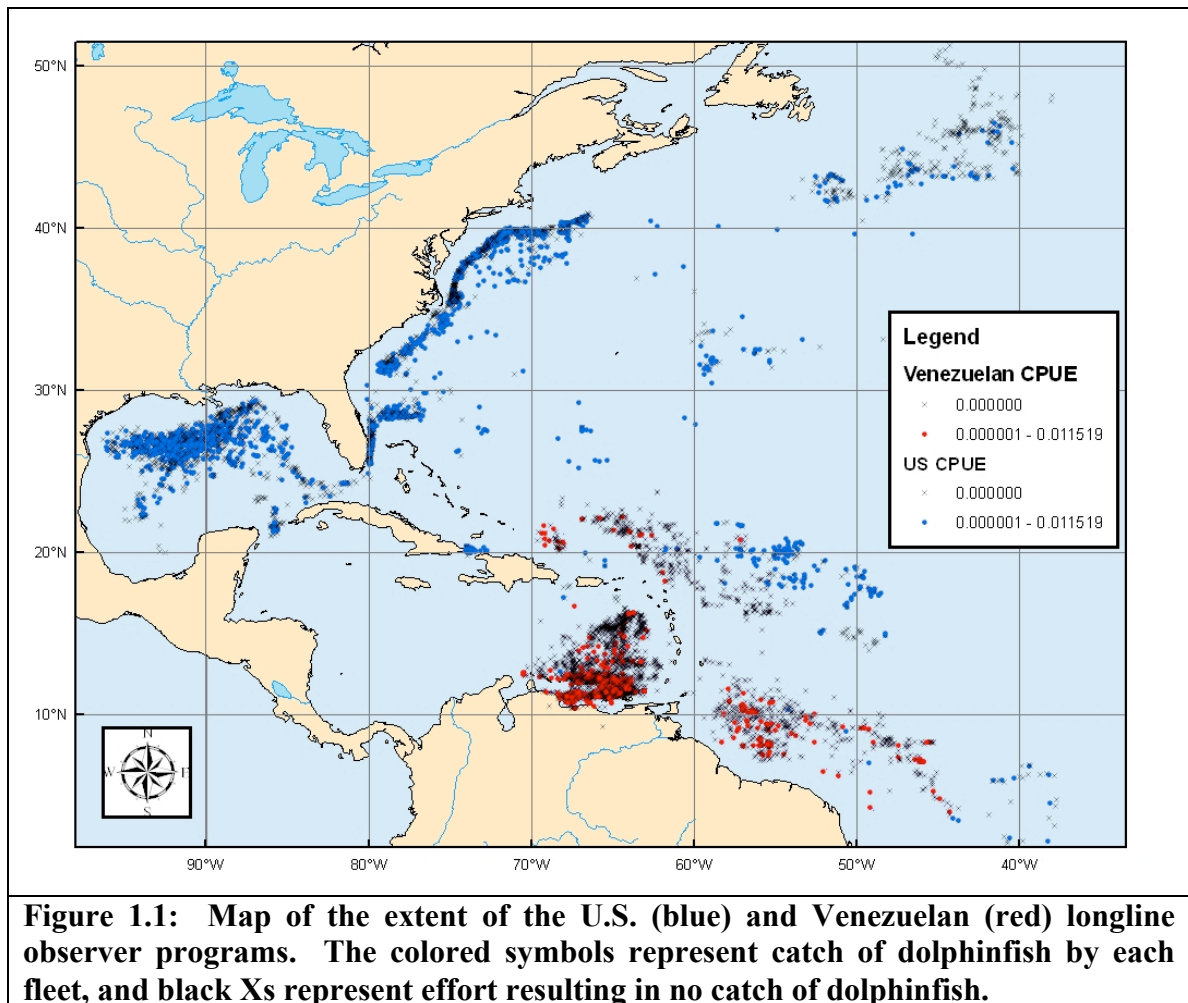
As Mahon (1999) noted, “Given the migratory, shared nature of the dolphinfish resource, a regional approach to assessment and management is required.” With this in mind, the focus of this dissertation is to present a review, for the western Atlantic, of the biological information on dolphinfish ecology, the fisheries for this species, the oceanographic environment, and to present some alternative methods to the tools currently used to estimate relative abundance and stock status. This chapter begins by describing the information on geographic distribution, management, and existing assessments for dolphinfish. Because this species is believed to be strongly affected by environmental conditions, the oceanography of the region is presented in detail. Additionally, there is a brief introduction to the methods, objectives, and hypotheses presented in the dissertation. The second chapter of the dissertation will focus on the abundance of dolphinfish across the western Atlantic, species assemblages and environmental parameters that are associated with variation in the catch rates of dolphinfish. The primary spotlight is on two of the largest commercial harvesters of dolphinfish: the U.S. and Venezuela, which together are fishing within the majority of the western Atlantic area. Chapters three and four will narrow the focus to the U.S. commercial longline fleet in the Gulf of Mexico in order to test novel techniques for incorporating spatial variability into indices of abundance. The techniques introduced in these chapters will also be used to evaluate the abundance of another species caught by the longline in this area, swordfish, *Xiphias gladius*, in order to examine the differences in the techniques for two pelagic species with very different habitat usages. The chief aim of chapter five is to develop an integrated Bayesian assessment modeling approach to examine differences in the biological parameters predicted by the models when spatially-

and nonspatially-explicit indices are incorporated into the stock assessment model and to address uncertainty within the components.

Geographic Context of Western Atlantic Dolphinfinh

Both the common dolphinfinh (*Coryphaena hippurus*) and the pompano or lesser dolphinfinh (*Coryphaena equiselis*) are notable for their life history traits and physiology. The dolphinfinh is renowned for its aggressive feeding behavior and its prized status as a game and food fish. The dolphinfinh is a highly migratory pelagic species that has been shown to be capable of swimming more than 80 miles in 24 hours (Hammond, 1998). Dolphinfinh inhabit tropical and subtropical surface oceanic waters worldwide and are reported in the literature to be bounded in the north and south Atlantic by the 20°C isotherm (Palko *et al.*, 1982) and in the Pacific by the 23°C isotherm (Kraul, 1999). There have also been recent reports of a poleward extension of this species in the Pacific in response to continued warming of the oceanic habitat (Norton, 1999). The range for dolphinfinh in the western Atlantic has been recorded to be from Nova Scotia (Vladykov and McKenzie, 1935; Tibbo, 1962) to Rio de Janeiro, Brazil (Ribeiro, 1918; Scherbachev, 1973). However, this species is generally considered to be common only from North Carolina throughout the Gulf of Mexico and Caribbean to the northeastern coast of Brazil, and they are only seasonally abundant at these locations (Oxenford, 1999). In spite of this noted range, the U.S. longline fleet reports high dolphinfinh catch-per-unit-effort (CPUE) north of North Carolina. In this research, the area of study is defined by the areas fished by the U.S. and Venezuelan longline fleet, the two main sources of fisheries data used. The fisheries of several Caribbean nations are also encompassed within this area and reference to these fisheries will be in the context of the

study area. The eastern limit of the study area is determined to be 45°W longitude, the northern border is 55°N longitude, and the southern border is the equator. The western border is the U.S., Canadian, Mexican, and Central and South American coastline, and the study area encompasses the entire Caribbean Sea and Gulf of Mexico (Figure 1.1). This area encompasses all of FAO statistical fishing area 31 and most of FAO statistical fishing area 21.



Migration

Dolphinfish are a significant part of artisanal and large- and small-scale commercial and recreational catch within the western Atlantic. In spite of their

significance, landings are most likely greatly under-reported due to the difficulties in estimating the abundance of a migratory species. To address this issue, Oxenford (1986) examined the seasonality of the catch in various locations of the Caribbean and Oxenford and Hunte (1986) formulated a two stock hypothesis. In Oxenford's study, it was found that dolphinfish seemed to follow a northern route and a southern route. The northern stock was represented by higher catches off of the northern coast of Puerto Rico in January and February, off of the coast of North Carolina in June and July, and off of Bermuda in July and August. The southern stock was believed to be off the Windward Island chain in February and March, and off of the Virgin Islands in April and May. Both stocks were believed to follow a clockwise rotation. This proposed migration circuit has never been thoroughly re-examined with new spatial environmental data.

There have been other estimates of seasonality and peak catch rates that do corroborate the movement pattern described by Oxenford. Rose and Hassler (1968) made a survey of the recreational fleet in 1961 and 1962. They determined that dolphinfish were caught off the coast of North Carolina from early May to the end of September with a peak in June/July. Gentle (1977) found dolphinfish to be most abundant in Florida from March through August. In Puerto Rico dolphinfish are caught from January through March with a peak in February and March (Perez and Sadovy, 1996). Dolphinfish are caught in abundance first on the north coast and then later in the year on the south coast, and also in the Mona Passage on the west side of the island. They are generally not caught off the east coast over the Puerto Rico-Virgin Islands shelf (Rivera and Appeldoorn, 2000). Off the coast of Bermuda, 45-60% of landings are estimated to occur in the third quarter (June-Sept) (Luckhurst and Trott, 2000).

Additionally, landings since 1975 have not shown an increasing trend, but have oscillated within a smaller range with no clear trend (Luckhurst and Trott, 2000).

In spite of these data, it is impossible to say with certainty what the exact movements of the dolphinfish stock(s) are. While Oxenford does address this question with data from the northern and southern Caribbean, there are several caveats of the analysis that need to be addressed. First, the landings of dolphinfish in the Gulf of Mexico and western Caribbean were not examined to determine whether the dolphinfish in these regions are part of the migration proposed in the east. Secondly, there is evidence of catch data in locations that do not follow the path of the migration proposed by Oxenford. In the U.S. Virgin Islands, there are increases in catch rate in the spring in the southeast around St. Croix, and then higher catches are observed moving in the direction of St. Thomas-St. John (Rivera and Appeldoorn, 2000). These catch rates imply that the direction of movement is therefore from southeast to northwest—opposite to the direction proposed by Oxenford. In the Gulf of Mexico dolphinfish are caught from April to December, with peaks in May and August (Palko *et al.*, 1982). Additionally, there is no study that takes into account the Venezuelan fishery for dolphinfish. In Venezuela the majority (90%) of the landings take place between March and August with May and June as the peak months (Arocha *et al.*, 1999). This is a seasonal fishery with two different size groups arriving at different times. The first group of dolphinfish (>90 cm FL) arrive in March and mature by May and the second group (50-80 cm FL) arrives in July in the northeast region, moving westward to the central coast by the time they are ready to spawn in October. This contrasts with the proposal put forth by Oxenford because the majority of the Venezuelan catch is taken when the

“southern group” is purported to be moving north. In order to determine if there is westward movement of the stock, catch data from Colombia, Panama and Costa Rica would need to be examined. Colombia, particularly the area of San Andrés Island, may provide some insight to the question of westward movement because there is a small artisanal fleet that operates in this area (Martha Prada, *pers. comm.*). The dolphinfish fisheries of Costa Rica and Panama are primarily in the Pacific because these countries have reduced Exclusive Economic Zones (EEZs) in the Caribbean. Therefore in this region, there is not a significant collection of data.

Management Context

Until recently there has been very little management of dolphinfish. The 1994 FAO document addressing the management of highly migratory species notes that *Coryphaena hippurus* is included in Annex I of the 1982 Convention on the Law of the Sea which lists highly migratory pelagic species (FAO, 1994). In spite of this acknowledgement, the International Commission for the Conservation of Atlantic Tunas (ICCAT), which manages highly migratory species, does not specifically take responsibility for the management of Atlantic dolphinfish. Ironically, during the first meeting of the Commission, it was decided to create four panels for species that would be managed under ICCAT: 1) tropical tunas (yellowfin tuna and skipjack), 2) temperate tunas, north (northern bluefin tuna and northern albacore), 3) temperate tunas, south (southern bluefin tuna and southern albacore), and 4) other species (bigeye tuna, bonito, billfishes and others). Dolphinfish could theoretically fall into the fourth panel, but has not been included in this grouping due to the fact that the “other species” category is usually reserved for major bycatch species that are caught primarily in tuna fisheries such

as sharks (Restrepo, *pers. comm.*). In comparison, the Pacific version of ICCAT, the Inter-American Tropical Tuna Commission (IATTC), established by international convention in 1950 to conserve and manage fisheries for tunas and other species taken by tuna-fishing vessels in the eastern Pacific Ocean, recently established regulations that require the release of live dolphinfish that are caught in purse seines and have begun to identify areas of high dolphinfish bycatch in order to protect artisanal fisheries that are targeting dolphinfish (IATTC, 2005). Despite this, ICCAT has mandated no such regulations in the Atlantic. The two North Atlantic Fisheries Commissions: the Northeast Atlantic Fishery Council (NEAFC) which is advised by the International Council for the Exploration of the Sea (ICES), and the Northwest Atlantic Fisheries Organization (NAFO) do not include dolphinfish in their lists of managed species because they do not regulate any highly migratory species as defined by Annex I of the 1982 Convention on the Law of the Sea. The two FAO commissions, the Western Central Atlantic Fisheries Commission (WECAFC) and the Commission for the Eastern Central Atlantic Fisheries (CECAF), do include dolphinfish as a species of interest, but neither of these commissions deal with the actual management of fisheries as they were established by FAO as advisory bodies to FAO member countries. They can set guidelines, but cannot enforce regulations.

Within the entire Atlantic region however, there are two organizations that do manage dolphinfish. The General Fisheries Commission for the Mediterranean (GFCM), which is part of FAO, manages dolphinfish within the Mediterranean, the Black Sea and connecting waters. This area coincides with FAO Statistical Area 37. The only organization in the western Atlantic that includes dolphinfish in its list of managed

species is the Caribbean Regional Fisheries Mechanism (CRFM) which assessed dolphinfish species from catches recorded from the Caribbean Community (CARICOM) countries in early 2006 (Parker *et al.*, 2006). The findings were inconclusive due to the sparse data for the Caribbean countries. The report concluded that additional data from larger countries with more developed fisheries such as Venezuela could greatly benefit the results. Also, the simple surplus production model that was used in ASPIC gave highly uncertain results probably due to the complex spatio-temporal structure of the stocks.

Dolphinfish within the western Atlantic are managed by individual countries within their respective EEZs, and because of the size of its EEZ, the US manages dolphinfish over a large part of the study region. In this context, the recent approval in January 2003 of the Fishery Management Plan (FMP) for Dolphin and Wahoo in the Atlantic Region by the U.S. Secretary of Commerce (SAFMC, 2003) is particularly important. The management plan, developed by the South Atlantic Fisheries Council in conjunction with the Mid-Atlantic and New-England Fisheries Councils, sets limits on catches of dolphin and wahoo for commercial and recreational fishermen in federal waters along the entire Atlantic coast. The precautionary management plan also establishes a framework for long-term management of both dolphinfish and wahoo.

The benefit of the FMP is that it identifies several issues with dolphinfish and the need for regulation of this species. One of the main points highlighted by the FMP is that dolphinfish are not the direct target species for the commercial fisheries, though they are caught in significantly high numbers. Indeed they represent the fourth highest landed species of the US longline operations in the western Atlantic. This high fishing pressure

from the commercial fishery, in combination with the fishing pressure from the recreational fishery, may lead to localized reduction of fish abundance and subsequent disruption of markets. Additionally, dolphinfish are generally only one component of multispecies fisheries for large pelagics, and in most cases they are considered bycatch from these fisheries. Therefore, it is necessary, when evaluating fishing effort for dolphinfish, to understand trends in fishing effort for the large pelagic species being targeted. This is significant when one considers the shifts that were made by the U.S. longline fleet in targeting swordfish. As the numbers of swordfish declined, and moratoriums were enforced on the catch of swordfish, other species became more valuable, including dolphinfish. This is likely one of the possible causes of the increased landings of dolphinfish in recent years. Additionally, as other commercially important species are fished down, the commercial fleets shift fishing grounds to more productive areas. This has included a shift into shallower inshore shelf-break waters that are important for dolphinfish and have traditionally been the fishing grounds of the recreational fishery. Increasing fishing effort in these waters may have an adverse impact on stock levels, which in turn may lead to conflict and competition between recreational and commercial user groups of dolphinfish potentially leading to reduced social and economic benefits.

Regionally, other countries within the Caribbean have addressed the management of dolphinfish at the national level. The formulation and acceptance of formal FMPs is a relatively long process with many review and comment stages at both the national and stakeholder levels, leading to the final approval by the head of state. Many of the island

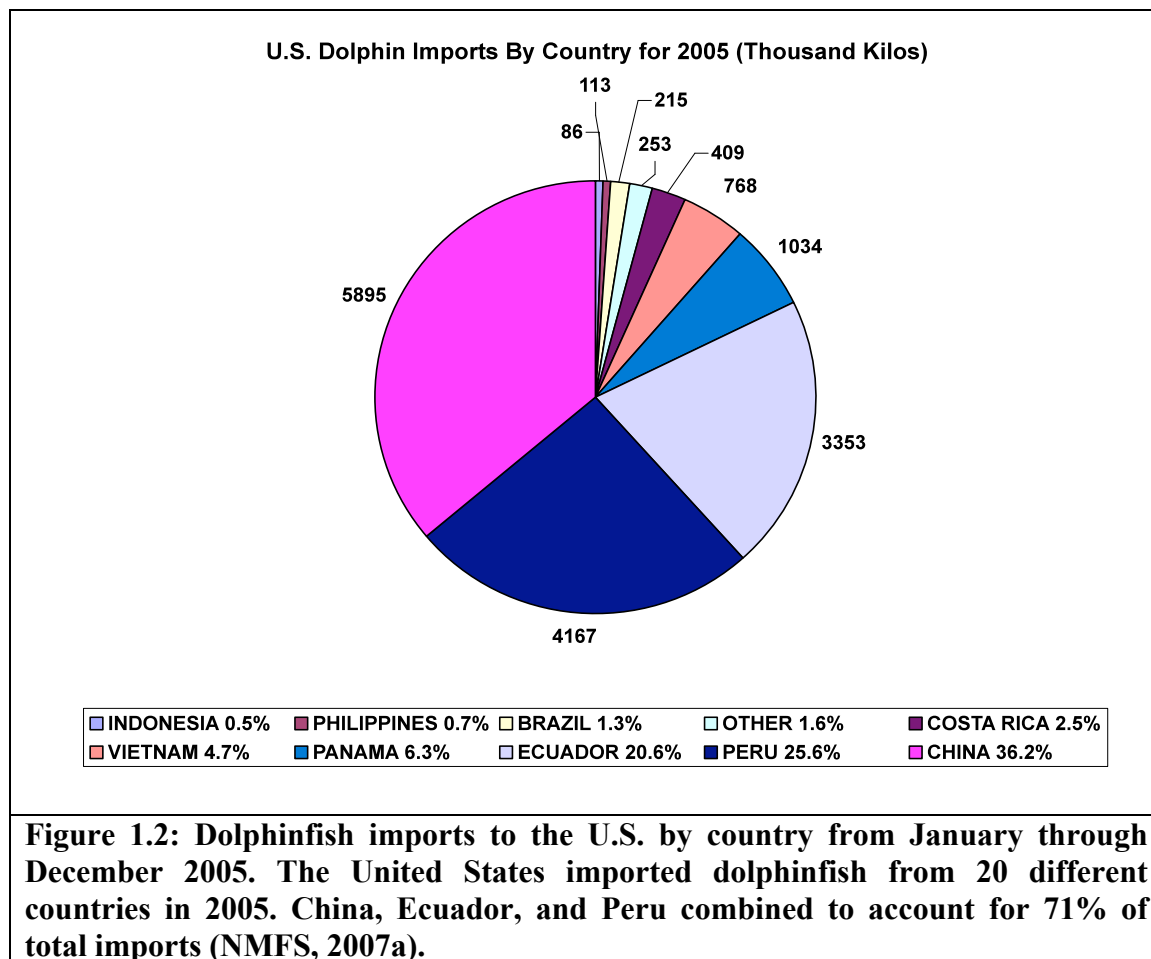
nations in the Caribbean either have finalized FMPs that have undergone this process, or are in the process of drafting their FMPs. Table 1.1 gives the status of each FMP.

Country	Remarks
Anguilla	Draft FMP sent to the Department of Fisheries and Marine Resources in 2005/2006 for review, comments and provision of data/information.
Antigua & Barbuda	Draft FMP sent to Fisheries Division in 2006 for review, comments and provision of data/information.
Guyana	Draft FMP revised after Final National Consultation in November 2006. Awaiting approval.
Montserrat	Draft FMP presented at National Consultation in 2006. Being revised.
St. Kitts and Nevis	Draft FMP sent to Fisheries Department for review, comments and provision of data/information.
St. Lucia	Draft FMP presented to National Consultation in 2006. Being revised.
St. Vincent & the Grenadines	Draft FMP sent to Fisheries Division in 2006 for review, comments, and provision of data/information.
Turks and Caicos Islands	Draft FMP accepted by the Ministry responsible for fisheries, but awaiting approval at the Cabinet level.
Barbados	Final FMP approved by the Ministry responsible for fisheries in 2006.

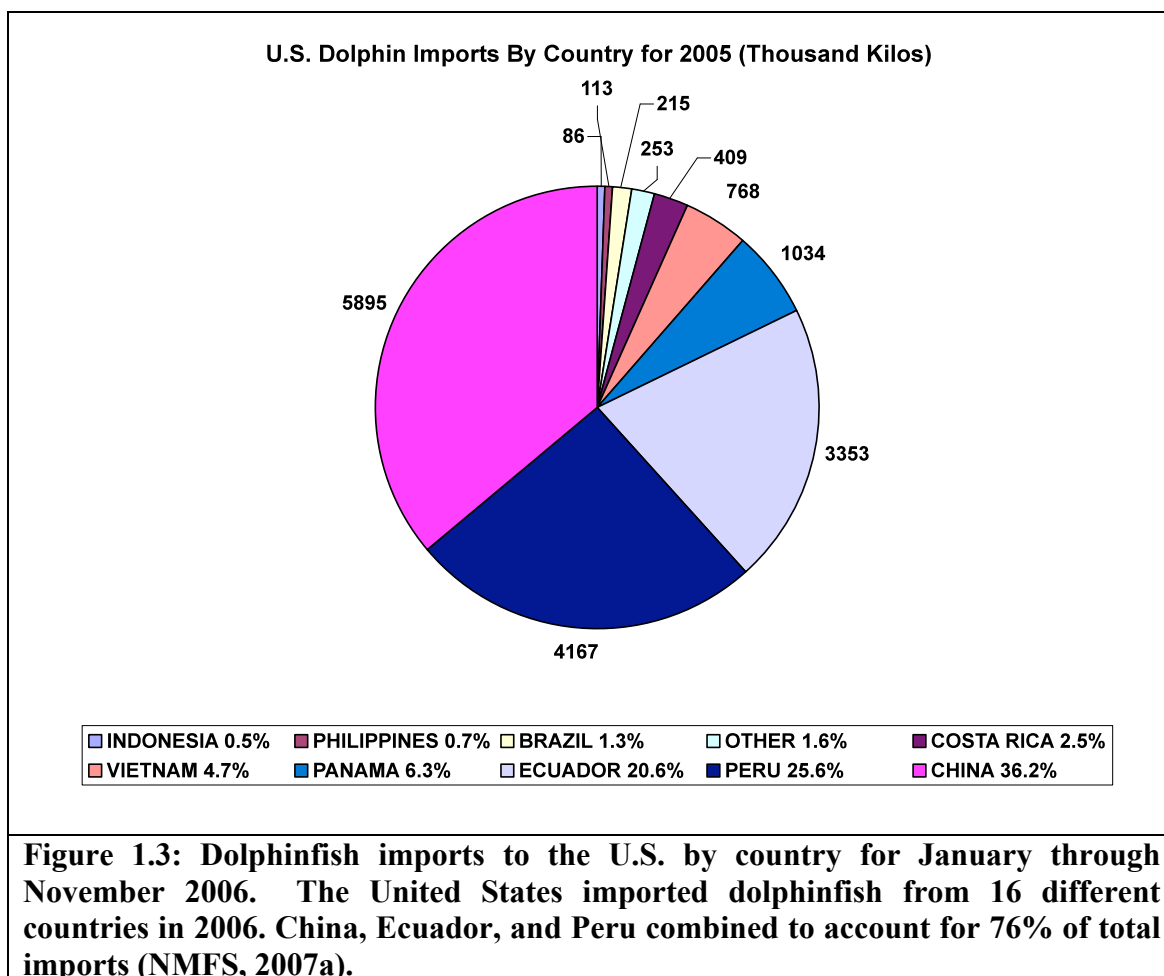
Table 1.1: Status of FMPs in the Caribbean.

Ecologically, the dolphinfish is an interesting species because it is not an apex predator, but rather a mid-trophic level species. They represent a prey base for the larger tunas and billfish, which as mentioned previously are economically very important. Additionally, they are voracious predators on numerous smaller species as well as juvenile stages of the tuna and billfish. Therefore, it is important to understand the predator/prey relationships that exist between dolphinfish and other pelagic species that are both above and below them in the predator food chain as these relationships are fundamental in clarifying the role of dolphinfish in the pelagic environment.

Dolphinfish represents an important import species for the U.S. seafood market. The U.S. demand for dolphinfish has likely increased the harvesting pressure on dolphinfish at the National and International level. In 2005, the U.S. imported 16,292,514 kg of dolphinfish. The greatest extent of the imports came from China, Ecuador, Peru, Panama, and Vietnam respectively (Figure 1.2) (NMFS, 2007b).



From January through November 2006, the U.S. imported 1,181,971 kilograms (Figure 1.3).



Given its seemingly central role in the ecosystem and the market, it is difficult to understand why the species has received such little attention from fisheries management. This lack of attention has also led to a dearth of biological, habitat, economic, and social information on dolphin stocks and fisheries.

Regional Dolphin Fisheries

The U.S. Fisheries—Recreational

In recent years, landings of dolphin from the Atlantic, Caribbean, and Gulf of Mexico waters have risen rapidly. In the U.S., recreational landings have increased gradually from about 4 million pounds annually to about 10-14 million pounds, whereas

commercial landings have increased also, with recent landings varying between approximately 600,000 and 1.4 million pounds (Figure 1.4) (NMFS, 2007c, d).

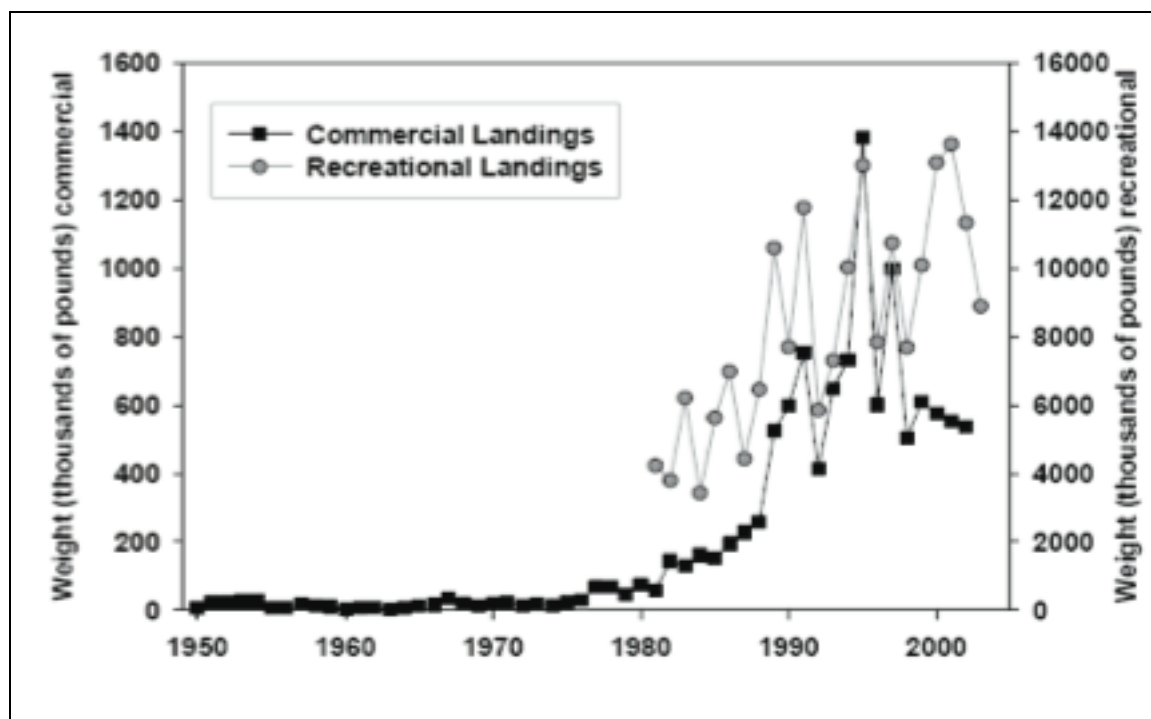
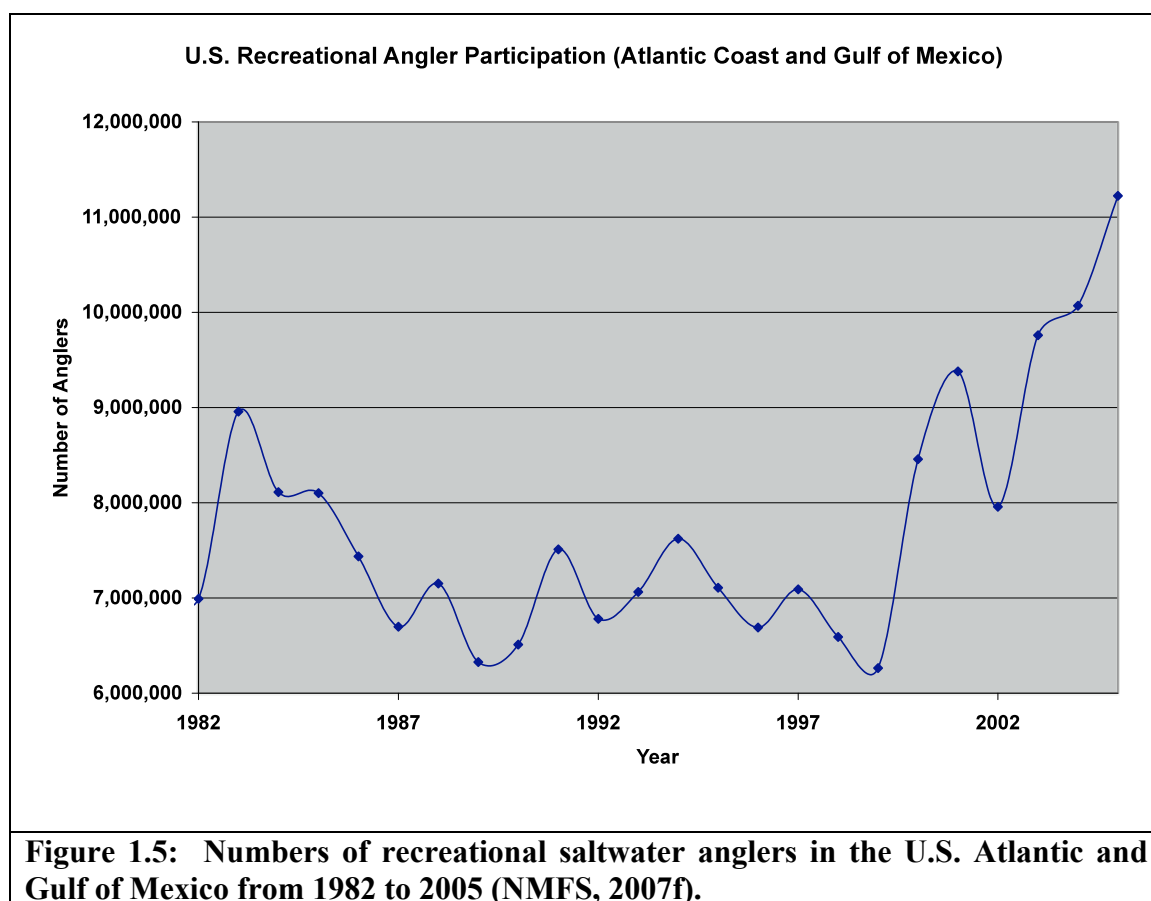


Figure 1.4: Annual landings of dolphinfish from the east coast of the United States. Annual commercial landings (on the left Y-axis) are in thousands of pounds from 1950 to 2002. Annual recreational landings (on the right Y-axis) are in thousands of pounds from 1981-2003. Data taken from the National Marine Fisheries Service (NMFS) marine recreational fishery statistics survey (MRFSS) and commercial landings data (NMFS, 2007 c, d).

Historically, recreational fisheries have caught the majority of dolphinfish in U.S. waters (roughly 87%), and it is not uncommon for sport fishermen to bring in buckets of small dolphin, or schoolies as they are commonly called, when the larger bulls and cows are not migrating through the area (Hammond, *pers. comm*). The recreational sportfishing fleet is composed of commercial and private sectors. The commercial recreational fleet is made up of for-hire charterboats (more expensive trips with up to 6 anglers onboard) and headboats (also called party boats, offering less expensive trips to more anglers). In total

there are now over ten million saltwater recreational anglers in the U.S., with the sport growing as much as 20 percent in the last ten years (Figure 1.5) (NMFS, 2007e).



This is compounded by the fact that dolphinfish catch by recreational anglers was unregulated until 2004, when the 10 dolphinfish per angler bag limit was enacted.

It is in response to this heavy catch by recreational fisheries that the Florida Fish and Wildlife Conservation Commission instituted new rules and limits for dolphinfish in early 2005, and emphasized the need for management of this species. These concerns have been raised in spite of the fact that dolphinfish are known to be very fast growing, and to mature early. These attributes are most likely an adaptive response of this fish to survive in a highly predatory environment where its main predators, billfish and tuna are

also voracious feeders with some of the highest recorded growth observed among fish species. Despite this, it is probably an unwise assumption to think that humans are unable to adversely affect this species when fishing pressure is increasing each year. It is hypothesized in this thesis that these levels of exploitation could result in localized depletion of stocks and a shift in the historical levels of catch between commercial and recreational fishers.

The U.S. Fisheries—Commercial

The primary commercial fleet in the Atlantic off the coast of the U.S. is the longline fishery. The U.S. pelagic longline (PLL) fleet fishes along the east coast of the U.S. from Nova Scotia to Florida and from Texas throughout the Gulf of Mexico into the Caribbean. The fleet is comprised of over 300 vessels ranging in size from 34 to 85 feet, and specifically targets highly migratory species. The fishery in the western Atlantic primarily targets swordfish and yellowfin tuna in the Gulf of Mexico, the northeastern Caribbean, and along the eastern U.S. seaboard in various seasons. Secondary target species include dolphinfish, bigeye tuna, albacore tuna, and sharks. There are several regional sectors to keep in mind when analyzing this data: The Gulf of Mexico yellowfin tuna sector, the Caribbean tuna and swordfish sector, the U.S. Atlantic distant-water swordfish sector, the Mid-Atlantic and New England swordfish and bigeye tuna sector, and the South Atlantic swordfish sector (Beerkircher *et al.*, 2004). The longline is typically set at different times of the day and depths depending on the target species. When swordfish is the target, the lines are generally deployed at sunset at shallower depths and hauled in at sunrise to take advantage of the nocturnal near-surface feeding habits of swordfish (Berkeley *et al.*, 1981). Conversely, when targeting tuna, the

longliners generally set the gear in the morning, deeper in the water column, and bring it in at dusk. With the exception of the vessels that are making distant, extended trips, the longliners preferentially target swordfish during full moon periods to take advantage of the species' tendency to spend increased amounts of time at the surface (Carey and Robison, 1981).

Data on landings and effort by the pelagic longline fleet are collected by NMFS in the form of logbooks. There is also a pelagic observer program (POP) that targets 8% coverage of the vessels based on the fishing effort of the fleet. The observers record fish species, length, weight, sex, location, and environmental information. This source of data is important because the spatial resolution is some of the best recorded for fishery dependent data. Other sources of commercial data include the Accumulated Landings System (ALS), which collects landings data in the form of monthly totals of the quantities landed and the value of the landings for each species, and the Trip Interview Program (TIP), which was developed to gather size frequency and age-at-length data. This program also provides CPUE data.

The Caribbean Fisheries

The dolphinfish fishery in the wider Caribbean is characterized by multiple gears which overlap in space and time. In the Caribbean, large pelagic species are exploited by the local artisanal and small-scale fisheries as well as large-scale commercial operations like the longline fisheries. Additionally, recreational sportfishing for large pelagics is an ever-increasing activity in many areas, often in connection with tourism (Mahon, 1991). Unfortunately, the status of the major commercial fish stocks are, in many cases, not known with much certainty because of a lack of historical, systematically collected data

on catch and effort, especially for recreational fisheries (Mahon, 1991, Mahon, 1999). The comprehensiveness of current data collection programs also varies from country to country. Because of this, definitive assessments of numbers and sustainable yields for the various Wider Caribbean fishery resources are not available. Vessels that fish for dolphinfish and other pelagics are usually targeting a variety of species, therefore, the numbers of vessels fishing do not accurately represent the amount of effort directed specifically at dolphinfish or even at large pelagics in general (Mahon, 1999). In spite of the difficulty in determining effort directed by these fisheries at dolphinfish, there are trends in eastern Caribbean fleets that are showing increasing effort for large pelagics including dolphinfish (Mahon, 1999). Large-scale commercial fishing fleets such as the U.S. longline fleet or the Venezuelan longline fleet have been fishing for large pelagics in the Caribbean region since the late 1950s. Since the 1970s, there have been purse seine and tuna pole and line vessels fishing the Caribbean waters as well. Unfortunately, with the exception of the U.S. and Venezuelan longline fleets, there has been a paucity of information regarding catches of dolphinfish by these fleets. A recent FAO report of large pelagic fisheries in CARICOM countries is the exception (Die, 2004).

Another potentially confounding factor is the fact that dolphinfish, like other pelagic migratory species have been seen by many Caribbean countries as a possible target of expanded fishing activities through the use of Floating Aggregation Devices (FADs). Many Caribbean countries have justified the movement towards FAD programs as a means of diversification of the regional or national fishing activity, and as a way to shift fishing pressures from areas that had been depleted of bottom fish resources (Reynal et al. 2000, Morales-Nin et al. 2000). This shift represents a significant change in the

exploitation patterns of pelagic fish, including dolphinfish. Several issues associated with the increased use of FADs by artisanal and commercial fisheries in the Caribbean have been identified. First, recruitment overfishing may pose a problem as fishing pressure on small pelagics increases around the FAD (Fonteneau et al. 2000). Secondly, FADs may change the ecology of pelagic species by altering migration routes, and growth and predation rates (Taquet et al., 2000; Marsac et al., 2000). This expansion of the fisheries to FAD fishing is partially fueled by subsidies from the European Union (EU)

This fishery presents complex management challenges in that information about the population is uncertain and management needs span across national and international jurisdictions. Dolphinfish are believed to be highly migratory, leading to variation in seasonal abundance. Also, dolphinfish may be more closely associated with the interface between the shelf regions and the pelagic environment than either billfish or tunas. Therefore, this species may exhibit more complex stock structure than the larger species, and pose a need for a comprehensive evaluation of the stock dynamics.

Synopsis of Fisheries Catch Data for the Study Area

In an angling survey of the Atlantic coast, U.S. Fish and Wildlife Service provided one of the first records of the catch of dolphinfish (Clark, 1962). In this survey, point estimates were made of the number of dolphinfish caught in the Mid-Atlantic, South Atlantic, and Gulf of Mexico. Although no confidence limits were placed around these estimates, dolphinfish was reported to be most abundant in the Gulf of Mexico, or at the very least most frequently caught in this area. In the Caribbean, trends in increasing catches of dolphinfish have been reported throughout the western-central

Atlantic region over the last 3 decades—1700 mt in 1970-1974 to around 2800 mt in 1989-1993 and 2829 mt in 1989-1993 (Mahon, 1999). Overall dolphinfish landings have shown an increasing trend from 1970 through 1992. This increase has been attributed mainly to increased landings by the U.S. However, an analysis of FAO reported landings of coastal pelagics, a group that includes dolphinfish, suggests that the actual landings may be double that which is reported to FAO due to uncertainty in the “unclassified species” categories (Die, 2004). Table 1.2 shows the annual landings from the longline and other fisheries by country. The catch by the U.S. has consistently been less than 15% except in 1990.

Country	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Antigua and Barbuda	4	7	7	10
Barbados	906	715	1,470	513	499	758	849	721	482	745	728	574	553	550	550
Brazil	1,700	1,738	1,710	1,710	1,720	3,186	2,500	4,028	4,117	2,848	4,359	4,326	4,956	7,266	6,393
British Virgin Islands	5	2	6	3	2	3	1	3	1	2	1
Costa Rica	-	-	-	-	-	-	-	-	-	-	-	-	<0.5	1	1
Cuba	-	-	-	-	-	-	5	362	.	591	386	335	416	331	339
Dominica	211	203	200
Dominican Republic	230	150	200	225	405	89	237	113	151	175	255	232	570	197	221
Grenada	137	154	157	103	124	182	130	171	153	162	167	221	178	130	164
Guadeloupe	700	640	640	650	650	700	730	800	670	670	700	700	700	700	700
Martinique	185	350	330	400	400	350	250	350	320	300	250	220	220	220	220
Mexico	12	20	39	49	175	88	244	871	1,078	376	308	315	350	319	340
Puerto Rico	83	111	74	53	52	57
Saint Kitts and Nevis	3	13	20	34	13	26	26	40	25	8
Saint Lucia	144	200	351	455	264	588	552	427	402	286	376
United States of America	718	945	506	496	620	980	739	763	322	555	498	411	389	381	380
Uruguay	3	4	1	2
US Virgin Islands	16	31
Venezuela, Boliv Rep of	50	191	208	244	274	447	.	.	.	290	141
Total	4638	4903	5260	4390	5016	6985	6054	8657	7593	7399	8482	7871	9050	10687	9993
% of U.S. catch regionally	0.15	0.19	0.10	0.11	0.12	0.14	0.12	0.09	0.04	0.08	0.06	0.05	0.04	0.04	0.04

Table 1.2: Annual Caribbean catch of dolphinfish by the U.S. and several other Caribbean nations by various effort sources.

Preliminary Assessments of Dolphinfinch to Date

The issue of stock is an important one when making a fishery assessment. The work by Oxenford and Hunte (1986) suggested two separate stocks. However, a study by Wingrove (2000) found that there was not significant mitochondrial DNA variation between dolphinfinch from different areas in the wider Caribbean, and therefore that the dolphinfinch in the western central Atlantic belonged to a single stock. It is important to note that in the case of separate stocks, minimal exchange could be sufficient to maintain genetic homogeneity. This is an area that has not been investigated by any genetic studies. However, no difference in growth was found around Puerto Rico by Rivera and Appeldoorn (2000) in an age and growth study and this further weakened the two stock hypothesis. Additionally, the period of peak availability of dolphinfinch to the artisanal fishery is not consistent with the northward migration of the southern stock as Oxenford suggested (Arocha *et al.*, 1999).

Prager (2000) made an initial assessment of what is purported to be the northern stock of western Atlantic dolphinfinch. This assessment was conducted exclusively from U.S. pelagic longline data for 1986-1997. In the assessment, he estimated that dolphinfinch was not overfished in 1998 because biomass was 150 percent of B_{MSY} . Similarly, Prager determined that fishing mortality in 1997 was 50 percent less than F_{MSY} and therefore dolphinfinch were not experiencing overfishing. The estimated MSY for this stock is 12,200 tons with an 80 percent confidence interval of 8,500~21,100. No decline in abundance is suggested by the CPUE indices. In fact, the biomass seems to have increased significantly from the late 1980s to the early 1990s. Prager acknowledged that these population indices are uncertain and may contain artifacts of the data that are

contributing to the apparent increase in abundance. This assessment did not evaluate the impact of the recreational fishery on the dolphinfish population, and according to this research, the mean size of dolphinfish caught has not declined historically although anecdotal evidence from local Miami anglers is to the contrary. The assumption of this assessment is also that the US longline catch is representative of all of the removals of the northern stock of western Atlantic dolphinfish. This is obviously not the case as removals by U.S. and Caribbean recreational anglers, Caribbean commercial fisheries, and fisheries of countries such as Venezuela represent a large portion of the removals.

Mahon and Oxenford (1999) chose a yield per recruit analysis to attempt to delineate benchmarks for Caribbean dolphinfish stock status. They concluded that life history traits, namely the rapid growth and short lifespan of this species, suggested that yield per recruit could be maximized at exploitation rates that would lead to spawning stock sizes that were too low to maintain the species. The conclusion was that yield per recruit analysis should not be used for dolphinfish due to uncertainty in the model.

Parker *et al.* (2000) assessed the dolphinfish stock in the eastern Caribbean with a combination of two types of length-based models (length-based catch curve and length-based virtual population analysis (VPA)). The results of this analysis suggested that fishing mortality is much greater than the fishing effort at MSY and that the harvest is above MSY. These results were deemed to be highly uncertain and dependent on growth parameters that were not well estimated (Die, 2004). The results of this research may also be skewed due to the fact that a separation in the population to create a northern and a southern stock is not well supported, and again, the assumption is that the analysis was

on a representative portion of the removals for the stock. Therefore, the high mortality may be attributed to a migration from the eastern Caribbean to other regions.

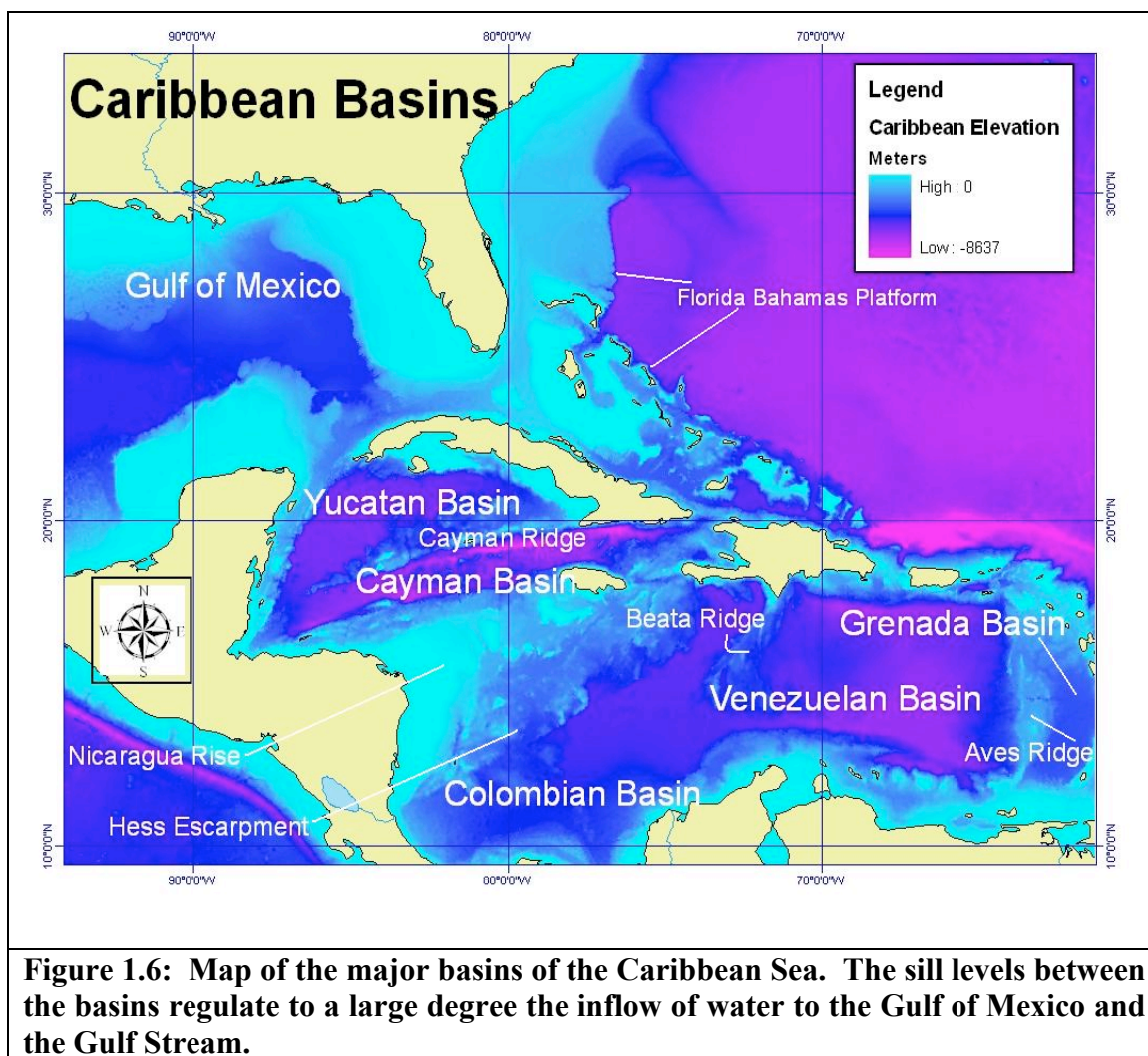
1.2 Oceanography

Regional Overview

The western Atlantic is characterized by a diverse and unique oceanography. This fact has been noted by researchers studying larval transport (Cowen *et al.*, 2003), connectivity (Cowen *et al.*, 2000), and movement of large pelagic species (Prince *et al.*, 2005). As oceanographic processes are essential in determining the distribution of pelagic fish, and to help develop accurate abundance indices for dolphinfish, it is appropriate to describe the oceanography of the study area in detail.

Caribbean Sea

The Caribbean Sea has 3 major parts: the eastern Caribbean north of Venezuela, the Cayman Sea in the west and the SW Caribbean Sea. In terms of topography, there are five major basins: (1) Grenada Basin lies between the Lesser Antilles Arc and Las Aves Ridge, (2) Venezuelan Basin lies between the Las Aves Ridge and Beata Ridges, (3) Colombian Basin lies between the Beata Ridge and the Central American Rise, (4) Cayman Basin lies between the Central American Rise and the Cayman Ridge, and (5) the Yucatan Basin lies between the Cayman Ridge and the Yucatan Strait where the Caribbean ends (Figure 1.6).



The climate of the region is regulated to a large degree by the position of the Intertropical Convergence Zone (ICTZ), an area of low pressure that forms where the Northeast Trade Winds meet the Southeast Trade Winds near the earth's equator creating a band of heavy precipitation (Holton *et al.*, 1971). It is due to this variation in rainfall that the water structure in the Caribbean Sea is highly stratified in the upper 1200 m. Below this depth, the water column is weakly stratified to 2000 m and nearly homogeneous below 2000m (Gordon, 1967).

It is important to note that there are two major rivers which have a considerable influence on the southern Caribbean: the Orinoco and the Amazon (Muller-Karger, 1993). These rivers are significant enough to cause changes in the salinity and the nutrient levels of the waters along the north coast of South America. In contrast to this, most of the Caribbean Islands in the Antilles chain are more affected by the inflow of the nutrient-poor North Equatorial Current, which enters the Caribbean between the eastern Antilles islands. This main current along with the outflow from the rivers influence the types of water present in the basins of the Caribbean. Within the various basins, Morrison and Nowlin (1982) identified the presence of several types of water masses. The first is Caribbean Surface Water, which is located in the upper 50-75m of water column and has a salinity of less than 35.5 ppt because of the presence of Amazon River water. Subtropical Underwater is characterized along the section by a salinity minimum found at 150-200m. The third, 18°C Sargasso Sea Water, is characterized by an upper level oxygen minimum within the Venezuelan Basin. Tropical Atlantic Central Water is characterized by its dissolved oxygen minimum at depths of 400-600 m. Antarctic Intermediate Water has a salinity minimum observed at depths of 600-900 m and a relative maximum of silicate, phosphate, and nitrate. And lastly, North Atlantic Deep Water is characterized by decreasing silicate to a minimum at 1600-1800 m. This water type is found only in the western Caribbean.

Surface circulation in the region consists of a general westward flow called the Caribbean Current. The majority of the water enters through the Lesser Antilles passages (<1200 m deep). The volume transport in this region can be broken up by area. The transport around eastern Venezuela is 26 Sv, Central Venezuela is 33 Sv, Colombia is 28

Sv, Colombia-Cayman-Yucatan is 33 Sv, Cayman-Yucatan is 36 Sv, and Yucatan Straits 28 Sv. This gives an average flow throughout the region of $31 \times 10^6 \text{ m}^3/\text{s}$, which is consistent with what is reported to leave the Caribbean through the FL Straits (Larsen *et al.*, 1985, Leaman *et al.*, 1989). There is intense flow (speeds approaching 80 cm/s) in the Grenada Passage, along the Colombian coast, south of the Nicaraguan Rise, and from the Yucatan Current south of the Yucatan Straits. These areas are likely to be areas containing higher numbers of large pelagic species due to the swift current.

The mesoscale variability and sea level fluctuations in the Caribbean have been related to “eddy waves” (Andrade and Barton, 2000; Carton and Chao, 1999) that may be continuously shed from the Northern Brazil retroflexion system, which is unstable. The sea level variability in the Caribbean rises from about 7cm in the east to 12cm in the west—decreasing to the north (Carton and Chao, 1999). The amplitude of these eddies generally grows as they progress westward. The majority of eddies have been found to spin down in the western Caribbean, near the coast of Nicaragua, before passing the Yucatan peninsula. The Caribbean supports strong eddy activity with about 7-17 month time scales and about 250 km spatial scales.

Loop Current

The Loop Current is a portion of the Gulf Stream that extends into the Gulf of Mexico in a horseshoe shape. The Loop Current is the main feature joining the Yucatan Current flowing along Belize and Mexico to the Florida Current (Watts, 1983). The Yucatan Current is an example of western boundary current intensification. This fact has been displayed by the dynamic height fields in Molinari (1977), which contribute directly to the strong upwelling frontal system (up to 1Sv) along the Yucatan coast (Olson, 2001).

There are two dominant and semi-permanent features of circulation in the Gulf of Mexico basin: (1) the Loop Current system in the eastern Gulf with a predominately annual cycle (Leiper *et al.*, 1970) and (2) the anticyclonic cell of circulation along the western boundary. The first feature has been described as a large, time-dependent intrusion of Caribbean waters into the Gulf, which remain distinct from the waters of the western Gulf due to differentiation of the thermocline depths due in part to temperature decreases in the winter and upwelling of the western boundary current (Nowlin and McLellan, 1967; Cochrane, 1972). The later phenomenon is illustrated by Ichiyes' 1962 hypothesis: In the east, anticyclonic rings separate from the Loop Current and travel west and break down along the western boundary. The decay of rings is expressed as a gradual flattening of the isotherms across the ring's radius in concert with a gradual shrinking of the radius (Nof, 1982; Hamilton *et al.*, 1999). The movement of the rings is proposed to be the primary mechanism for salt distribution throughout the basin and early numerical models suggested that variability in the Loop extension and ring formation are intrinsic in the dynamics of the frontal system in the Gulf (Hurlbert and Thompson, 1980). The flow from the Yucatan Strait penetrates northward into the Gulf to varying degrees before turning anticyclonically and exiting through the Straits of FL. The general patterns of the Loop Current are that there is an annual cycle of growth and decay of the Loop Current, the major exchange of heat, salt, and momentum from the current into the Gulf is made through the separation of an anticyclonic eddy or current ring, and circulation in the eastern Gulf of Mexico is associated with the annual cycle of mass transport (Maul, 1977; from observational studies). Currently, while the period of

oscillations is still believed to be roughly annual, there have been noted deviations from this pattern (Sturges, 1994; Sturges and Leben, 2000).

Vertically, the Loop Current front has three layers with two permanent thermoclines in the southern North Atlantic Subtropical Gyre (Schmitz and Richardson, 1991). Olson *et al.* (1984) proposed a three layer reduced-gravity model of the frontal region in order to predict frontal parameters. Applying the model to the Loop Current, the resulting radius of deformation (e-folding scale) for the front is 46 km. The upper thermocline itself has a smaller adjustment scale of 25 km in the layered model.

Gulf Stream and Florida Current

The Gulf Stream is a major western boundary current with the mean path of the stream along the east coast controlled by a combination of boundary shape, bottom topography, entrainment of a fluid from the gyre interior, and adjustment of the flow to increased vorticity as the fluid is advected northward (Olson *et al.*, 1983). The variability in the Gulf Stream is believed to have a strong climatic impact. A significant part of the meridional heat transfer is due to the gyre circulation and the Gulf Stream is associated with an intense heat loss that could fuel the atmospheric storm track. The variation in the Gulf Stream is related to: (1) wave-like fluctuations primarily associated with the Gulf Stream meandering and instability and (2) large-scale lateral shifts reflecting seasonal and interannual changes (Frankignoul, *et al.*, 2001). The use of a satellite altimeter to measure the sea surface height illustrated the prominent seasonal variability in the transport of the Gulf Stream with a maximum in late winter and early spring, and a minimum in late fall and early winter (Fu *et al.*, 1987). The path of the Gulf Stream tended to shift northward in the summer/fall when the current was weakest. In the FL

Straits, the transport increased from 29.6 Sv off of the Keys to approximately 53 Sv off of Cape Fear (Leaman *et al.*, 1989).

The exact cause of the Florida Current seasonal cycle is not well understood. Observational evidence suggests that the wind stress curl over the western Caribbean may force the seasonal cycle and the annual cycle is most affected by the wind stress curl over the topography of the NW Atlantic (Lee and Williams, 1988). Transport was considered to be barotropic because the increase in transport tended to be constant with depth. Also, the presence of a dominant NW wind causes an Ekman transport east, which establishes a westward barotropic pressure gradient that drives a northward geostrophic transport (Lee *et al.*, 1985). At the annual period, the western FL Straits contain all the variation whereas the east side (Bimini) shows almost no response.

The formation of the N. Atlantic Deepwater (NADW) in Greenland and Norwegian Sea leads to a thermohaline circulation that transports deep, cold water southward along the western margin of the Atlantic Basin, balanced by warm return flow in thermocline (Lee *et al.*, 1990). Observational evidence such as that derived from one year moored current measurements east of the Bahamas does not support the existence of a reversing boundary current (Schott and Zantopp, 1985). If a reversing circulation actually exists, Schott and Zantopp (1985) felt that it must be “a rather unfocused stream” with low speeds in midbasin instead of a boundary jet along the outer Bahamas.

Venezuelan Basin

The Cariaco Basin is a “small, east-west-trending pull-apart basin” (Schubert, 1982) located on the northern continental shelf of eastern Venezuela. The Cariaco Basin is actually two smaller subbasins, each having maximum depths of about 1400 meters.

The basins are separated by a central saddle that is about 900 m maximum depth. The Cariaco Basin is separated along its northern margin from the open Caribbean by the shallow Tortuga Bank that extends from Margarita Island west to Cabo Codera on the Venezuelan mainland. The exchange of deep waters with the rest of the Caribbean is limited by the surrounding topography and the shallow inlet sills (<146 m). This lack of circulation and the high primary productivity in the region create anoxic conditions below about 250 m (Muller-Karger *et al.*, 2001). A project called the CARIACO (CARbon Retention In A Colored Ocean) Program has studied the relationship between surface primary production, physical forcing variables like the wind, and the settling flux of particulate carbon in the Cariaco Basin. This project has found that annual primary production rates exceed 500 gC/m² of which over 15-20% can be accounted for by events lasting one month or less.

The upwelling of cold, nutrient-rich waters occurs seasonally along the northern Venezuelan coast in response to changes in the prevailing trade-wind field driven by the annual movement of the Intertropical Convergence Zone (ITCZ), an area of low pressure that forms where the Northeast Trade Winds meet the Southeast Trade Winds near the earth's equator (Muller-Karger and Aparicio-Castro, 1994). Between January and March, the ITCZ is south of the equator and strong trade winds in the tropical North Atlantic induce a slow Ekman drift to the west and northwest. The Ekman drift is significant because it helps to maintain the N. Brazil and Guyana Current systems that are part of the NW flow that enters the Caribbean basin through the southern Lesser Antilles channels. At the same time, there are strong winds along the northern coast of Venezuela that result in intense Ekman drift-induced upwelling. In the Cariaco Basin, this vertical advection is

generally most active during January and February, with isotherms raised by as much as 175 m and sea-surface temperatures (SSTs) recorded as cool as 22°C (Herrera and Febres-Ortega, 1975). Regionally, the upwelling season is also the dry season because the ITCZ, along with its associated low pressure and rainfall, lies at its southernmost position.

In about June or July, the ITCZ moves north to a position near the Venezuelan coast, the trade winds diminish and the coastal upwelling weakens. Sea-surface temperatures over the Cariaco Basin typically warm to 27°-28°C. The northward motion of the ITCZ triggers the rainy season north of ~5°N (Hastenrath, 1990), which has a strong influence on sea-surface salinity in the western tropical Atlantic and southern Caribbean through the discharge of the Amazon and Orinoco Rivers, as well as the smaller local rivers that drain directly into the Cariaco Basin (Dessier and Donguy, 1994). This region is important biologically because the strong upwelling provides a forage base for higher trophic levels. This is evidenced by the fact that the area is important economically for the artisanal commercial longline fishery of billfish and other large pelagics.

The Guiana-Brazil Basin

In the Brazil Basin, three major water masses are found beneath the permanent thermocline: the relatively cool, fresh, and oxygen-poor Antarctic Intermediate Water (AAIW) formed in the Southern Ocean, the warm, salty, well-oxygenated North Atlantic Deep Water (NADW) derived from the North Atlantic and the Arctic seas, and the colder, fresher, oxygen-poorer Antarctic Bottom Water (AABW) formed around Antarctica. There is a strong vertical temperature gradient and a deep thermocline in this

region which inhibits the movement of the nutrients and salts from these waters to the euphotic zone (Hazin, 1993). However, while the tropical Atlantic is predominantly oligotrophic, this region has localized areas of high biological primary productivity due to several oceanographic phenomena. A primary source, the Amazon River outflow, discharges large quantities of nutrients into the basin. Additionally, the North Brazil Current retroflexion produces anticyclonic eddies and upwellings around 6°N and 8°N (Didden and Schott, 1993). Upwelling in the region can also be attributed to the interaction of local currents with subterranean features of the basin (Trevassos *et al.*, 1999). In general, the bottom topography is characterized by abyssal plains, but near to the coast, there are islands and rocks, which produce upwelling regions and locally increased primary production. Because of these features and the enhanced production that they induce, a significant fishery for pelagic species is found in these areas.

There are two main surface currents in this area: the North Brazil Current (BC) and the Guiana Current (GC). The NBC is a warm western boundary current that brings warm water northward along the coast of Brazil and into the northern hemisphere. The NBC produces large anticyclonic rings (greater than 450 km/270 miles in diameter and 2,000 m/6,600 ft in vertical extent) that are carried northwest parallel to the South American coast until they collide with the Lesser Antilles islands (Fratantoni *et al.*, 1995; Bischof *et al.*, 2003). The shedding of these rings one of the methods of transport of South Atlantic surface water, including nutrient- and sediment-rich Amazon and Orinoco River discharge, into the North Atlantic (Johns *et al.*, 1998). On average, six NBC rings are generated annually and are responsible for up to a third of the

equatorial/subtropical mass and heat transport that is derived from the Atlantic meridional overturning circulation (Frantantoni *et al.*, 1995).

The NBC diverges as it reaches the coast of French Guiana. At this point, part of the current separates and joins the North Equatorial Current. The rest of the flow continues northwestward to form the Guiana Current (Bischof *et al.*, 2003) and the main flow enters the Caribbean Sea between the coast of South America and Grenada and the Lesser Antilles. The flow entering through these passages is about 10 Sv in strength, and represents about 70% of the total water volume flowing into the Caribbean (Johns *et al.*, 1990).

The ITCZ is one of the most important forcing mechanisms in the region. Associated with the ITCZ are atmospheric surface low pressures, low winds, strong cloud cover, and heavy precipitation—conditions which create a strong seasonal cycle in the atmosphere and oceanography of the region. There is a reduction in the strength of the winds along the Guiana Coast when the ITCZ shifts to its northern position. This corresponds to a general weakening of the Guiana Current in the fall.

Sargasso Sea

The Sargasso Sea is, geographically, the center of the North Atlantic Ocean. It is located between 20° and 35°N and 30° and 70°W. This is a special region of the ocean because it is a relatively slow moving body of water arising from the subtropical gyre circulation in the North Atlantic, surrounded by the fast moving currents of the Florida Straits and the Gulf Stream in the west, the Canary Current in the east, and the North Equatorial, Antilles, and Caribbean Currents in the south and south west. The circulation of the gyre drives Ekman downwelling in the central area (McClain and Firestone, 1993),

and there is a slow, geostrophic recirculation of water from the northeast toward the southwest (Worthington, 1976). These strong currents separate the Sargasso Sea from the rest of the Atlantic, giving this region some unique characteristics. In particular, the waters of the Sargasso Sea are generally warmer and higher in salt content than other parts of the North Atlantic. The waters are clearer and generally were considered to be lower in productivity with the exception of the floating mats of *Sargassum* for which the sea is named (Ryther and Menzel, 1960). Contrary to this view of the Sargasso Sea as a desert-like region in terms of biodiversity, current research has shown that new production in this area is primarily sustained by nitrogen injection via mesoscale eddies and winter convection (Steinberg *et al.*, 2000; Lipschultz *et al.*, 2002).

The Sargasso Sea is often considered to be two regions. In the northwest, 18°C subtropical mode water forms in the winter due to convective mixing. This convection brings nutrients to the surface layer (stratification) thereby stabilizing the water column. The 18°C subtropical mode water then subducts under the seasonal mixed layer and the summer months in this region are characterized by oligotrophic waters (Worthington, 1976). In contrast, the southern, tropical Sargasso Sea is stratified and oligotrophic throughout the year.

Importance of Fronts

One of the factors which make the dynamics of the open ocean more complicated is the frequent occurrence of fronts. These are regions with enhanced horizontal gradients of hydrographic properties. According to Federov (1983), fronts are “vertically inclined interfaces between water masses.” Fronts in the ocean or in the atmosphere can be defined as regions where properties change markedly over a relatively short distance.

How short this distance is depends on the scale of the process responsible for the front's existence (i.e. coastal upwelling, eddy formation, major current regions like the Gulf Stream). Regardless of the process, the change of some hydrographic property—temperature, salinity or both—across the width of the front is an order of magnitude larger than changes of the same property over the same distance on either side of the front. Frontal dynamics are often nonlinear, which makes the quantitative study of frontal behavior a difficult task. Understanding the formation, movement and persistence of frontal systems is important for many practical oceanographic studies.

Frontogenesis, or the creation of fronts, occurs when there is horizontal convergence associated with baroclinic instability (Cushman-Roisin, 1981; Spall, 1995). This creates horizontal shear, which acts upon the density field causing forced vertical motions (i.e. Ekman upwelling, inertial adjustment). Also associated with this process is differential vertical mixing along tidal fronts (Humston *et al.*, 2004). Intense biological activity is usually associated with fronts because the convergence of different water masses concentrates a narrow band at the surface of phytoplankton and zooplankton in the subducting water mass, leading to aggregations of predators and to increased secondary production (Olson, 2002). Vertical diurnal migration of midwater micronekton occurs at night, with most of the biomass accumulating above the thermocline, creating intense vertical patchiness in addition to the horizontal patchiness at the surface convergence. This enhanced biological productivity is one of the main reasons why the longline fleet concentrates its efforts in frontal areas. One of the key features of the U.S. and Venezuelan Observer program data is that there is excellent spatial and temporal resolution. The area in which the U.S. longline fishes is extremely

dynamic and is comprised of several areas exhibiting complex physical regimes and circulation patterns. The main areas of interest are the Gulf Stream, the Loop Current, and the Venezuelan upwelling region. These areas are indicated in Figure 1.7 which displays SST in the region from the AVHRR satellite. The CPUE of dolphinfish by the U.S. and Venezuelan longline observer programs is displayed on the map illustrating that the fishing locations of both fleets are predominantly located in frontal regions.

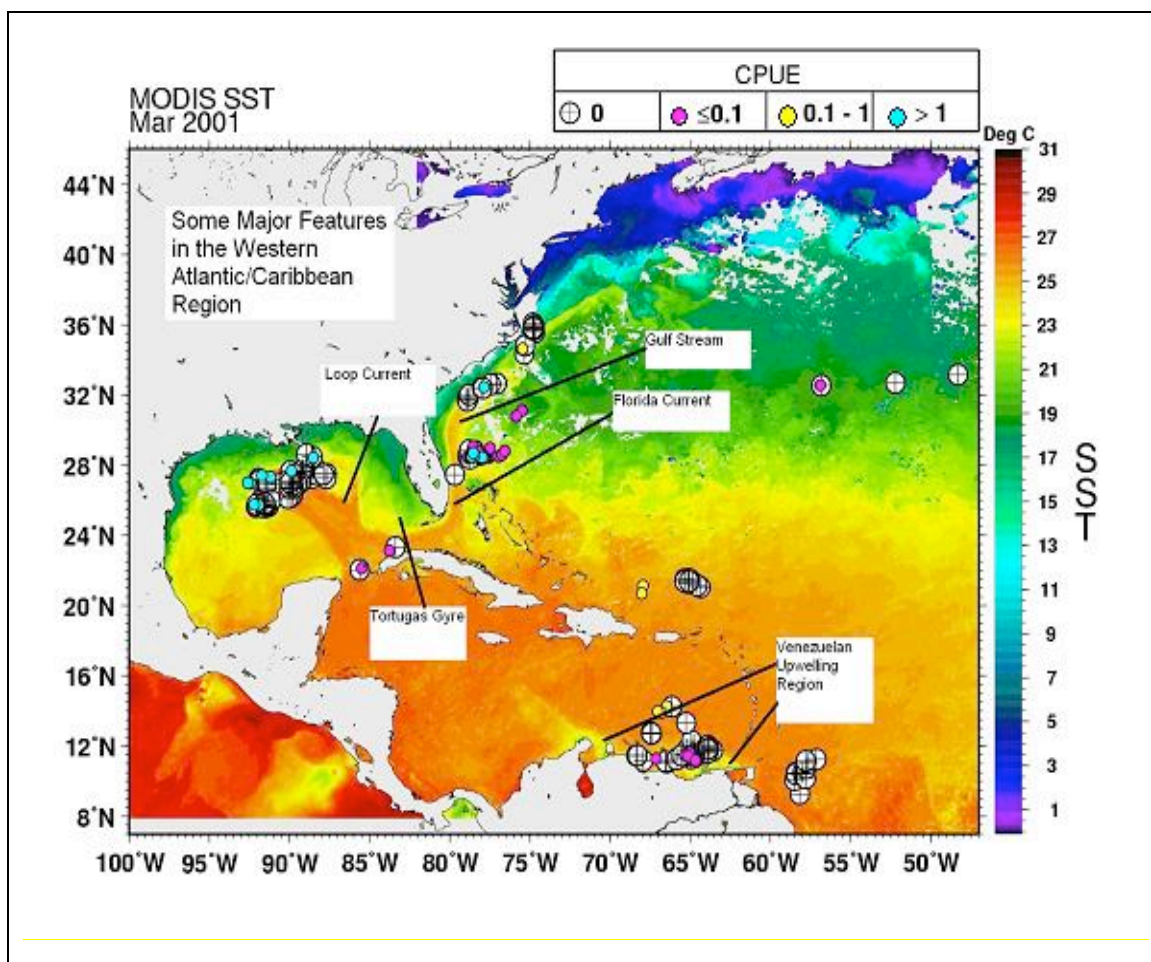


Figure 1.7: Map of the SST from the MODIS satellite in March 2001. Major frontal features of the western Atlantic are distinguishable from the temperature gradients. White circles containing crosses represent zero CPUE of dolphinfish. Pink, yellow, and blue circles represent increasing CPUE of dolphinfish respectively. Note the presence of fishing in the proximity of frontal features.

1.3 Estimation of Abundance and Modeling Approach

Overview

One of the major research efforts in fisheries today is the determination of the distribution, abundance, and population trends of marine fish species. In particular, an emphasis of this work is on fish stocks that are affected by fishing activities. Unfortunately, we face two substantial challenges when inferring abundance from catch rates from pelagic fisheries (Stephens and MacCall, 2004). First, the open ocean is prohibitively large to allow for a cost-effective fishery-independent survey. As a result, we have to rely on catch rates from the commercial and recreational fisheries, which are not fishing in a random fashion. Second, many factors may influence the distribution of a pelagic, highly migratory species whose abundance changes in time and space with production and movement. For highly mobile species in dynamic environments, such as the dolphinfish, the variability in natural systems may induce migratory behavior as a species attempts to remain in suitable habitat for locating prey, reproduction, reducing competition and avoidance of predators, or to maintain a high level of production (i.e. optimal temperature regimes). This movement can create biases in observed patterns and can make it very difficult to detect trends in abundance and also to interpret what observed trends are actually indicating because abundance estimates for a fixed region may be based on a different proportion of the population at each time. For example, dolphinfish is migratory throughout the western Atlantic and Caribbean, and this can cause a shift in the distribution of the dolphinfish throughout the region. This adds variability and reduces the statistical power of any models used to detect trends. In spite of these limitations, this source of data does provide a means of understanding the

patterns and trends in species abundance and distribution, and the main question with this type of data is how to explain the variability in the dataset in relation to a set of explanatory variables.

CPUE data have often been utilized to obtain a relative index of abundance of a fish stock. CPUE is usually assumed to be proportional to abundance and is therefore included in a stock assessment as a relative index of abundance. The nominal or observed CPUEs are affected by changes of year, season, area in which fishing occurs, and many environmental factors. It is important therefore that these types of factors which influence CPUEs be removed from the index. There are many statistical methods available to “standardize” these indices to account for variations that occur because of these types of factors. Examples of these include the Generalized Linear Model (GLM), the Generalized Additive Model (GAM), neural networks (NN), regression tree analyses (RTAs), and many others (Maunder and Punt, 2004; Stone, 1985; Hastie and Tibshirani, 1990; Bellman, 1965). Of these methods, the GLM is the most commonly used. The GLM assumes that the conditional mean is a linear function. The GAM relaxes this constraint by expressing the observations as a sum of non-parametric, nonlinear functions on the kinematic parameters. In this study we consider GLM methods and a geostatistical approach (which will be presented in Chapters 3 and 4) to index formulation.

Generalized Linear Models

GLMs are commonly used to standardize abundance estimates. These models are preferred by stock assessment scientists because they are well understood, and have accepted methods to statistically choose the factors or variables in the model that explain

the most variance. They linearly quantify the relationship between several independent or predictor variables (i.e. temporal, spatial, vessel, or environmental effects) and a dependent or response variable such as CPUE. A stepwise procedure is often used to determine which factors to include based on the degree to which each factor improves the fit of the model to the data (Derksen and Keselman, 1992). The major disadvantage of this method is that it is limited to describing linear relationships. Complexity can be added to these relationships by adding higher order terms or interaction (XY) terms. However, it is still a drawback that they describe linear relationships when many of the factors affecting abundance are non-linear.

It is common practice when using a GLM to group continuous variables into intervals (i.e. daily data into months, or group data into areas). This is done to provide indicators for nonlinear relationships, to account for the limiting effect of degrees of freedom in the model (Hocking, 1976; Cook, 1979, Neter *et al.*, 1990), and to reduce problems that arise due to large numbers of zeros in the data. A dataset with many zeros is one issue that arises when there is effort in an area at a certain time of year, and no catch of the species under study. The delta-lognormal method is generally a favored method to account for strata with positive effort and no catch. This method models zero catches separately and then models the positive catches using a GLM. These two models are then combined to generate the index of abundance.

A different, but related issue is that it may be difficult to resolve the variables in a stepwise factor selection even when the variables are categorized. It is a common occurrence that some factors and interactions may be deemed a significant reduction of the variability of the model, but will not be able to be included in the model due to

constraints on the Hessian matrix (Golub and VanLoan, 1989). This can be a common occurrence when the covariance parameters are on a different scale. A non-positive definite Hessian matrix can indicate a surface saddlepoint or linear dependencies among the parameters (Golub and VanLoan, 1989). Additionally, the classification of variables is in a sense a smoothing of the data, and it is expected that some important variability will be lost that may be important in detecting abundance trends.

Bayesian Surplus Production Model

A simple surplus production model, or biomass dynamic model, is the most common choice for stock assessment when there is a lack of age structured data (Hilborn and Walters, 1992). These models fit a trend to catch and relative abundance time series. In a Bayesian surplus production model, prior information can quantitatively be incorporated, with the posterior distributions directly reflecting the prior assumptions (Punt and Hilborn, 1997). One of the main draws of a Bayesian model is the ability to infer parameters of interest that have a relationship to observed data and background information on the parameter (Gelman *et al.*, 1995). The prior can be input to the model through the use of a probability density function (PDF). An informative prior for r was developed by assessing the likelihood that the given species would have an r parameter similar to the r parameter of other species with similar life histories (Babcock and McAllister, 2003). The key to this technique is the ability to estimate r from the slope of the stock-recruitment relationship (Myers *et al.*, 1997; Myers *et al.*, 1999). This methodology will be described in detail in Chapter 5. Models for both dolphinfish and swordfish were developed to test whether the incorporation of spatially or non-spatially explicit indices of abundance gave statistically different model results. Specifically, the

interest was to see if the estimates of biomass, maximum sustainable yield (MSY), and other measures of productivity from each of the models would lead a stock assessment scientist to a different conclusion about the status of the stock.

1.4 Aims and Objectives of Dissertation

Overview

The main goal of this research is to provide a scientific basis to improve the knowledge of the status of the stock or stocks of dolphinfish in the wider Caribbean and western Atlantic. This research aims to use spatial fisheries information and environmental data to assess the status of dolphinfish in the western Atlantic by identifying physical oceanographic features that may define higher abundance of the species. This work will demonstrate that environmental variables play a role in affecting dolphinfish CPUE and will be important in the standardization procedures for indices of abundance. These indices will form the basis of a Bayesian surplus production model that will incorporate environmental influences through indices of abundance that are standardized with environmental information.

One approach will be to identify and classify the pelagic habitat that the species occupies more thoroughly than has been previously attempted using oceanographic products derived from satellite data. These types of information (sea surface temperature and distance to nearest front) will be used to identify and define quantitative relationships between the distribution of fish and their ecosystems using multivariate techniques such as detrended correspondence analysis (DCA), principal components analysis (PCA) and simple population models. By identifying environmental attributes, gear configurations, and significant species assemblages that account for high dolphinfish CPUE, these factors

can be added to a GLM or GAM model to construct more robust indices of abundance. Additionally, addressing spatial autocorrelation within the catch rates will also lead to better indices of abundance. These indices will form the cornerstone of a simple stock assessment model. Several questions will be addressed in this thesis:

- 1) What gear configurations and species assemblages are important for dolphinfish CPUEs?
- 2) What physical oceanographic features specifically define the habitat of dolphinfish? Are certain oceanographic and circulation features more important as descriptors of habitat than others?
- 3) Can spatial autocorrelation be quantified in catch rates and be introduced a priori to a simple stock assessment model by incorporation into the indices of abundance?
- 4) What is the type and quality of information necessary to conduct a sound assessment of dolphinfish?

General Objectives

- 1) To analyze and select environmental parameters, gear configurations, and species assemblages which define the pelagic habitat of dolphinfish using multivariate techniques;
- 2) To couple the oceanographic multivariate analysis with fishery information to develop a functional understanding of the spatial and temporal occupation and movement tendencies of dolphinfish through a simple stock assessment model;
- 3) To construct indices of abundance that incorporate environmental data and explicit spatial data to be used in a stock assessment model;

- 4) To estimate priors using demographic methods that incorporate information about similar species for biological parameters such as r , the intrinsic rate of growth of a species, for use in a Bayesian surplus production model;
- 5) To qualitatively analyze the difference between the productivity parameters of the Bayesian surplus production model when a spatial and a non-spatial index are used.

General Hypothesis

H₀: Dolphinfinch is a highly migratory pelagic species that will benefit from stock assessments that take into consideration their environment, significant species assemblages, and gear configurations. Multivariate techniques should reveal patterns within complex environmental data that would not be apparent otherwise, and this can enhance indices of abundance by corroborating the use of this type of data in their formulation. Additionally, spatial variability may be accounted for and incorporated into an index of abundance.

Specific Hypotheses

H₀₁: There will be no significant environmental variables, gear configurations, and species assemblages found with multivariate analyses.

H_{A1}: Multivariate analyses will highlight specific environmental variables, gear configurations, and species assemblages that are important to dolphinfinch.

H₀₂: There will be no difference in the trend between a traditional GLM standardized index of abundance and a geostatistical index that accounts for spatial variability.

H_{A2}: An index of abundance for a pelagic species may be enhanced when spatial autocorrelation is accounted for. The differences between the indices may be increased

when the level of spatial autocorrelation is significant (i.e., the species displays a long range of spatial autocorrelation).

H₀₃: Dolphinfish can be assessed with a simple surplus production stock assessment that does not incorporate spatial information.

H_{A3}: Dolphinfish can be assessed with a simple surplus production stock assessment model that incorporates a priori spatial information within catch rate indices.

CHAPTER 2: TOWARDS AN UNDERSTANDING OF DOLPHINFISH ABUNDANCE: A MULTIVARIATE ANALYSIS OF THE RELATIONSHIPS BETWEEN ENVIRONMENTAL VARIABLES AND SPECIES ASSOCIATIONS FROM THE U.S. PELAGIC LONGLINE FLEET.

2.1 Challenges of Assessing Dolphinfinh

Estimation of abundance is a cornerstone of fisheries stock assessments (Hilborn and Walters, 1990). Trends in population abundance are nearly essential in exploring how fishing mortality has affected fish stocks (Maunder, 2001; Maunder and Punt, 2004). Yet estimating abundance can be challenging, particularly for highly migratory species such as the dolphinfinh, *Coryphaena hippurus* (common) and *C. equiselis* (pompano). These species are not conducive to cost-effective fishery-independent surveys, which would use stratified random sampling to assure catch rates were representative of the action of the stock (Stephens and MacCall, 2004). As a result, abundance trends must be gleaned from catch rates in the fishery, where fishing activity is anything but random. To complicate matters further, variability in the natural environment may induce variation in migratory behavior. This may be due to attempts to remain in suitable habitat for locating prey, reproductive requirements, the need to reduce competition and avoid predators, or the maintenance of a high level of production (i.e. optimal temperature regimes) (Palko *et al.*, 1982; Oxenford, 1999). It is especially important to standardize catch rate data for highly migratory species because of the potential for biases in observed patterns, which can make it difficult to detect trends in abundance and also to interpret what the observed trends are actually indicating (Campbell, 2004).

Traditional stock assessment techniques often assume that stocks and fishing operations are spatially and temporally homogeneous. This is a pattern that does not hold true for most fisheries, especially for those that target highly migratory species. In spite of these limitations, fishery dependent data does provide a means of understanding the patterns and trends in species abundance and distribution, and the main question with this type of data is how to explain the variability in the dataset in relation to a set of explanatory variables.

Typically, a modest set of factors is available for standardization of catch rates. At worst, minimal data are self-reported by fishing crews and are limited to dates, roughly specified locations, and a few descriptors of the fishing methods and duration. We do better with highly migratory species in the western Atlantic, where pelagic observer programs have been in place in the U.S. and in Venezuela since 1992. Through these programs, independent observers collect precise information on timing, location, gear configuration, and even intended target species. Though the motivation for observer programs is often concern about bycatch of protected species, these data dramatically improve our ability to characterize effort and, to some degree, to standardize catch rates. Consequently, they allow us to estimate abundance using something that more closely approximates a stratified random sampling regimen.

When attempting to determine abundance or distribution patterns from fishery dependent data, it is typical to use a form of regression where CPUE is the dependent variable which is defined by several explanatory variables. A common model choice is a linear model with a stepwise selection of factors to standardize CPUE against the variables of interest. When dealing with models other than orthogonal, linear Gaussian

models, the order in which parameters are added or dropped from the model can have a large impact on the final model, meaning that some variables of interest may be dropped from the final model and important relationships may be ignored (Miller 2002). Conversely, if the majority of the factors are kept in the model, supplemental analyses will likely be required to understand complex interactions.

A PCA is a useful way to understand the significant correlations and importance of the variables because it reduces and orthogonalizes the original variables (Legendre and Legendre 1998). The focus of this chapter is on the understanding of the use of the commercial pelagic longline fishery data to determine an abundance index for dolphinfish and on understanding the relationship of dolphinfish to other species caught by the longline. The goal is to test the applicability of environmental and fisheries-based indices as a measure of the variation in the abundance of dolphinfish, *Coryphaena hippurus*.

To date, little oceanographic research has been conducted with regards to dolphinfish fisheries in the western Atlantic. There are several key oceanographic processes that may influence the movement of dolphinfish. These include SST ranges, chlorophyll, salinity, bottom depth or topography, prevailing currents in the area in which the dolphinfish is caught, and proximity to thermal fronts. It is well known that many fish species are associated with frontal boundaries in the ocean (Olson, 2001). These areas are prime locations for catching fish because of the tendency for prey to be aggregated by dominant current regimes. In fact, many longliners use *in situ* water temperatures and satellite-derived SST to focus effort along thermal fronts (Podesta *et al.*, 1993). Without satellite-derived data, it would be impossible to adequately account for

the increased ability of longline vessels to find and fish fronts when standardizing catch rates.

Because of the likelihood of interdependence of these factors, a multidisciplinary approach is needed to tease apart the relative importance of each of the factors influencing dolphinfish CPUE. This analysis aims to evaluate the usefulness of oceanographic data for this purpose and explores a further refinement in abundance indices by linking the time and location reported by observers with remotely sensed environmental data collected by government satellite programs. Though the observer program collects some information on environmental conditions, the satellite data provide more accurate and consistent measurements of ocean temperatures, and allows for examination of the neighborhood to identify such phenomena as ocean fronts. The hypothesis that these data improve standardization and, in doing so, increase confidence in the estimates of abundance as measured through catch rates is explicitly tested in this chapter.

Description of the Longline Fishery

Dolphinfish is a species of great importance in both commercial and recreational fleets of the western Atlantic. Both *C. equiselis* and the more common *C. hippurus* are caught by the U.S. and Venezuelan longliners, however, the catch of this animal is identified only to species level. Therefore, dolphinfish in this dissertation will refer to the undifferentiated catch of both types of dolphinfish. The fleets operate in overlapping realms.

The U.S. fleet fishes the entire western Atlantic from the equator to the Grand Banks, at about 50°N latitude, with the majority of the effort concentrated above 20°N

latitude (see Figure 1.1). The vessels range in size from 35 feet to 90 feet and trips typically last 2-45 days. The Pelagic Longline Observer Program (PLOP) at the National Marine Fisheries Service (NMFS) Southeast Laboratory in Miami began in May of 1992. This program provides unusually high quality data because total catches (including discards) are recorded for every set, along with precise location, timing, gear configuration, intended target species, and some vessel-derived environmental information. The observer corps is invaluable in monitoring about 70-75% of the longline vessel trips, and observes the catch from about 500 longline sets per year. This is no small task as the distance of a longline set can range from 10 to 50 miles with 200 to 1000 hooks per set. The fishery in the western Atlantic primarily targets swordfish, *Xiphias gladius*, and yellowfin tuna, *Thunnus albacares*, in the Gulf of Mexico, the northeastern Caribbean, and along the eastern U.S. seaboard in various seasons. Secondary target species include dolphinfish, bigeye tuna (*Thunnus obesus*), albacore tuna (*Thunnus alalunga*), and sharks. There are several regional sectors to keep in mind when analyzing this data: The Gulf of Mexico yellowfin tuna sector, the Caribbean tuna and swordfish sector, the U.S. Atlantic distant-water swordfish sector, the Mid-Atlantic and New England swordfish and bigeye tuna sector, and the South Atlantic swordfish sector (Beerkircher *et al.* 2004). The longline is typically set at different times of the day and depths depending on the target species. When swordfish is the target, the lines are generally deployed at sunset at shallower depths and hauled in at sunrise to take advantage of the nocturnal near-surface feeding habits of swordfish (Berkeley *et al.* 1981). Conversely, when targeting tuna, the longliners generally set the gear in the morning, deeper in the water column, and bring it in at dusk. With the exception of the

vessels that are making distant, extended trips, the longliners preferentially target swordfish during full moon periods to take advantage of the species' tendency to spend increased amounts of time at the surface (Carey and Robison 1981).

The Venezuelan fleet fishes in the southern Caribbean from the equator to the northernmost Lesser Antilles at about 20°N latitude (see Figure 1.1) and is characterized as an artisanal longline fleet. Traditionally, the fleet was smaller in scale and targeted snapper (*Lutjanidae*) and grouper (*Serranidae*). The catch was used mainly for local consumption and a small portion was processed and exported to countries like the U.S. Other species that were caught commercially were sardines (*Sardinella aurita*), and other demersal fish and invertebrates; however these were caught by small commercial vessels deploying purse seine nets. Approximately 65% of this small-scale longline operated near the home ports within the EEZ in relatively shallow waters (Arocha, *pers. comm.*). Currently, though the main target species of the Venezuelan fleet is yellowfin tuna (*Thunnus albacares*) dolphinfish represents approximately 25% of the total catch by weight. Similar to the U.S. longline fleet, the Venezuelan national fishery administration developed and implemented an observer program (Venezuelan Longline Observer Program, VPLOP) for its pelagic tuna longline fishery, and now collects data from roughly 13% of the longline trips observed annually. Like the U.S. PLOP, this dataset begins in 1992 and runs through the present, with data entered and checked for errors through 2003.

In both fisheries, there are several dominant species, both target and nontarget, that make up the majority of the catch, and it is important to understand the habitat preferences of these species when analyzing this data. The bigeye tuna (*Thunnus obesus*)

are found worldwide in tropical and subtropical waters between 50°N and 45°S and are believed to be among the deepest swimming members of the tuna family ranging from the surface to 250 meters (Allen and Punsley 1984). Blue sharks (*Prionace glauca*) are found in the Atlantic from New Foundland, Canada to Argentina in both near shore and open-ocean waters (Skomal 2003). They are a relatively deep species, inhabiting surface waters to 200 m depth (Compagno 1984). Yellowfin tuna (*Thunnus albacares*) inhabit tropical and subtropical waters of the Atlantic from latitudes of approximately 40°N to 35°S, with a preference for the upper 100 meters of the water column (Collete and Nauen 1983). The swordfish (*Xiphias gladius*) ranges from approximately 60°N to 45°S (Seki *et al.* 2002). While swordfish prefer warmer waters from 18-22°C, this species has the widest temperature tolerance of any billfish, but usually is found in waters warmer than 10°C (Carey and Robinson 1981). Generally a midwater fish with a depth range of 200-600m, the swordfish is commonly found in surface waters and in frontal zones, where productivity is high (Olson 2001). Dolphinfin (*Coryphaena hippurus*) inhabit tropical and subtropical surface oceanic waters worldwide and are reported in the literature to be bounded in the north and south Atlantic by the 20 degree Celsius isotherm (Palko *et al.* 1982). The dolphinfin is generally a pelagic fish that is found both offshore and near the coast under floating objects (Taquet *et al.*, 2000). It is believed to be mostly associated with surface waters, with a total depth range from 0-279 feet (0-85 m). They represent the fourth highest catch by the longline fleet, yet their populations have not been fully assessed.

Chapter Goals and Objectives

The ultimate goal of this work is to better define the oceanographic variables, species assemblages, and gear configurations that influence fishery catch. In particular, this work examines the utility of adding satellite-derived environmental data into catch rates standardization processes. The quantified catch rates are used to document the abundance of dolphinfish in the western Atlantic. This is accomplished by comparing GLM-standardized abundance indices with and without the inclusion of the satellite-derived data for both the U.S. and Venezuelan data. This process also enhances knowledge of dolphinfish ecology by examining the links between dolphinfish catch rates and specific environmental conditions. PCA is used to couple the oceanographic features of the western Atlantic with fishery information to develop a functional understanding of the spatial and temporal occupation and movement tendencies of dolphinfish. These techniques build on our understanding of dolphinfish spatial ecology and its implication for estimating abundance and the movement, migration, and stock structure of dolphinfish.

2.2 Methodology for Multivariate Analysis

This work consisted of three steps. First, a major effort was made to compile data from satellite imagery and from pelagic observer programs in the U.S. and Venezuela. The second part of the chapter examines the relationships between dolphinfish catch from the U.S. longline fleet and several environmental and species assemblage factors further using PCA. PCA is a useful way to understand the significant correlations and importance of the variables because it reduces and orthogonalizes the original variables (Legendre and Legendre 1998). Finally, GLMs were developed to standardize the U.S.

and Venezuelan catch rates, with one set of models relying on conventional data and the other relying on that data plus satellite-derived environmental data.

Fisheries Dataset Preparation

The U.S. commercial longline observer program database contains 5979 unique sets spanning the period from 1992 to 2003. The pelagic longline observer program is a useful tool for studying correlations between environmental and vessel parameters and the various species caught by the longline fleet because longline sets are recorded at a higher spatial resolution than most other fishery dependent datasets. A coordinate position is recorded at the beginning and ending of the set and the haul of the gear. These points allow for analysis on a finer scale and allow an association between the coordinates and times of the specific haul with data derived from satellites such as SST, ocean color (*K*) and distance to nearest front. Other data includes vessel characteristics such as vessel size, horsepower, gross tonnage, and haul capacity, information on the gear configuration such as the amount of gear deployed, depth of hooks, type of bait and other gear attributes, and catch characteristics, such as the target species, weight and length measurements and condition of the catch. Access to the U.S. dataset was provided by NMFS. This dataset was cleaned and checked for anomalies by staff at NMFS, and is the principle source of data used in constructing indices of abundance for pelagic species assessments by U.S. researchers. Each longline haul was identified as a unique entity. Effort was defined as hook hours—the number of hooks set multiplied by the number of hours they were deployed. Catch was converted to weight from length measurements using a formula from Oxenford (1986) where:

$$\text{Weight in kg} = 1.45 \cdot 10^{-8} \cdot L^{2.91} \quad (\text{Length is measured in mm}). \quad (1)$$

The Venezuelan longline observer program (VPLOP) database was set up in a similar manner to the U.S. dataset; however, there were no records for bottom depth or average hook depth. Therefore, the preparation of the Venezuelan data was identical to that described for the U.S. data with the exception of these factors.

Environmental Dataset Preparation

The satellite derived environmental factors of interest for this analysis were SST and distance of CPUE point from the nearest front. The spatial information collected by the observers onboard the longline vessels provides coordinates for the CPUE data in terms of a latitude and longitude for the beginning and ending points of the set or placement of the longline gear into the water and the haul or retrieval of the longline gear from the water as described above. An average of these four points was used in linking the CPUE at a point to the environmental factor of interest.

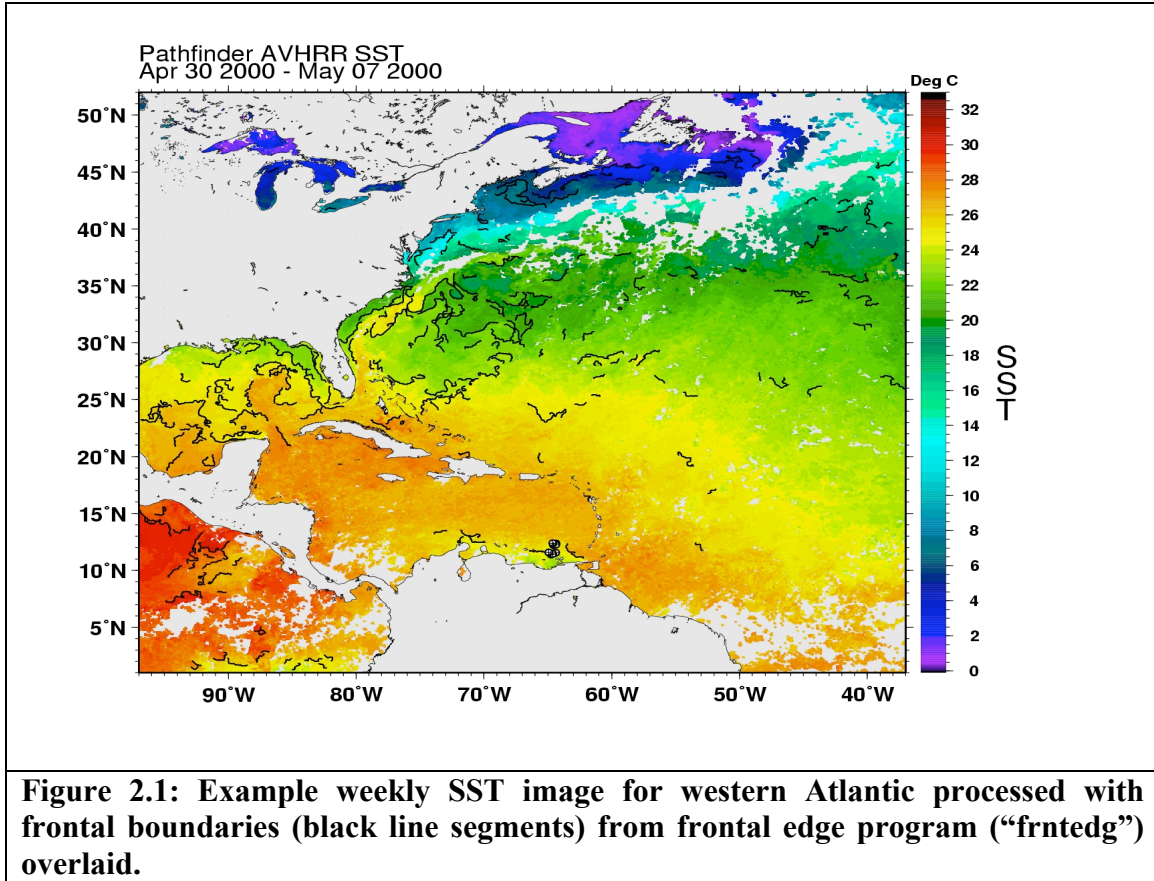
SST

SST was derived from MODIS and AVHRR satellite imagery. MODIS views almost the entire surface of the Earth every day, acquiring data in 36 spectral bands over a 2330 km swath. MODIS has higher resolution than the AVHRR sensor; however, it has only been in operation since 2000. Therefore, the AVHRR satellite, which operates in a very similar manner to the MODIS satellite was used to interpolate SST and ocean color data for the longline data from 1992-2000. For the more recent time period (2000 to the present) SSTs for MODIS (4mm) and AVHRR (multiple bands) can be compared. The daily SST data for the region was converted in ArcGIS 9 to raster data and individual daily rasters were overlaid to create a weekly composite because cloud cover left gaps

otherwise. These weekly composites were then temporally linked to the average CPUE data point in a particular week.

Distance to Fronts

In order to examine the relationship between dolphinfish and their proximity to fronts, the single image edge detection algorithm (SIED) of Cayula and Cornillon (1992) was applied to the weekly SST images. This algorithm is unique because it determines the location of a front not merely by a change in temperature over the raster image. Instead, a histogram of the SSTs in a window of the weekly raster image is examined for statistically significant bimodality based on differences in the SST modes and variances of two water masses. In this way, regions of high spatial gradient will correspond to edges based on absolute gradient magnitudes. The algorithm was not used on daily raster images because the significant cloud cover caused difficulties in frontal determination. Therefore, the weekly composite images were used for the frontal analysis. Map algebra in ArcGIS 9 was used to calculate the straight line distance from the derived front and the average CPUE coordinate (Figure 2.1).



2.3 Preliminary Analysis

Principal Components Analysis

PCA and the calculation of empirical orthogonal functions (EOFs) is one of the most popular dimensionality reduction techniques for the analysis of high-dimensional datasets and has been frequently used in the field of oceanography (Mariano and Chin, 1996; Weare *et al.*, 1976; Hardy and Walton, 1978). This analysis tool is a multivariate technique that is used to both reduce the dimensionality and efficiently summarize the information contained in multivariate data (Gauch, 1982). Additionally, it has been noted that EOFs are the most efficient basis for representing data (Mariano and Chin, *in prep.*). The benefit of PCA is that the correlation matrix of the variables of interest is the input for the analysis and therefore, the analysis technique relies only on the data matrix

(Pielou, 1984; Gauch, 1982). This, in and of itself, makes PCA a more objective method of analysis than many other ordination techniques (Gauch, 1982), and also eliminates the issue of different scaling of the factors. Additionally, some environmental parameters are highly correlated, for example, SST and latitude. Therefore, the intrinsic dimensionality of the data may actually be explained by fewer than the actual number of indices or variables. A principal component model can be used to summarize a set of original variables into a new set of uncorrelated variables, and hence is a tool for data reduction (Gnanadesikan, 1977). The first step is to create a matrix of the correlations between the original variables. The principal components are determined by computing the eigenvalues and eigenvectors of the correlation matrix. The principal components are computed so that the first component describes the largest part of the data variability. The second component is orthogonal to the first and describes the largest part of the variability left over after the first is factored out, and so on. The new “variables” are uncorrelated to one another and reduce the dimensionality of the data set because fewer are needed to explain the relationships existing among the original variables (Afifi and Clark 1984). The use of PCA to identify factors important for describing dolphinfish abundance may enhance traditional techniques such as GLM, and the set of normalized principal components or EOFs can be utilized as the predictors or factors in regression techniques such as the GLM. The benefit of this is the avoidance of ill-conditioning of the matrix of factors and the reduction of artificial predictability of the model (Mariano and Chin, *in prep.*).

U.S. PCA of Dolphinfin CPUE and Environmental Variables

PCA was performed on the whole U.S. dataset as a preliminary means for examining the important patterns in the data and detecting the trends in the factors that may be influencing CPUE of dolphinfin. To begin, the strong seasonal component of the SST was removed from the data by fitting a harmonic curve to the SST data. The residuals were derived as the difference between the model's fit to the data and the actual SST value. The fit of the model essentially acts as a high-pass filter of the data, and because dolphinfin CPUE also has a strong seasonal component, a curve was also fit to this data to remove the seasonal trend. The residuals of SST and dolphinfin CPUE were incorporated into a PCA along with the variables of latitude, longitude, distance from the nearest front, hook depth, and bottom depth. Due to the different scales of the variables, a correlation matrix was used as the input to the PCA. The eigenvalues of the correlation matrix were used to determine the significance of the principal components.

PCAs of Species Assemblage and Environment by Region

In second part of the analysis, a PCA was developed using only the CPUEs for the main catch of the longline fleet: bigeye tuna—BET (*Thunnus obesus*), blue shark—BSH (*Prionace glauca*), dolphinfin—DOL, swordfish—SWO (*Xiphias gladius*), yellowfin tuna—YFT (*Thunnus albacares*), a skate and ray category—SRX, and a general shark category—SHA. This analysis will be referred to as the “species PCA.” The purpose of the species PCA is to organize the CPUEs in order to determine which species, if any are correlated with each other. The PCA again analyzed the U.S. data, but this time the analysis was done for different regions within the fishing area. The pelagic longline observer data is predominantly in two areas: the Gulf of Mexico and along the eastern

seaboard into the Sargasso Sea. Because these areas are very different in a biophysical sense, the observer dataset was split by the -82°W longitude line. The analyses are referred to as west and east. The eastern portion of the data was also truncated east of -65°W in order to homogenize the eastern dataset.

This PCA is important for several reasons. First, the correlations between the species dictate to what degree there is enhanced variability in the data. For example, if the catch of dolphinfish is highly correlated with the catch of swordfish, this would indicate that there must be a means developed to extract the source of this correlation. This is inherently difficult because the cause of the correlation may be attributed to a particular biophysical interaction between the species or to some particular of the directed fishing effort of the longline gear. Because the PCA organizes the species by importance on each of the axes, the dominate axes are defined to be those with eigenvalues greater than one following the convention of Kaiser (1960). The correlation matrix from the eastern (Table 2.1) and western (Table 2.2) species PCAs reveal that there are no significant correlations between any species.

Eastern Catch PCA--3726 Observations							
Correlation Matrix	BET	BSH	DOL	SHA	SRX	SWO	YFT
Bigeye	1	0.0124	-0.0384	-0.0388	0.0864	-0.0365	0.0182
Blue Shark	0.0124	1	-0.0716	-0.0203	0.0471	0.0376	-0.0057
Dolphin	-0.0384	-0.0716	1	0.0011	-0.0336	-0.021	0.0088
Sharks	-0.0388	-0.0203	0.0011	1	-0.0413	0.0238	0.0243
Skates/Rays	0.0864	0.0471	-0.0336	-0.0413	1	-0.0688	0.0185
Swordfish	-0.0365	0.0376	-0.021	0.0238	-0.0688	1	-0.0501
Yellowfin	0.0182	-0.0057	0.0088	0.0243	0.0185	-0.0501	1

Table 2.1: Correlation matrix for the eastern species PCA.

Western Catch PCA--2062 Observations							
Correlation Matrix	BET	BSH	DOL	SHA	SRX	SWO	YFT
Bigeye	1	0.004	-0.0282	0.0095	0.1852	0.0443	0.1408
Blue Shark	0.004	1	0.0141	0.029	-0.0309	0.0437	-0.0353
Dolphin	-0.0282	0.0141	1	0.0132	-0.0484	-0.0093	0.0253
Sharks	0.0095	0.029	0.0132	1	-0.034	0.6949	-0.0547
Skates/Rays	0.1852	-0.0309	-0.0484	-0.034	1	0.0314	0.1432
Swordfish	0.0443	0.0437	-0.0093	0.6949	0.0314	1	-0.1341
Yellowfin	0.1408	-0.0353	0.0253	-0.0547	0.1432	-0.1341	1

Table 2.2: Correlation matrix for the western species PCA.

Therefore, this is evidence that the species could be analyzed separately from each other with the environmental factors. Subsequently, PCAs of dolphinfish CPUE and the environmental characteristics were performed for the total regional datasets and by season. Season 1 is defined to be the winter (January-March), season 2 is spring (April-June), season 3 is summer (July-September), and season 4 is fall (October-December). This allows an understanding of any seasonal pattern in the data.

Generalized Linear Model

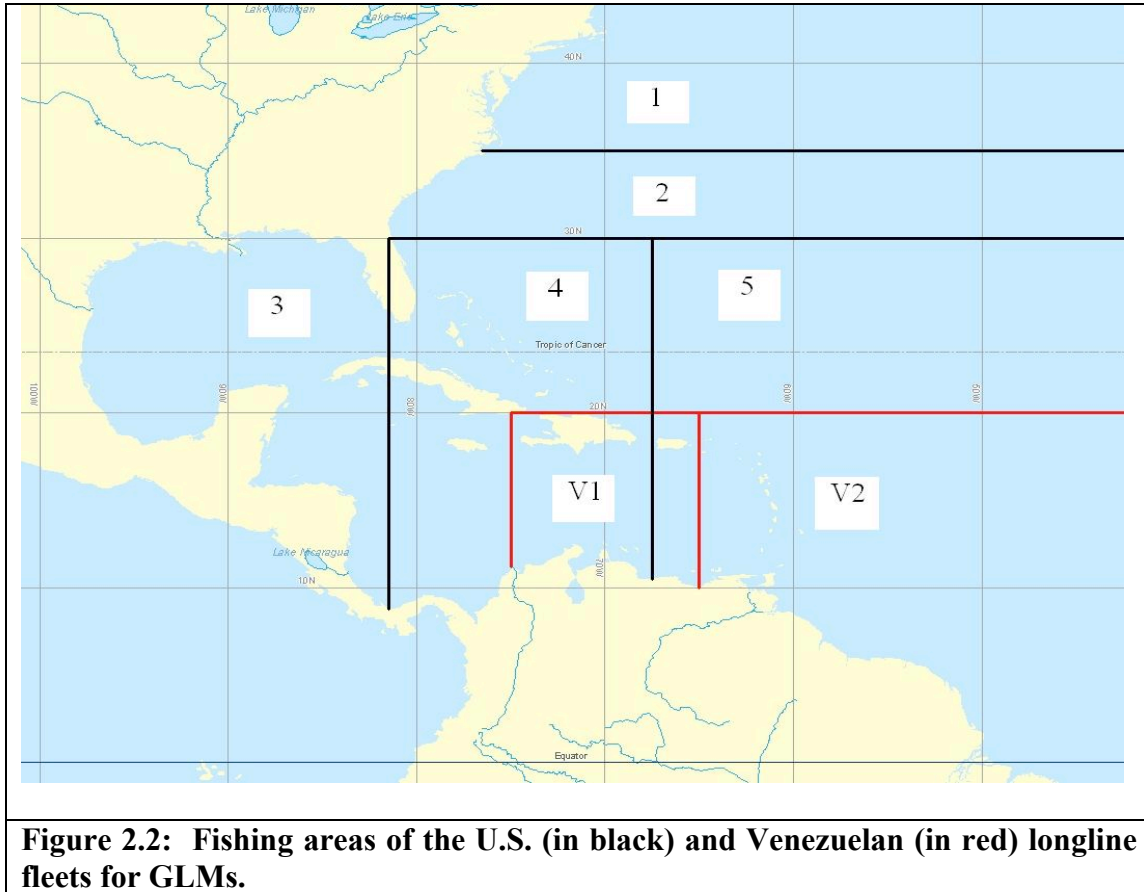
GLMs are commonly used to standardize abundance estimates. They linearly quantify the relationship between several independent or predictor variables (i.e. temporal, spatial, vessel, or environmental effects) and a dependent or response variable such as CPUE. The GLM analysis utilizes a stepwise procedure to determine which factors to include based on the degree to which each factor improved the fit of the model to the data (Derksen and Keselman, 1992). This can be problematic when some of the variables are highly correlated, and may require the categorization of most of the variables in the analysis due to the limiting effect of degrees of freedom (Hocking, 1976; Cook, 1979, Neter *et al.*, 1990, Francis, 1999). Additionally, this procedure can have problems resolving the factors in the stepwise factor selection even when the variables

are categorized. It is a common occurrence that some factors and interactions may be deemed a significant reduction of the variability of the model, but will not be able to be included in the model due to constraints on the Hessian matrix (Golub and VanLoan, 1989). This can be a common occurrence when the covariance parameters are on a different scale. A nonpositive definite Hessian matrix can indicate a surface saddlepoint or linear dependencies among the parameters (Golub and VanLoan, 1989). In our case, the model would not converge when including two key satellite-based datasets (SST and distance from fronts). The classification of variables is in a sense a smoothing of the data, and it is expected that some important variability was lost that may have been important in detecting abundance trends.

The Delta approach (Lo *et al.*, 1992) was used to model the probability of obtaining a zero catch and the catch rate, given that the catch is non-zero, separately (Maunder and Punt, 2004). A Generalized Linear Mixed Model (GLMM) approach in SAS 9.0 was used to estimate relative indices of abundance for the U.S. and Venezuelan dolphinfish fishery (Littell *et al.*, 1996), using a binomial distribution for analyzing the presence of dolphinfish and a lognormal distribution for analyzing catch rates on positive trips (trips that land dolphinfish). This type of combined model is a standard analysis tool for evaluating datasets where there are a large proportion of zero catches (i.e. the species is not the main target of the fishing fleet) (Ridout *et al.*, 1998; Ortiz and Arocha, 2004).

The influence of the following factors on the relative abundance was investigated in the U.S. dataset: year, quarter, area, target species, SST, and distance from nearest front. Two additional factors, depth of hooks and bottom depth, were evaluated only for

the U.S. dataset because they were not collected by Venezuelan observers. Quarter was defined in three month increments starting in January. The fishing area for the U.S. fleet was divided into five areas that provided for a balanced design of observations of CPUE in all years, quarters, and in terms of target species, and the Venezuelan fleet was divided into 2 areas (Figure 2.2).



Restrictions were placed on the target species by eliminating the shark (SHX) and dolphinfish (DOL) target categories as having inadequate numbers of observations. Additionally, bigeye tuna (BET) and yellowfin tuna (YFT) were combined into the general tuna (TUN) category. There were three final target species levels: mixed (MIX),

swordfish (SWO), and tuna (TUN) for the U.S. fleet and only SWO and TUN for the Venezuelan fleet.

The GLM was run for the U.S. and Venezuelan datasets first without satellite data (SST and distance from nearest front) as a base, and secondly with these factors included. This was done to determine if the GLM would pick up the significance of the satellite-derived variables or determine other factors more significant.

2.4 Analysis Results

U.S. PCA of Dolphinfin CPUE and Environmental Variables

The first three principal components of the PCA on the U.S. data were successful in explaining almost 80% of the variance in the data (Table 2.3).

Correlation Matrix				
Component	Eigenvalue	Difference	Proportion	Cumulative
1	2.36120684	0.75163081	0.3373	0.3373
2	1.60957603	0.10365194	0.2299	0.5673
3	1.50592409	0.79572224	0.2151	0.7824
4	0.71020185	0.30465216	0.1015	0.8838
5	0.40554969	0.19459861	0.0579	0.9418
6	0.21095108	0.01436066	0.0301	0.9719
7	0.19659041		0.0281	1

Table 2.3: Eigenvalues of the correlation matrix: The highlighted boxes indicate the principal components that explain the majority of the variance.

For this reason, it is sufficient to examine the associations within these first three axes (Table 2.4).

Eigenvectors							
	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7
Cum %	33%	57%	78%	88%	94%	97%	100%
DOL	-0.01611	0.465934	0.546707	-0.200173	-0.63292	0.179672	0.10399
SST	0.138339	0.563157	0.405216	0.07161	0.677034	-0.17769	-0.066631
LAT	-0.59395	0.084974	-0.040523	-0.080639	0.277921	0.744664	-0.010002
LONG	0.41738	0.34136	-0.406801	0.291058	-0.014468	0.31677	0.59876
DIST	0.026422	-0.359957	0.488913	0.77086	-0.02749	0.183117	0.04671
DEPTH	0.605521	-0.02938	-0.033362	-0.086839	-0.00924	0.470021	-0.634682
BOTT	0.293723	-0.459979	0.360045	-0.51168	0.250485	0.163777	0.47025

Table 2.4: Eigenvectors of the principal components: The highlighted boxes indicate significant correlations.

Because the principal components are magnitudes, the signs of the dominant modes are simply indicative of direction along the axis. Dominant modes of the principal components are those that are greater than 0.20.

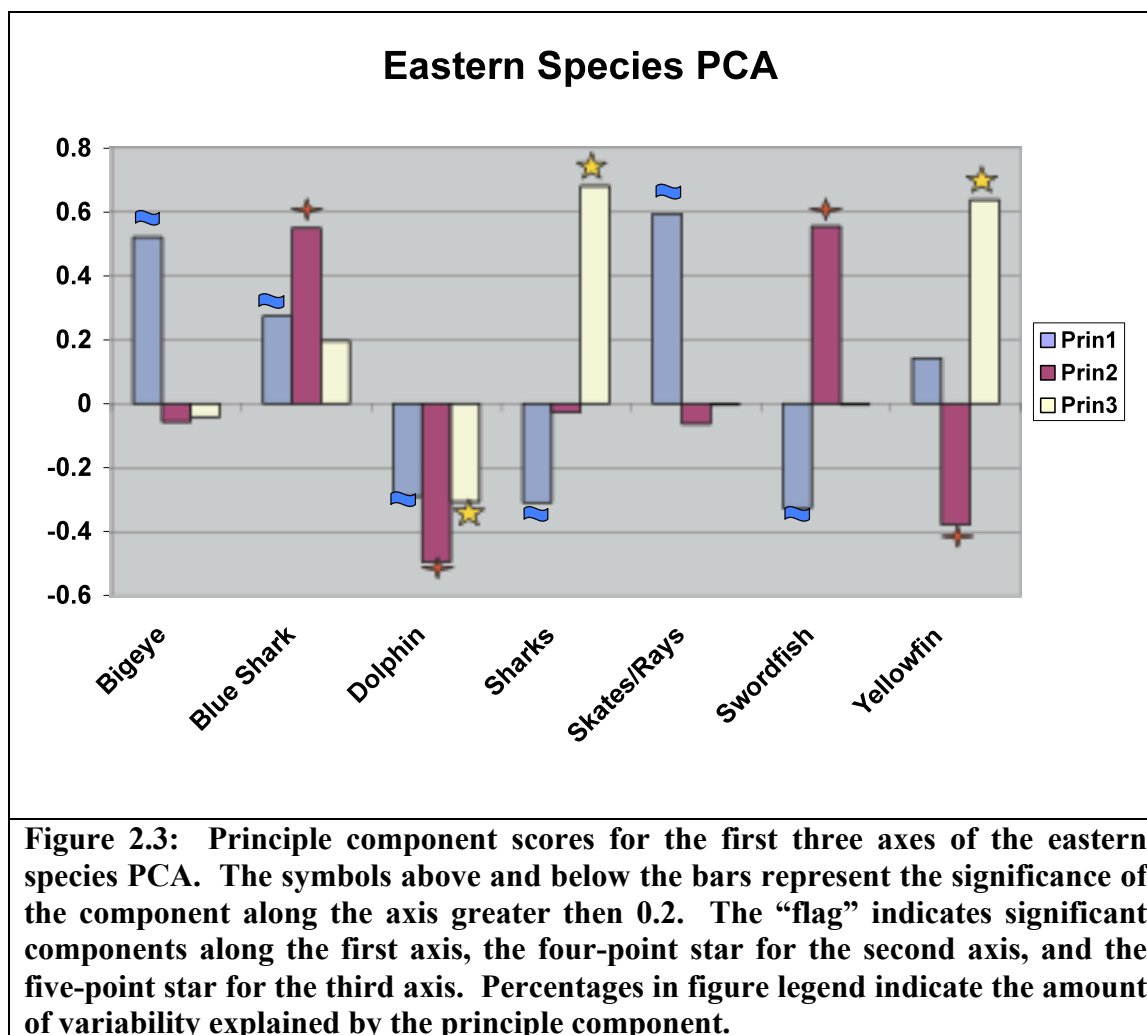
The dominant modes of the first principal component were latitude, longitude, hook depth, and bottom depth, but not dolphinfish CPUE. As such, this component describes distinct fishing activities. Since the sign on the modes for longitude, hook depth, and bottom depth were all positive, it indicates that they were positively correlated, while the negative mode for latitude shows it is negatively correlated. In other words, hooks were set more deeply in deeper water at more western longitudes and more southern latitudes. These factors demonstrate that longliners generally fished along a southwestern line, following the continental coastline/shelf, and that they fished deeper (i.e., in a way more typical of tuna sets) in the southwest and shallower (i.e., in a way more typical of swordfish sets) in the northeast. This component describes the most variation in the data and so indicates that fishing behavior played a large role in understanding differences among sets. The second principal component included dolphinfish CPUE as a dominant mode and thus indicates how dolphinfish CPUE changed with environmental factors. The other significant modes included SSTs

(positively correlated), bottom depths (negatively correlated), distance to fronts (negatively correlated), and longitude (positively correlated). These results indicate that dolphinfish were more likely to be caught in high SSTs, closer to fronts, and in shallower depths and farther west, generally indicating areas closer to shore. The dominant modes of the third principal component were dolphinfish CPUE, SST, longitude, distance from nearest front, and bottom depth. This component suggests that dolphinfish farther from shore were more likely to be caught in higher SSTs, further from fronts and at deeper depths. Its ranking as third component, though, suggests that the in-shore pattern described by the second component was more influential.

PCAs of Species Assemblage and Environment by Region

Eastern U.S.

The eastern species PCA explained 47% of the variability with three axes (Figure 2.3).



Each of the axes explained a similar amount of the variability, which was indicative of a set of variables that were not strongly covarying with each other. Along the first axis, higher CPUE of skates and rays, bigeye tuna, and blue shark were found when CPUEs of swordfish, sharks, and dolphinfish were lower. This made intuitive sense because bigeye tuna and blue shark especially are the deepest of the major species caught by the longline. This highlighted the fact that the type of set (i.e., shallow vs. deep) probably plays a large role in determining the species caught. Along the second axis, the CPUEs of blue shark and swordfish were high when dolphinfish and yellowfin CPUEs were low. The third

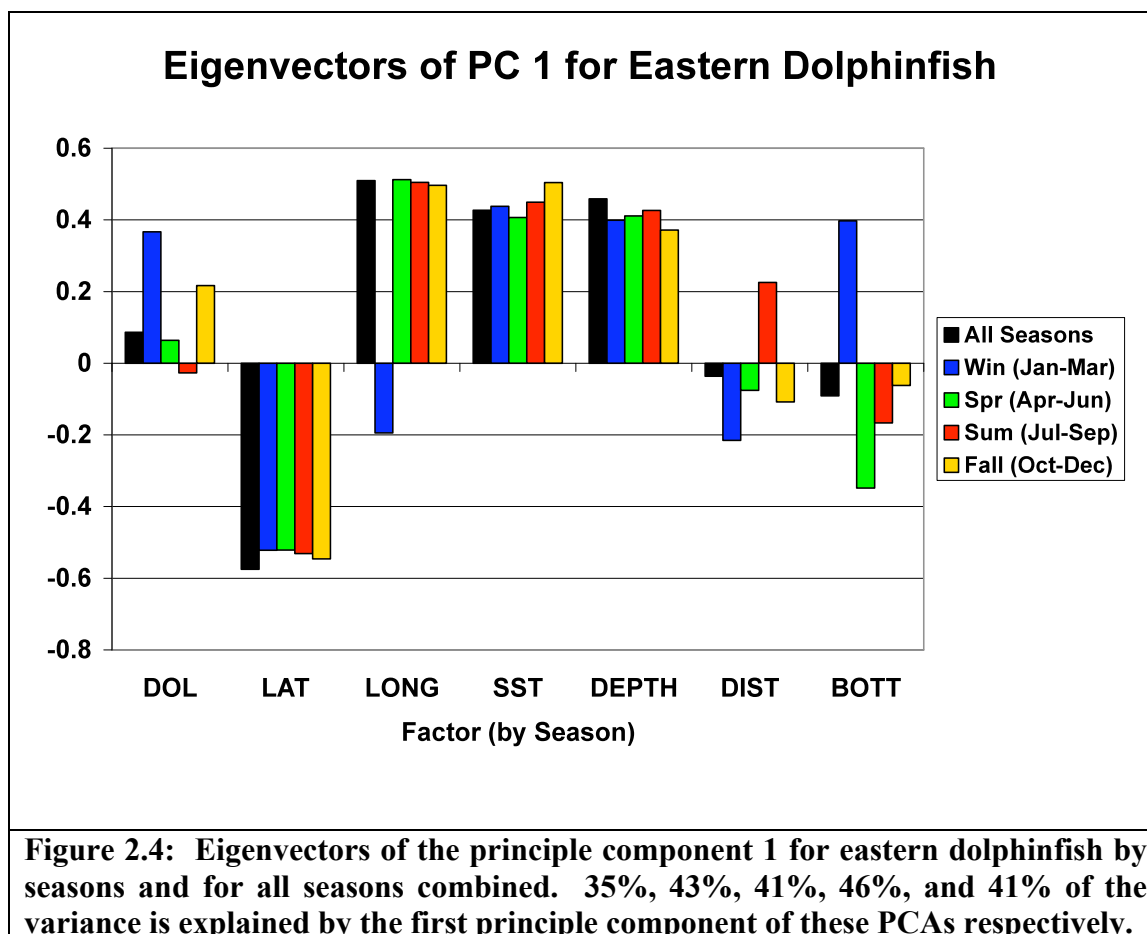
axis described an inverse relationship between both sharks and yellowfin tuna against dolphinfish. The most important result from this PCA was that there were no strong correlations between the species (see Table 2.1). This indicated that it was possible and probably desirable to analyze the relationships between the species and the physical data separately. Therefore one level of complexity was removed from this analysis: the species interactions.

The eastern PCA for the whole dataset revealed some interesting trends and 70% of the variation in the data was explained in the first three axes. The correlation matrix showed dolphinfish to be weakly correlated to western longitudes and warmer SST (Table 2.5).

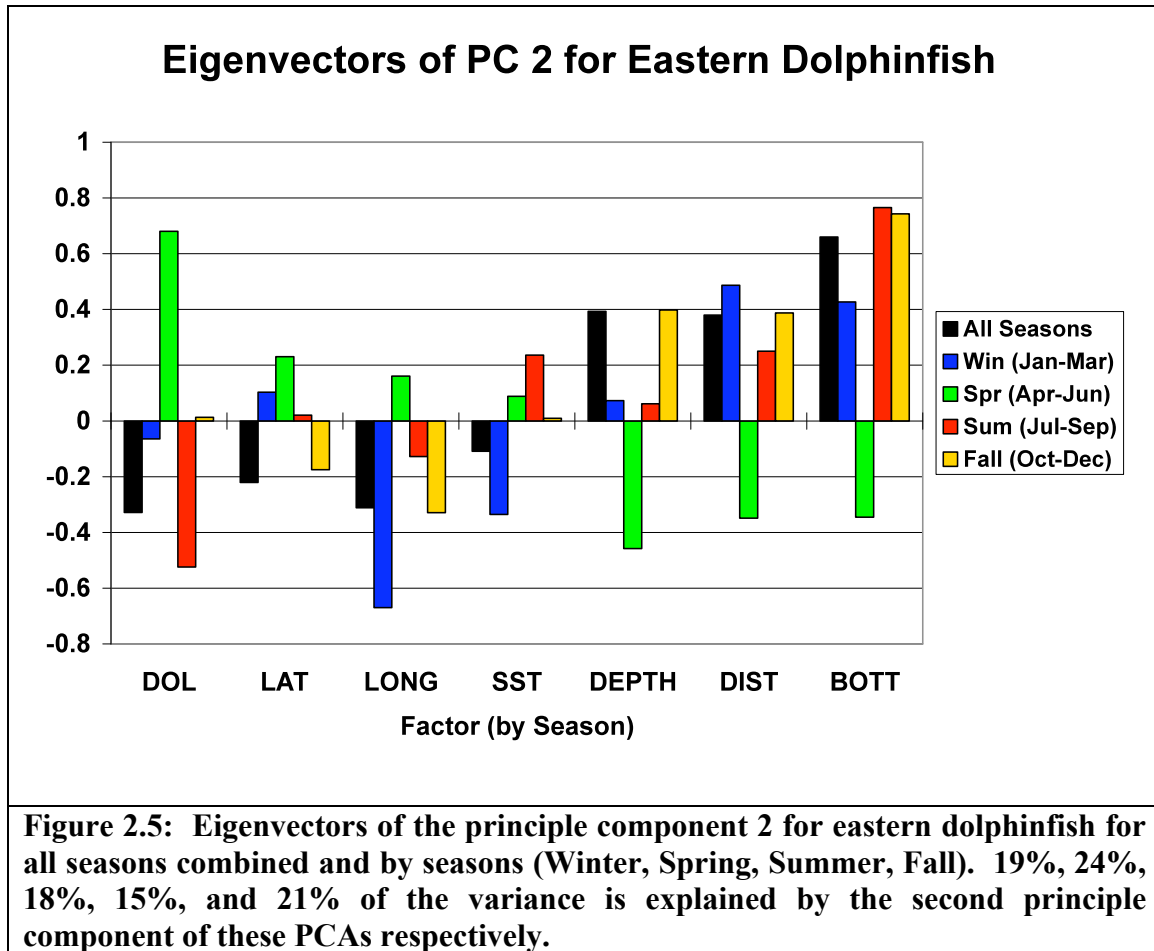
EAST: All Seasons--2906 Observations							
	DOL	LAT	LONG	SST	DEPTH	DIST	BOTT
DOL	1	-0.0415	0.113	0.1224	-0.0323	-0.0549	-0.0517
LAT	-0.0415	1	-0.6142	-0.4985	-0.6853	-0.0493	-0.0654
LONG	0.113	-0.6142	1	0.4013	0.3626	-0.0507	-0.4235
SST	0.1224	-0.4985	0.4013	1	0.2433	-0.2131	0.0073
DEPTH	-0.0323	-0.6853	0.3626	0.2433	1	0.0937	0.1059
DIST	-0.0549	-0.0493	-0.0507	-0.2131	0.0937	1	0.0289
BOTT	-0.0517	-0.0654	-0.4235	0.0073	0.1059	0.0289	1

Table 2.5: Correlation matrix of eastern dolphinfish CPUE with environmental variables.

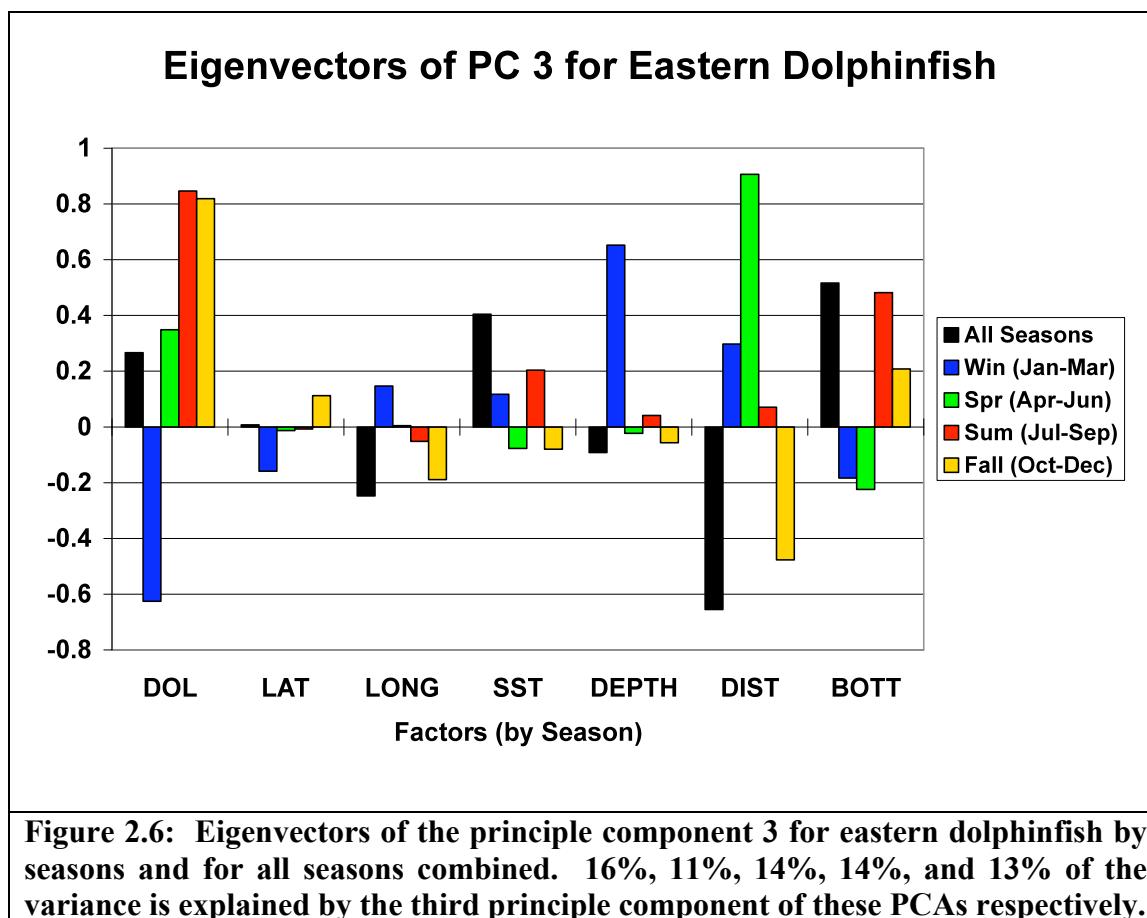
Dolphinfish was not a significant contributor to the first component and this related the fact that much of the variability in the data could be attributed to the effort of the longliners; where they chose to fish and how they set their lines, and to significant correlations between the environmental variables such as SST and latitude (Figure 2.4).



Dolphinfish was significant on the second axis and an interpretation would be that higher CPUE is found in the north, to the west, in warmer waters, with shallower hooks, closer to the fronts, and over shallower bottom depths (Figure 2.5).



Along the third component, higher CPUE was described as offshore to the east in deeper waters, closer to the front when the water is warm (Figure 2.6).



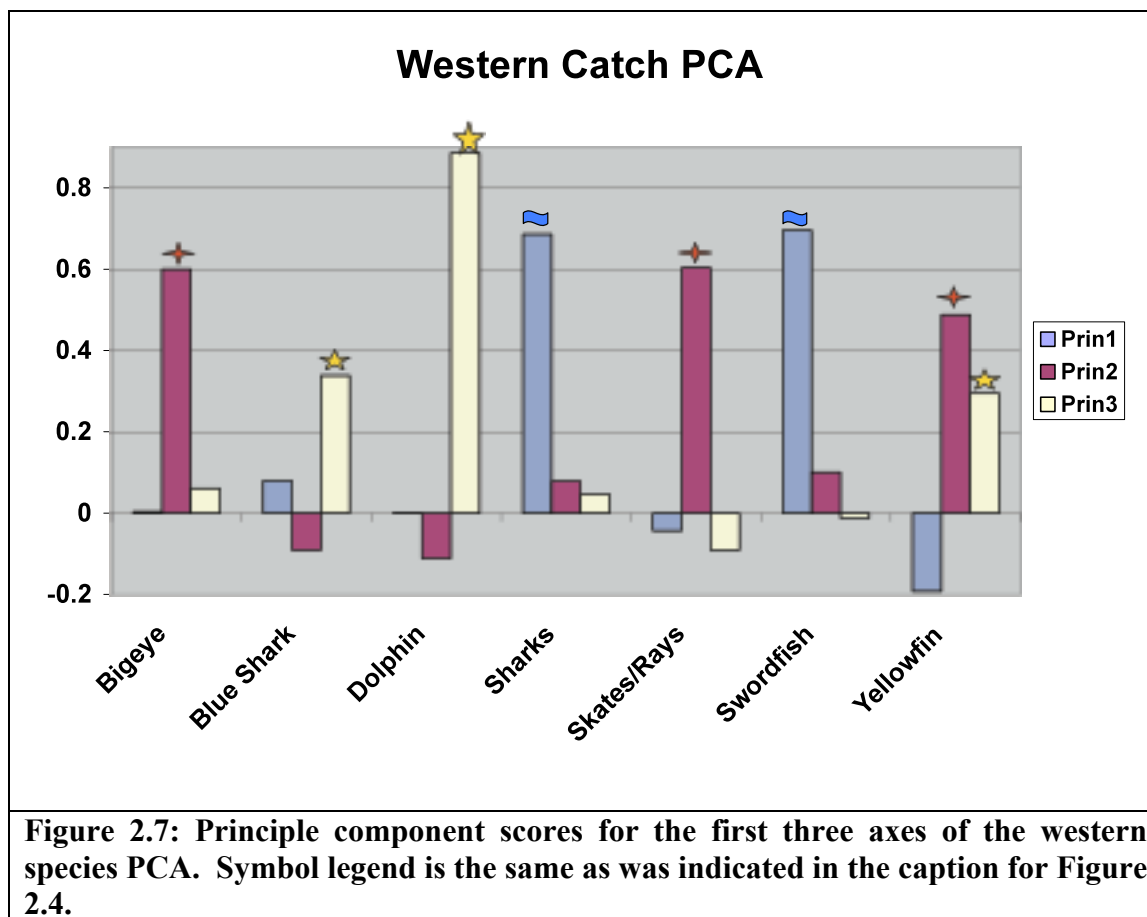
The trend that was evident here was that dolphinfish seemed to aggregate along the warmer side of the front regardless of whether they were fished on- or offshore.

The seasonal PCAs described between 73 and 78% of the variability in the system, an improvement over the PCA for the whole dataset. This was likely due to the fact that changes due to the effort of the fleet and movements of the fish were partitioned to roughly account for change in the climate. For this reason it was expected that there was a significant seasonality to the dolphinfish catch. The reader is asked to refer to Figure 2.4 for all references to principle component one, Figure 2.5 for principle component two, and Figure 2.6 for principle component three. In the winter months, the main pattern was explained by the first component (44%) with higher CPUE in the

southeast in warmer waters, using deeper hook depths, closer to the front, and over deeper bottom depths. This was probably indicative of the fact that dolphinfish were being caught offshore, perhaps on the shallower hooks of a deep tuna set. The second component was not descriptive for dolphinfish and the third component explained only 11% of the variability. In the spring, a similar pattern to that described for the complete dataset was found along the first and second axes, however the third axis described dolphinfish farther from the front in shallower waters. The summer was interesting because along the second and third components when dolphinfish are significant, the directional factors were not significant. This was likely due to a homogenization of the system whereby the range of the dolphinfish was extended along the Gulf Stream. The pattern for higher CPUE along the second axis was in western cooler waters, still in close proximity to the front and over shallow waters. This was likely a reflection of the fact that the longliners were catching dolphinfish over the shelf, probably at night on swordfish sets when the water over the shelf cools more rapidly. The third component related higher CPUE to warmer waters and deeper bottom depths. Finally in the fall, along the first axis, higher CPUEs were associated with the southwest, warmer waters, deeper hook depths, and closer to the fronts. The deeper hook depth was a surprising result, but may be attributed to the fact that it was impossible to know where on the line the fish was caught without temperature-depth recorders (TDRs) and hook-strike timers (Rice, P. *pers.comm.*). Therefore dolphinfish may have been caught on the shallower hooks of a deep set. On the third component, higher CPUE was described in northeastern offshore waters, close to the fronts.

Western U.S.

The western species PCA captured more of the variability within the first three axes: 58%. This result was anticipated due to the fact that the Gulf of Mexico is a more homogeneous area. In this case, the correlation matrix revealed several correlations, the strongest between sharks and swordfish (see Table 2.2). There were several weaker correlations: skates/rays were positively correlated with both bigeye tuna and yellowfin tuna, bigeye and yellowfin were positively correlated, and swordfish and yellowfin tunas were negatively correlated—the later relationship is probably attributable to the difference in the sets for these species. Figure 2.7 displays the eigenvector distribution for the first three principle components.



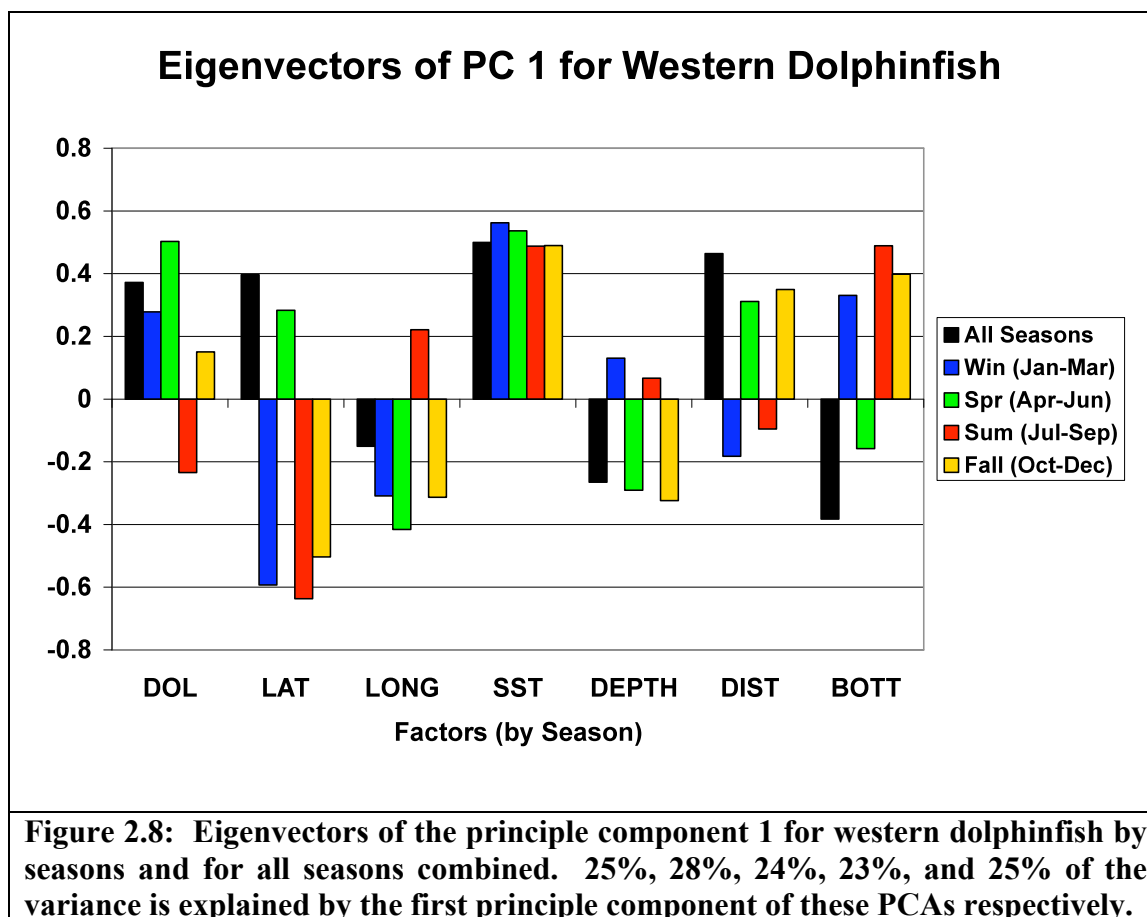
The first principle component explained 25% of the variability and shows that sharks were proportional to swordfish, and yellowfin was inversely related to both of these species. The second component (19%) seemed to describe a deep water species group with bigeye, skates/rays, and yellowfin tuna correlated and inversely related to dolphinfish, a species found in shallower waters. The third component explained only 15% of the variability and related dolphinfish dominantly with blue shark and yellowfin tuna. Because dolphinfish was not significantly correlated with any other species, it was again feasible to analyze the catch of dolphinfish against the environmental factors without including species interactions. If species interactions with dolphinfish were found to be significant for either the east or the west, the vector loadings of the most important principle components (i.e. the first three) could have been used in subsequent PCAs with the environmental factors, and the analysis would have had to account for the relationship between species and the environment.

The western analysis for the whole dataset explained less of the variability in the dataset than it did in the east (57%) and dolphinfish was not strongly correlated with any of the factors (Table 2.6).

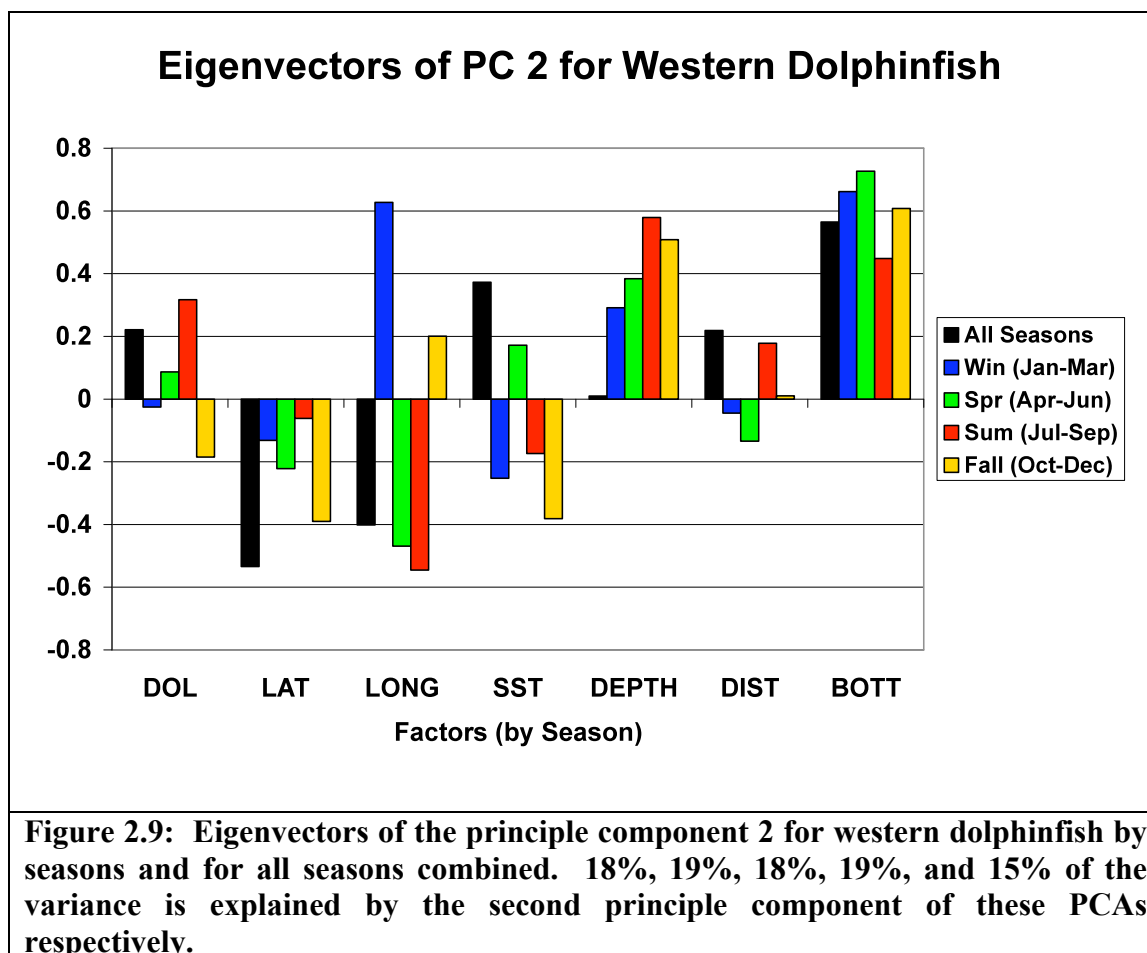
WEST: All Seasons--2062 Observations							
	DOL	LAT	LONG	SST	DEPTH	DIST	BOTT
DOL	1	0.1285	-0.1026	0.2093	-0.0582	0.1529	-0.037
LAT	0.1285	1	0.0254	0.0665	-0.0315	0.1186	-0.3892
LONG	-0.1026	0.0254	1	-0.1718	0.0139	-0.0024	-0.0229
SST	0.2093	0.0665	-0.1718	1	-0.1239	0.3588	-0.091
DEPTH	-0.0582	-0.0315	0.0139	-0.1239	1	-0.0998	0.1282
DIST	0.1529	0.1186	-0.0024	0.3588	-0.0998	1	-0.075
BOTT	-0.037	-0.3892	-0.0229	-0.091	0.1282	-0.075	1

Table 2.6: Correlation matrix of western dolphinfish CPUE with environmental variables.

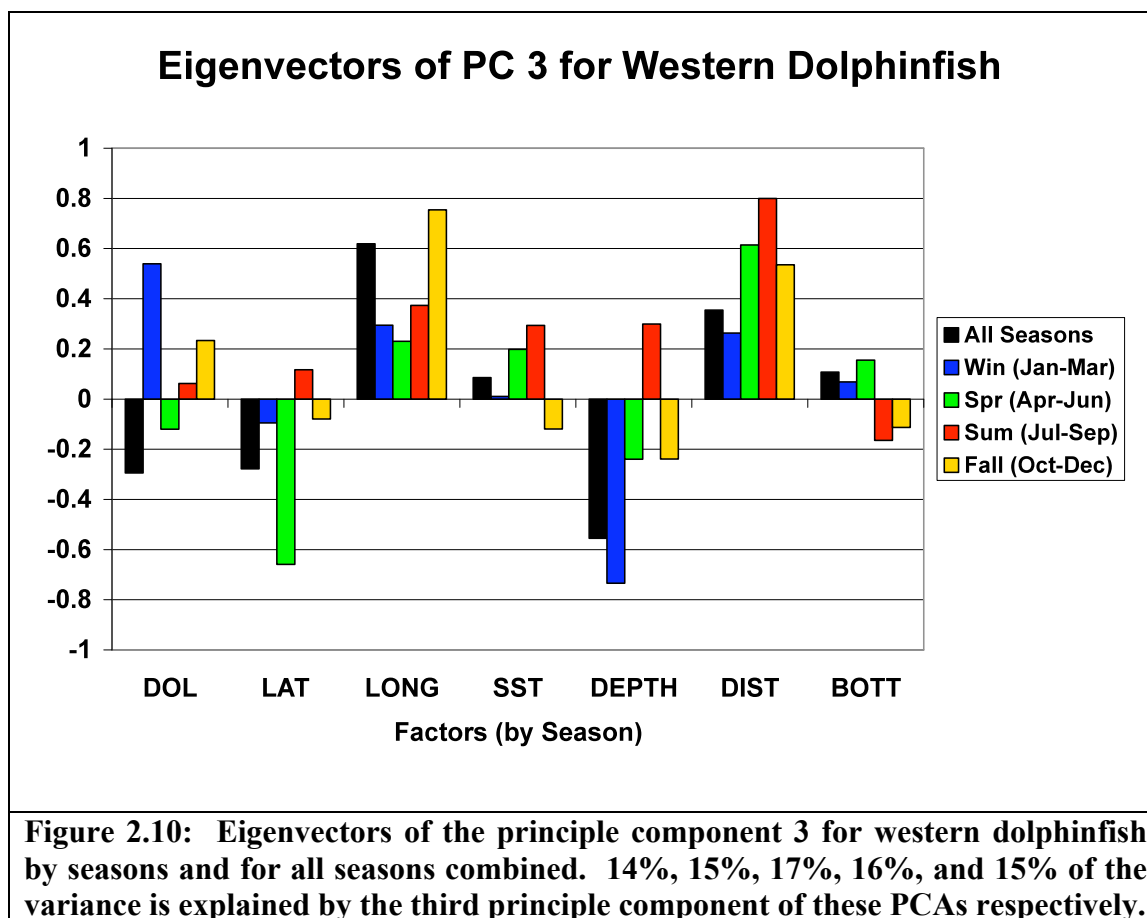
However, it is important to remember that this is a much more homogeneous system, and therefore there is inherently less total variability in this area than along the east coast. The first axis described higher CPUEs in northeastern parts of the Gulf, in warmer waters, shallower bottom depths (i.e. onshore), with shallower hooks, and further from fronts (Figure 2.8).



Along the second axis, higher CPUEs were found in southeastern warmer waters, further from the front, and in deeper bottom depths (Figure 2.9).



The third axis described higher CPUE in northeastern waters, with deeper hooks, closer to the front, and over shallow depths (Figure 2.10).



Seasonally, the picture was varied but interesting. Between 56 and 61% of the variability was captured in the first three axes of these PCAs. The reader is asked to refer to Figure 2.8 for all references to principle component one, Figure 2.9 for principle component two, and Figure 2.10 for principle component three. In the winter, along the first axis, dolphinfish CPUE was higher in the southeast when the waters were warmer, hook depths were deeper, over deeper bottom depths and closer to the fronts. Secondly, along the third axis, CPUEs were higher in the west with shallow hooks and farther from the front. In the spring, the first and third axes again described dolphinfish CPUE. Much of the higher CPUEs were found in northeastern Gulf of Mexico waters, with shallower hooks, farther from the front, and over shallow bottoms. Along the third

axis, there was again a tendency for higher CPUEs in the northeast Gulf, but the trend was in cooler waters, with deeper hooks, closer to the front, and over shallower bottom depths. The summer analysis was descriptive for dolphinfish along the first and second axes with higher dolphinfish in the northeast in cool, shallow waters. Along the second axis, higher CPUE was correlated with eastern cooler waters, with deeper hooks, farther from the front, and over deeper bottom depths. It is important to recognize that in the summer, the mean temperature is higher (29.593°C) and has a much smaller variance (0.725) than in any other season (Table 2.7).

EAST	Simple Statistics	DOL	LAT	LONG	SST	DEPTH	DIST	BOTT
All Seasons	Mean	0.00094	33.4978	74.7268	23.9014	20.2294	123.854	598.997
	StD	0.00351	5.58306	3.8344	4.03742	8.74942	140.253	528.043
Season 1	Mean	0.00025	29.7649	75.6625	22.0361	24.5799	185.307	689.02
	StD	0.00043	5.4886	3.23336	4.24007	9.23268	181.986	684.803
Season 2	Mean	0.00289	32.4487	75.9983	24.919	21.3322	103.739	649.153
	StD	0.00652	4.46596	3.46953	2.85065	8.37079	108.753	563.423
Season 3	Mean	0.00039	36.0875	73.378	25.6853	16.2564	81.4913	526.099
	StD	0.00077	4.65338	4.19904	3.09238	8.33934	101.657	461.947
Season 4	Mean	0.00017	34.5137	74.2801	22.2394	20.3169	145.126	561.584
	StD	0.00035	5.78335	3.56068	4.57912	7.00276	147.966	382.728
WEST	Simple Statistics	DOL	LAT	LONG	SST	DEPTH	DIST	BOTT
All Seasons	Mean	0.00026	26.5346	90.1633	26.1336	33.0104	116.55	1120.9
	StD	0.0008	1.47904	2.86536	2.97654	13.7766	113.285	485.645
Season 1	Mean	5.9E-05	25.8175	90.0415	22.9439	32.9652	78.9973	1250.82
	StD	0.00014	1.95426	3.0449	2.47961	15.892	75.9435	568.877
Season 2	Mean	0.00038	26.7634	90.4003	26.1452	33.5823	105.539	1105.99
	StD	0.0009	1.17443	2.61094	2.18797	14.7851	99.0178	451.311
Season 3	Mean	0.0005	27.0802	89.8998	29.5933	29.998	204.638	1014.34
	StD	0.00124	1.14912	2.57096	0.72463	6.4988	142.139	422.901
Season 4	Mean	9.4E-05	26.44	90.2786	25.7888	35.3369	78.8724	1117.3
	StD	0.00018	1.23642	3.18198	1.61084	15.1209	73.0214	465.677

Table 2.7: Mean and standard deviation of PCA factors for east and west coast data by season.

Therefore, the cooler water is relative to the season. In the fall, there were three axes that were significant for dolphinfish. The first described higher CPUE in the southeast in warmer waters, with shallow hooks, far from the front and over deep bottom depths. The second axis described greater CPUE in warm northeastern waters, with shallow hooks, and over shallow bottoms. These axes seem to describe an onshore, offshore component. Along axis three, there was a trend for higher CPUE in cooler western waters with shallow hooks, far from the fronts, and over shallow bottoms.

General Patterns

One of the trends in this analysis was the fact that along the east coast, dolphinfish were primarily found closer to the fronts. In the Gulf of Mexico, the pattern was not as clearly defined. This may have been due to the fact that the Gulf Stream had a stronger thermal effect—the fronts were more defined and the fish were more sensitive to warm waters (Humston *et al.* 2000). This finding would likely be enhanced by a higher resolution front detection. The one caveat of the automated algorithm that was used for this work was that it was not able to sufficiently define fronts on daily satellite images due to significant cloud cover. Therefore, weekly composites were used to detect fronts. This posed a problem when calculating exact positions of fronts because the movement of these features can be significant and the age of a front can play a significant role in the attractiveness of a frontal region to a large pelagic species. However, the distribution of the principle component scores against the distance from fronts clearly indicated that the fleet is fishing along fronts (Figure 2.11).

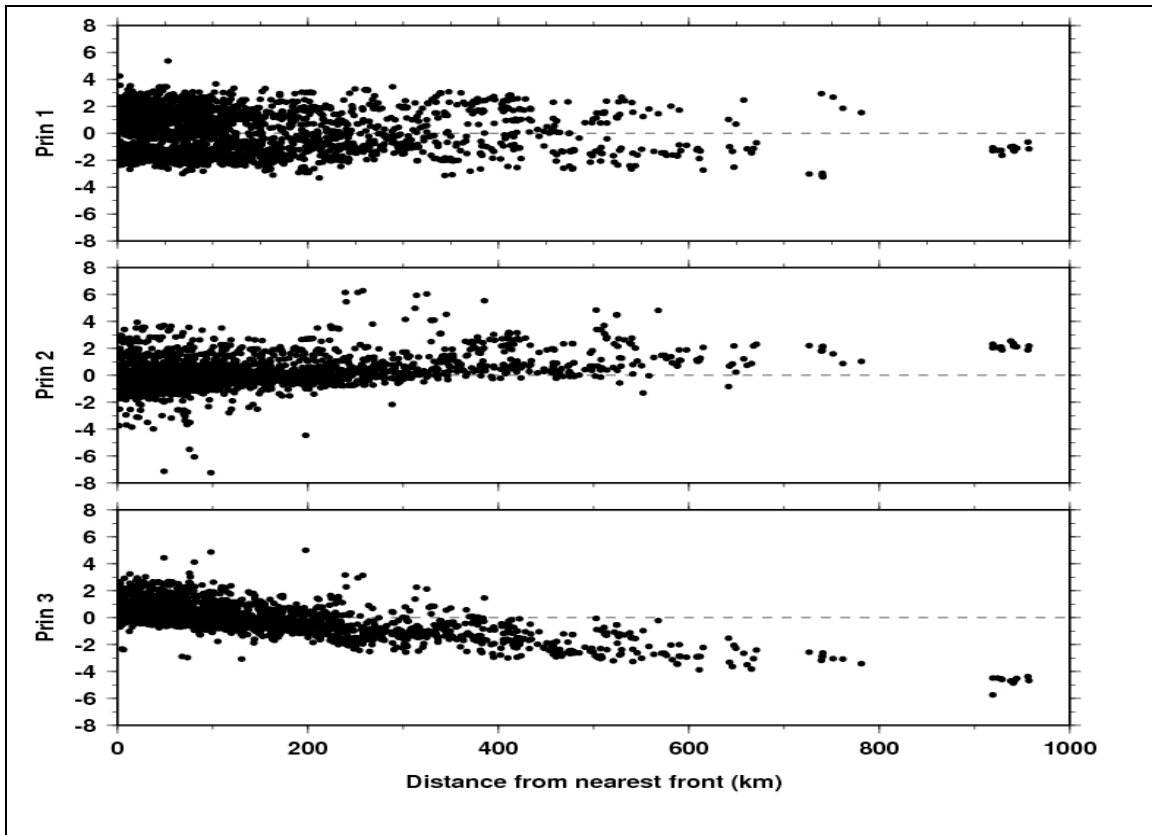
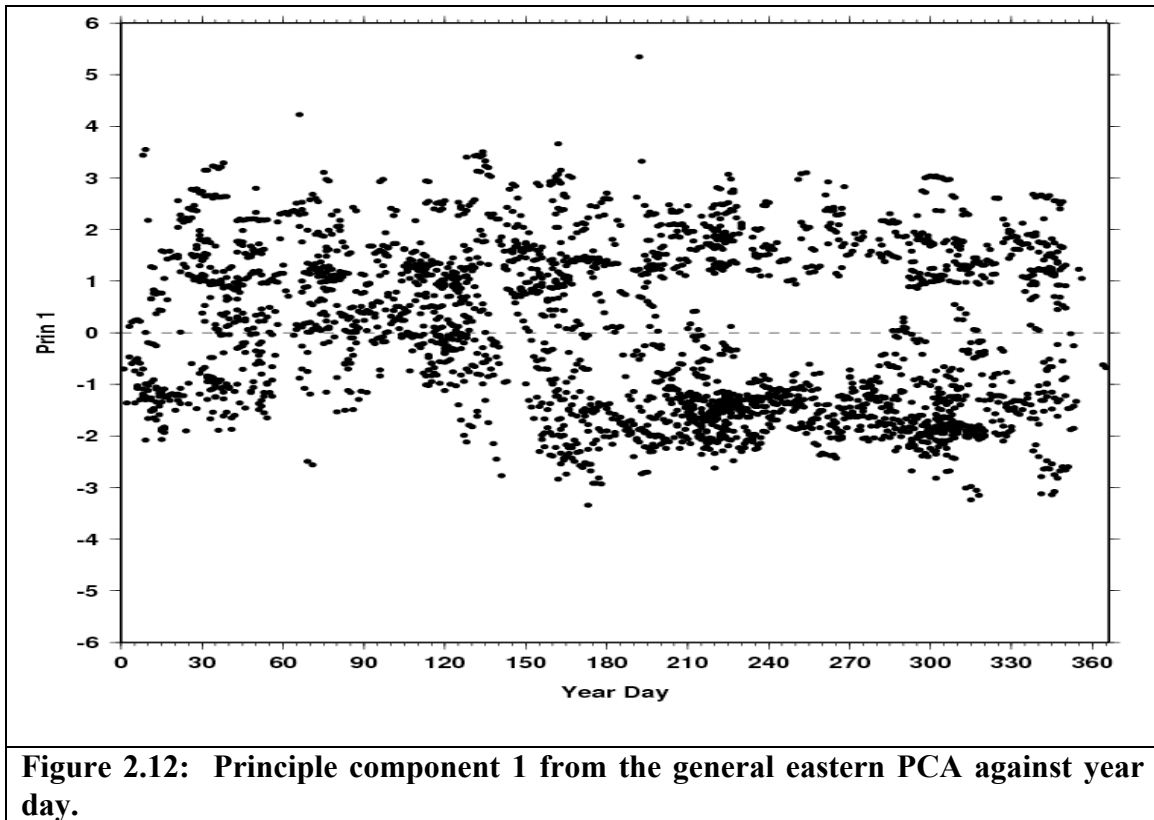


Figure 2.11: Principle components (1-3) from the general eastern PCA plotted against distance from front.

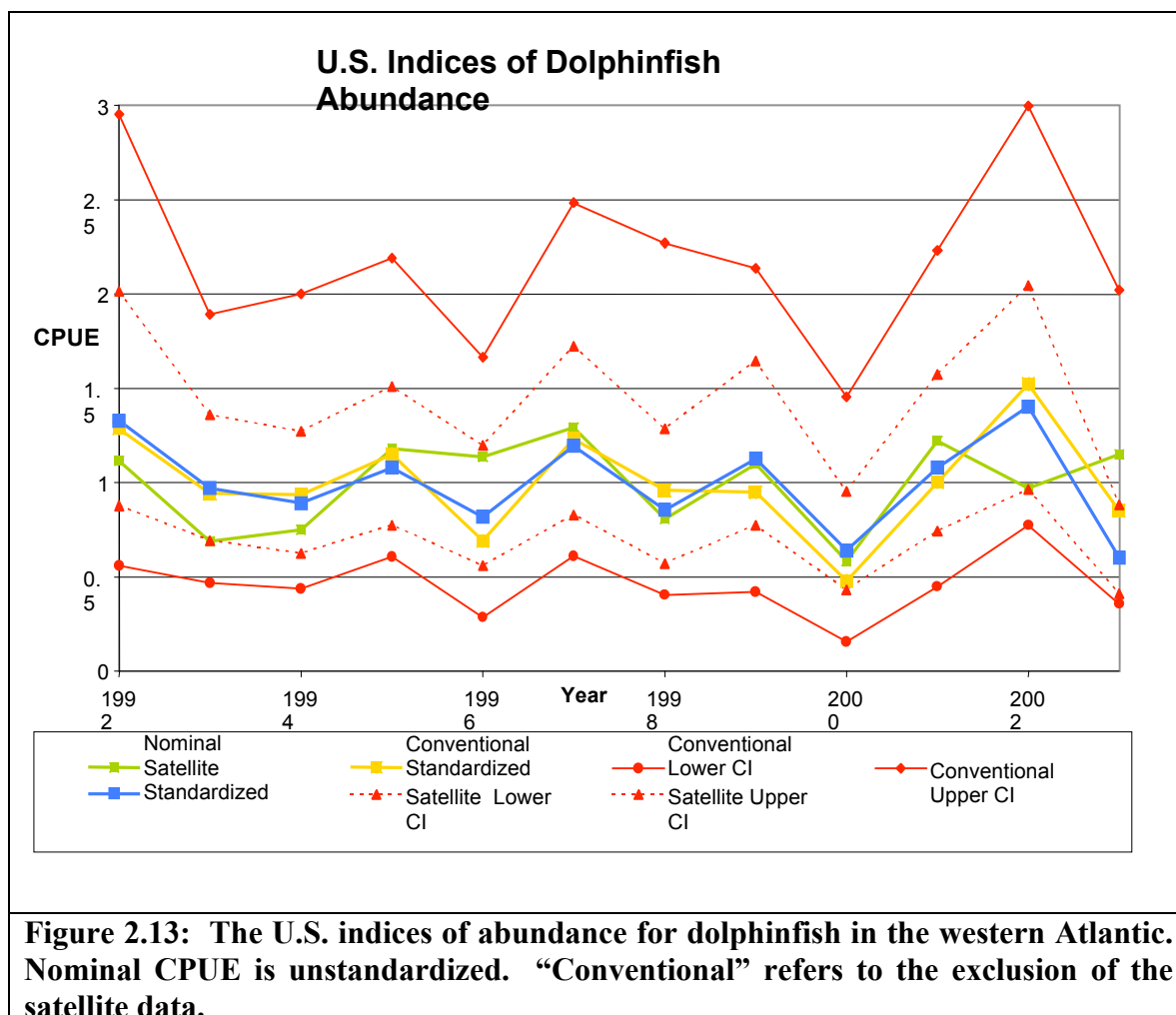
The apparent bimodality along the first axis was indicative of the patchiness of the fronts (Figure 2.12).



GLMs

U.S. Indices Excluding Satellite Data: “Conventional GLM”

The conventional U.S. GLM, where satellite data were not included, considered six factors: year, quarter, area, target, depth of hook and bottom depth. The lognormal portion of the model found all of these factors to significantly improve the fit, as well as three interactions: year*depth, quarter*area, and area*bottom depth. The binomial portion of the model found that year, quarter, and area, and the interaction of quarter*area sufficiently improved the fit of the model to be included in the final analysis. These factors were combined using the glimmix procedure (SAS 9.0) to explain the variability in the nominal CPUE index (Figure 2.13).



The results suggested oscillating abundance, with the minimum observed in 2000 and maximum in 2002. The confidence intervals for this model are quite wide meaning that there is significant uncertainty about these results.

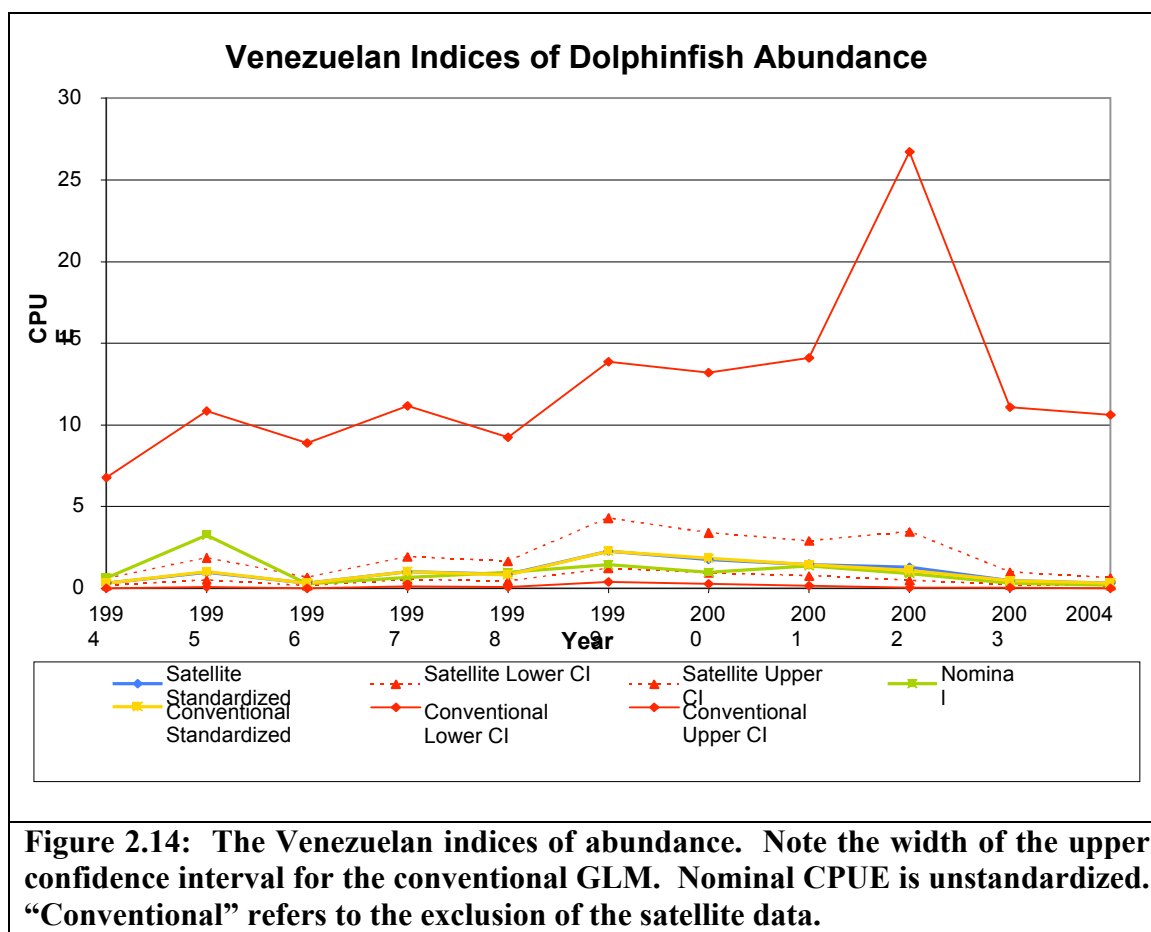
U.S. Indices Including Satellite Data

When SST and distance from nearest front were added to the model, they were identified as significant. The final lognormal model included year, quarter, area, and SST and the interaction year*SST. The binomial model included year and SST and no interaction terms. These factors were combined using the glimmix procedure (SAS 9.0) to explain the variability in the nominal CPUE index (see Figure 2.13). The resulting

series of abundance estimates was similar to the conventional U.S. index, with the most notable difference in the tightening of the confidence intervals.

Venezuelan Indices Excluding Satellite Data

The single conventional Venezuelan GLM, where satellite data were not included, considered four factors: year, quarter, area, and target. The lognormal portion of the model found year, quarter and the interaction year*quarter to significantly improve the fit. The binomial portion of the model also found year and quarter, and the interaction of year*quarter to significantly improve the fit of the model to be included in the final analysis. These factors were combined using the glimmix procedure (SAS 9.0) to explain the variability in the nominal CPUE index (Figure 2.14).



The general trend observed is the slightly fluctuating, but general rise to a peak in SST from 1994 to 1999. At this point, there is a steady decline in abundance through 2004. The confidence intervals for this model are extremely wide indicating significant uncertainty about the results of the model.

Venezuelan Indices Including Satellite Data

The lognormal model included year and quarter, SST, and distance to front, and the interaction of year*quarter. The binomial model included the single factor year by itself. These factors were combined using the glimmix procedure (SAS 9.0) to explain the variability in the nominal CPUE index (see Figure 2.14). However, this curve also followed the pattern of the conventional Venezuelan GLM, and in this case, the confidence intervals were greatly tightened compared to those of the conventional GLM.

2.5 Discussion of Multivariate Analysis Results

PCA

The results of the PCAs for both the east and the west conformed well to the patterns we anticipated from theory. These results demonstrated correlation between the variables that were available to understand the influencing factors on the CPUE of dolphinfish by the U.S. Pelagic Longline, but it is important to realize that correlation is not causation. These findings represent a way to indicate what the possible trends in the dataset might be, and the next step is to formulate hypotheses and models to explain the indicated phenomena (J. Sladek Nowlis *et al.* unpublished manuscript). Some of the trends may be attributed to the structure of the fleet itself, while others are reflective of the environment that is influencing these species. It is important to understand the relationship of both in order to take the next step of attempting to understand abundance.

The picture painted by the PCAs in the Gulf of Mexico and along the eastern seaboard allowed for an understanding of the driving environmental influences on the catch of dolphinfish both seasonally and regionally. In the Gulf of Mexico and along the eastern seaboard, there was a dominant annual seasonal signal (Figure 2.15) in the catch of the fleet that was evident from the yearly amplitude of the sinusoidal curve fit to the principle components of the general PCAs (Figure 2.16).

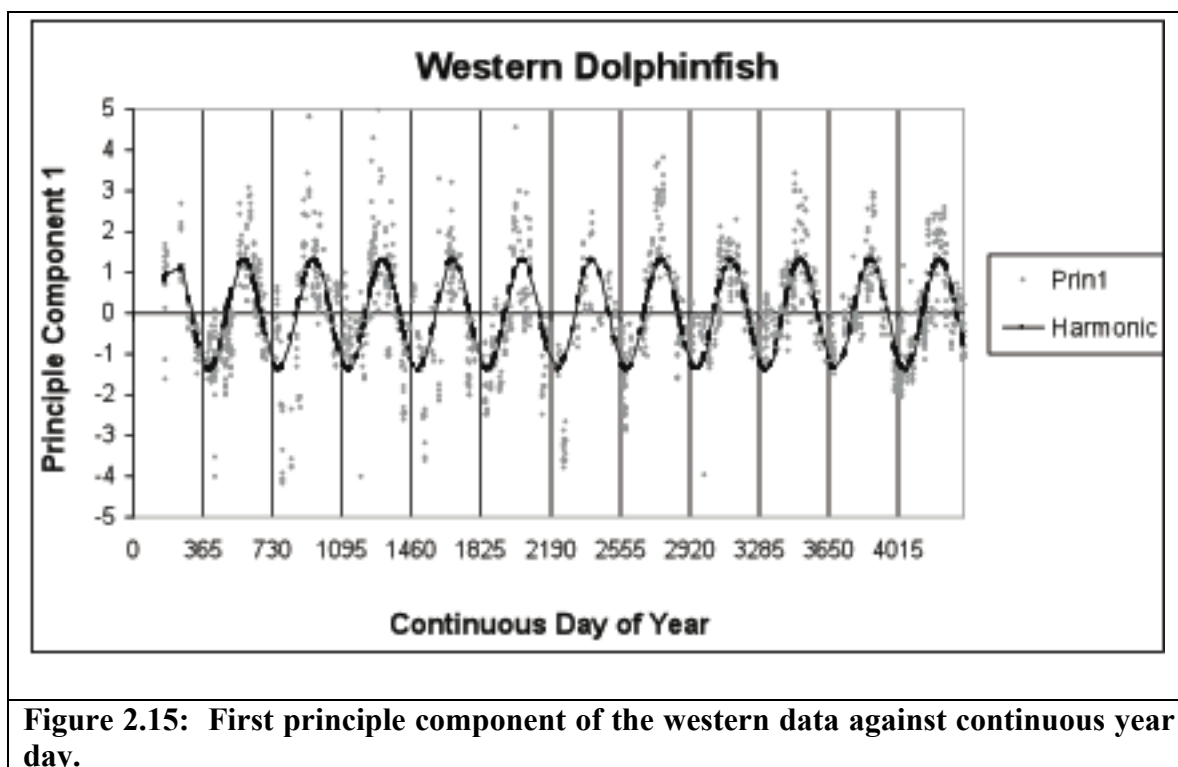


Figure 2.15: First principle component of the western data against continuous year day.

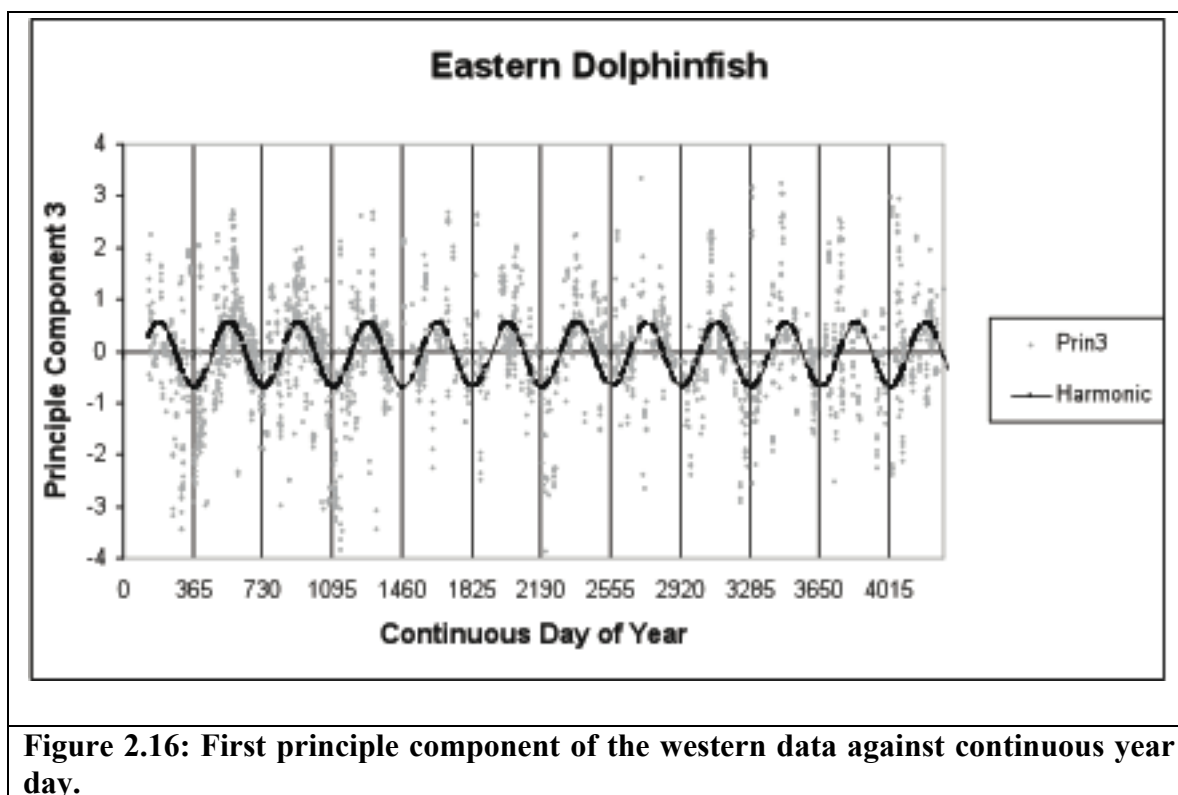


Figure 2.16: First principle component of the western data against continuous year day.

The annual signal was stronger in the Gulf of Mexico as is evidenced by the fact that this trend is picked up along the first principle component, whereas it is the third principle component that picks up this signal along the east coast. This was surprising, and may be related to the fact that there were other influences such as differences in fleet characteristics that played a greater role in the variability of the system. The fact that there was a dominant seasonal signal that is picked up by the data for the general PCAs was motivation to explore the patterns in separate seasonal analyses.

In the Gulf of Mexico, the general trend was for higher catch closer to the shelf in warmer waters. In general, and in all seasons except for winter, dolphinfish was caught predominantly on shallower set hooks. In fact in the fall and winter, the fleet appeared to catch more dolphinfish off the shelf, in a more southwesterly direction and closer to the Gulf Stream. In accordance with this was the fact that dolphinfish appeared to be caught

further from the front in general and in all seasons except for winter. This is likely attributed to the fact that due to the homogeneity of the temperature regime in the Gulf, the fronts were easier to locate in the winter, both for the fleet and for the dolphinfish. This addresses the fact that this analysis was interpreting not only the CPUE of the dolphinfish in the region, but the fishing patterns of the fleet. It is evident that more information on the types of vessels and the equipment used to find schools of fish would greatly enhance the understanding of the trends noted in this analysis. One allowance that can be made is that the data does come from a fleet that is specialized for targeting pelagic species. It is highly likely that the vast majority of the vessels were fishing with knowledge of not only where to fish based on experience, but also sophisticated frontal detection systems for specific areas that they are fishing. The PCAs in this paper describe a fleet that is fishing with respect to fronts. In the east, the fishing was closer to the fronts and the CPUEs were higher closer to the fronts (see Figure 2.11). This is interesting for two reasons. First, the fronts were probably easier to detect, and along the east coast there is the dominant Gulf Stream frontal system. Secondly, Figure 2.12 reveals an intriguing pattern of bimodality in the catch along the east coast in the later part of the year. This is indicative of a sort of “boom or bust” variability to the fishing. In other words, the longliners were either catching the fish or not after July. This may be related to the fact that while most longline vessels (especially the “high-liners” who have the larger vessels with more technology) were probably using the fronts to track the fish, they were probably not equipped to detect the age of the front. The age of the front may determine whether or not the front contains fish. Fronts are typically convergence zones that collect floating algae, debris, nutrients, and baitfish, that larger pelagic fish take

advantage of for food and shelter. Older fronts may be depleted of smaller bait fish and consequentially have less large pelagic fish. Conversely, older fronts have a better chance of being on SST analysis charts that are used by fishermen to find where they deploy the gear, but because the older fronts have a lower probability of yielding larger catches; this may have contributed to the bimodality seen in Figure 2.12.

GLM

These analyses showed that using remotely-based environmental data collected by satellites can explain some of the variability in the CPUE indices. This analysis also offered some insight into dolphinfish biology and fishing behavior of longline fleets. The pre-satellite abundance indices were already of relatively high quality due to the law of large sample sizes and the quality of observer-collected data. Nevertheless, the inclusion of satellite data in standardization resulted in important improvements to these abundance indices. In both cases, the abundance trends were quite similar with and without the satellite data. What changed was our confidence in the estimates. This is reflected in the confidence intervals, which are much tighter when satellite data were included. It is also apparent in the U.S.-based abundance series in that the peaks of the U.S. data are moderated.

The results were also informative about the dolphinfish population and the longline fishery. If we assume constant catchability, a standard assumption in the development of CPUE series, the GLM results provide insight into the distribution of dolphinfish. The U.S.-based analysis indicated that abundance was a function of season, area, and SST, with the SST effect varying with year. When satellite data were not included, many more factors were seen as significant, but the fact that they dropped out

suggests that they were perhaps serving as proxies for SST relationships. In contrast, the Venezuelan-based analysis indicated that more factors were identified as important when SST was included. In this case, the model went from including only a seasonal component to including SST, area, distance from front, and target. In this case, the inclusion of SST and distance from front provided enough additional information to the model to recognize the importance of area and target on dolphinfish abundance.

However, as the inclusion of target species in the GLM shows, it can be a bad assumption to assume constant catchability. The PCA results helped to clarify this distinction. More variation was explained by the first component than any other, and it distinguished fishing patterns. The fact that dolphinfish were not correlated with an axis that distinguished shallow northeastern fishing from deep southwestern fishing suggests that dolphinfish are likely to be caught using both techniques. This component explained the most variation, though, because the distinction between swordfish and tuna targeting is important in understanding the dataset. The second component provided a better sense of dolphinfish biology, and indicated that they were most likely to be found in warmer water closer to shore and thermal fronts. But, the third component showed that there was variation in this pattern that included some dolphinfish caught farther from shore and fronts and in deeper waters, but still in high SSTs.

Together, these analyses provide an example of the value of utilizing already-available satellite data when standardizing fishery-dependent catch rates, and also give insight into dolphinfish biology and the fishing behavior of longline vessels. Future extensions will look at additional ways of incorporating satellite data into stock

assessments as a way of improving those assessments and adding to our knowledge of fish and fishery.

CHAPTER 3: MODELING THE SPATIAL AUTOCORRELATION OF CPUE DATA IN THE GULF.

3.1 Spatial Patterns in the Environment

Because it is common for fish to school, the spatial distribution of a fish population is often patchy. It is likely that there is spatial autocorrelation present in a schooling fish population due to the fact that the fish move together with positive spatial dependence (Nishida and Chen, 2004) and the features which likely serve to aggregate or structure fish distributions also possess spatial autocorrelation (i.e., Rossby radius of deformation for eddy formation, temperature frontal patterns). This may result in the spatial autocorrelation of the catch data and the subsequent abundance index, which is one of the main inputs to a stock assessment model (Pettigas, 2001). Ignoring spatial patterns when using CPUE data to estimate stock abundance can sometimes lead to inaccurate assessments due to violations of the assumptions of random and uncorrelated samples (Pelletier and Parma, 1994). Typical abundance estimation procedures incorporate space as large statistical areas and make the assumption that these strata are internally homogeneous. Geostatistics provides a unique way to explore and model the changes in abundance in space and time, and through kriging allows the analysis and modeling of the variability of a population in space (Freire *et al.*, 1992).

Spatial autocorrelation is defined by Legendre (1993) as the “property of random variables taking values, at pairs of locations a certain distance apart that are more similar (positive autocorrelation) or less similar (negative autocorrelation) than expected for randomly associated pairs of observations.” This property is observed for most ecological variables in either a temporally or spatially explicit way. If we consider species abundance at a given location, it is likely that this variable is influenced

throughout its range by factors such as species assemblage, growth, reproduction, mortality, and migration at surrounding areas. These types of processes are known as contagious biotic processes (Legendre, 1993). It is therefore possible to predict the value of a variable at any locality based on the values at neighboring localities. This is in direct violation of the assumption that is typically made when standardizing abundances using traditional statistical methods: observations are stochastically independent from one another. Just as animals or plants are not distributed randomly, environmental processes are also linked temporally and spatially. Because these processes are not merely due to random noise, they can be quantified and used to reduce error and provide predictions in unsampled locations.

While spatial autocorrelation poses a hindrance in abundance index standardization, it forms the basis of geostatistical analyses. There are several examples of the use of geostatistics in fisheries applications including predictions of catch data and as alternatives to design-based estimators (Warren, 1998; Rivoirard *et al.*, 2000; Petitgas, 2001; Walter, 2006). Geostatistics takes the spatial autocorrelation between samples into consideration, and through kriging (the prediction of data based upon the spatial structure of the underlying data, see Chapter 4), allows the analysis and modeling of the variability of a population in space (Freire *et al.*, 1992). Therefore, geostatistics may represent an alternative approach to developing an index of abundance that takes the spatial structure of the data into account.

In order to determine the specific spatial and temporal distributions of exploited fish populations, scientists have relied on fishery-independent surveys and fishery-dependent catch records from the commercial and recreational fisheries. Fishery-

independent surveys follow standardized sampling protocols, provide precise spatial and temporal resolution, and by the nature of their design, lend themselves to unbiased statistical analysis. Many fisheries, however, lack such surveys and rely upon catch data recorded or observed during the fishing process. Such fishery-dependent data typically possess the following limitations:

- i) poor spatial resolution recorded (the spatial coverage can be limited to a large statistical polygon such as the FAO fishing statistical areas, which may be too broad for spatial analysis purposes),
- ii) the targeting of certain species leads to gaps in spatial-temporal coverage,
- iii) the absence of a standardized sampling design across space and time.

In some instances however, spatially explicit locational information is collected in fishery dependent data sources. In these cases, the fishery dependent data becomes more valuable as a tool for analyzing spatial and seasonal abundance patterns because of the relatively larger sample sizes, and typically more complete temporal and spatial coverage.

This study uses variograms (Cliff and Ord, 1973; Cressie, 1993) to measure the spatial structure and pattern of autocorrelation of the CPUE of two pelagic species, dolphinfish, *Coryphaena hippurus*, and swordfish, *Xiphias gladius*, within the Gulf of Mexico. The main goal of this work is to determine whether spatial autocorrelation exists in the CPUE data and if so attempt to determine if the range of autocorrelation is in fact reflective of the biology of the species or is confounded by the fact that the fishery is moving in space. Geostatistics provides a way to explain the variability in the catch rates

that is due to spatial differences and thus provides an alternative method of standardizing abundance indices to remove the influence of spatial heterogeneity on abundance indices. We also explore the variograms in relation to some of the oceanographic features that may influence the spatial structure of abundance of dolphinfish and other pelagics. Specifically, we consider whether the range of autocorrelation of a biological species can be linked to the patch size of the species by comparing the two species, dolphinfish and swordfish, using the same methodology (Upton and Fingleton, 1985; Legendre and Fortin, 1989; Walter, 2006). A species with a shorter range in the variogram of its CPUE may be indicative of smaller patch size, whereas a larger range may indicate a larger patch size and perhaps greater predictability of catch. The expectation is that there will be significant differences in the range of autocorrelation of the two species. Dolphinfish, being associated more with surface waters, should have a shorter range than swordfish, which makes deeper dives diurnally and therefore lives in a more homogeneous environment. Annual, seasonal, and species statistical differences between the variograms are explored using ANOVAs.

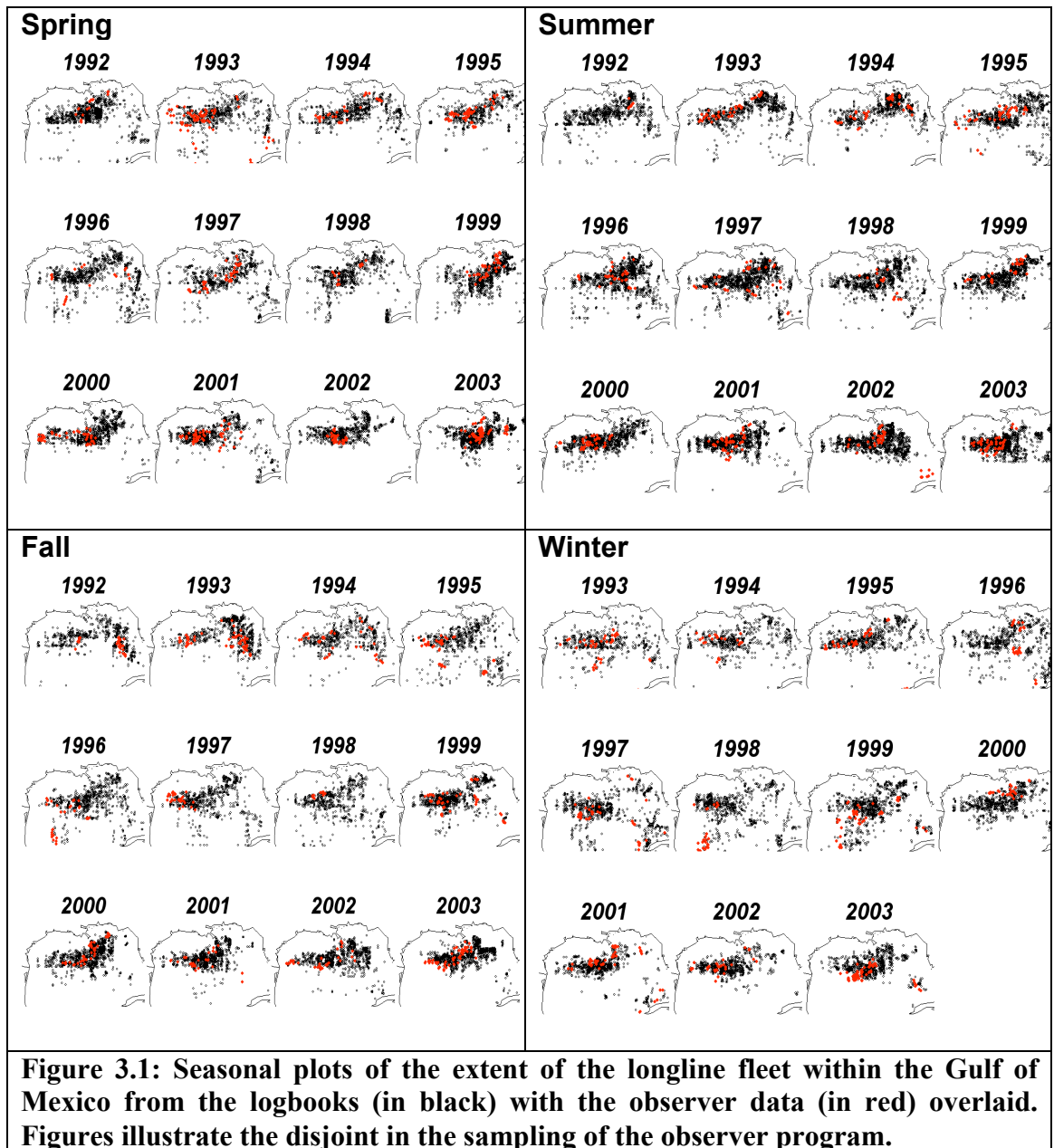
3.2 Data Analysis

Selection of Study Area and Temporal Scale of Analysis

An important issue when evaluating statistical associations between the distribution of a fish stock and environmental conditions is whether there are enough physical and biological data collected at appropriate temporal and spatial scales (Podesta *et al.*, 1993). For the purposes of this study, it is first necessary to select between the use of the logbook data, which offers complete coverage of the longline fleet, and the

observer data, which represents a sampling of the longline fishing effort. There are several benefits and disadvantages to each dataset, as will be detailed.

As described in detail in chapter 1, the U.S. logbook dataset is unique in that it covers a broad area spatially and consists of a relatively long time series (1986-2005). There are approximately 279,918 records in the total logbook dataset. In the Gulf of Mexico, there are 86,522 individual trips that are recorded in the logbooks. In addition to these data, more detailed information on the catch, environmental conditions, and vessel characteristics has been collected since 1992 on a subset of the longline fleet by observers stationed onboard the longline vessels. Approximately 2% or about 2062 of the longline trips have been sampled by observers (1992-2005) in the Gulf of Mexico. When aggregated over the entire time series, the spatial coverage by the observer fleet is relatively well matched to the logbook coverage (see Figure 1.1). The difference in the extent of the spatial coverage of the two datasets is noticeable when the data are mapped at a finer temporal scale (Figure 3.1).



The PCA (Chapter 2) showed that there was significant seasonal variation in the catch of the longline fleet. For the spatial analysis, a season was defined as Spring (March, April, May), Summer (June, July, August), Fall (September, October, November), and Winter (December, January, February), and the autocorrelation was modeled for each season within each year. Therefore, the time step was an individual season within a year, which

will be referred to as a year-season throughout this analysis. Catch within each time step was assumed to be stationary. A finer temporal resolution (such as month) could not be used due to constraints of sample size. Plots of the distribution of logbook and observer points in each season annually (Figure 3.1) show that at this resolution the logbook data offers a more complete coverage of the study area.

The advantage of the observer data is that it is collected by an independent scientifically trained observer who does not work for the fishing vessel, and is generally believed to be more accurate for trips that are observed. Spatial data are collected in the logbooks; however, it is only the position of the gear at some point during deployment or retrieval. Therefore, spatial uncertainty exists at approximately the range of the length of the gear (about 30-40 km in the Gulf of Mexico), in addition to the uncertainty due to the drift of the gear during set and retrieval and due to the rounding off of locational information. Observers record a spatial coordinate for both the beginning and ending of the set and haul back of the gear. This allows for a better estimation of a point of catch. For the purposes of a spatial analysis, a finer spatial resolution is preferred because the covariance between each individual catch point is a function of the distance from each observational location; unfortunately, the observer dataset does not provide adequate sample size. The logbook data represents the most temporally and spatially detailed U.S. catch and effort data for large pelagic species in the western Atlantic, and is therefore better for a geostatistical analysis.

The U.S. fleet operates in a relatively vast and oceanographically heterogeneous area of the Atlantic Ocean. Therefore, it is unlikely that spatial processes that determine pelagic fish abundance are the same throughout this area. The spatial distribution of fish

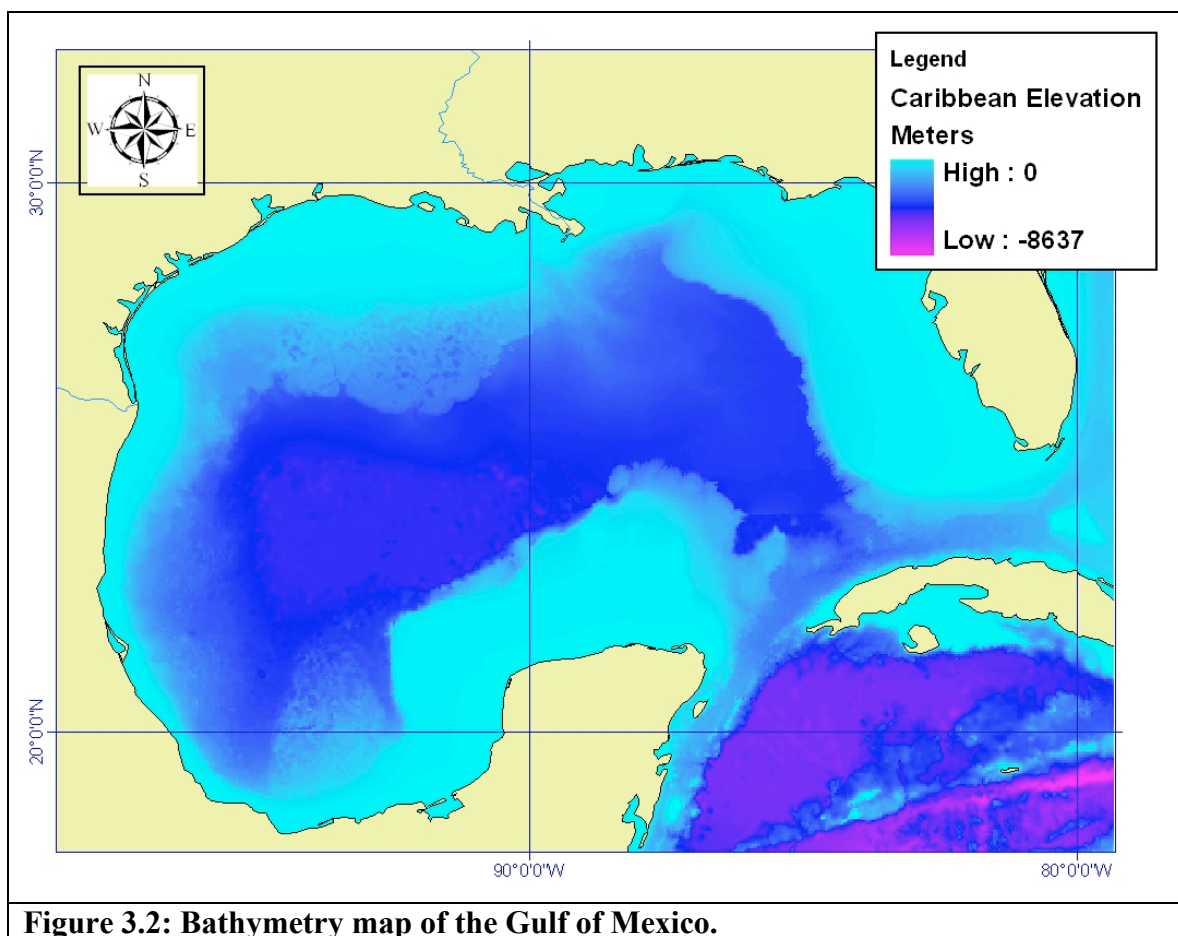
caught in the Caribbean would be assumed to have a different spatial structure than that of fish caught off of George's Bank. The Gulf of Mexico is a natural subsection of this vast fishery area. It is a relatively contained ocean basin where the U.S. longline fleet has operated regularly over the past twenty years. In addition the oceanographic environment of the Gulf of Mexico should have fewer problems with directionality or anisotropy of oceanic processes than might be the case with other subsections where the US longline fleet operates. Anisotropy, the property of being directionally dependent, presents a difficulty in a spatial analysis because it adds a layer of complexity. To properly describe the spatial autocorrelation in a system, any anisotropy must be identified and corrected for because the theoretical variograms used for kriging are based on isotropic models. Zonal anisotropy may be corrected by modeling and detrending the data or by choosing a nested variogram model. The neighboring east coast of the U.S. is another important section of the US longline fishery but it stretches along a broad diagonal gradient heavily influenced by the Gulf Stream.

Description of Study Area

Dolphinfish are an important species both ecologically and commercially to the recreational and commercial fisheries in the Gulf of Mexico. In the commercial longline which targets mainly yellowfin tuna (*Thunnus albacares*) and swordfish (*Xiphias gladius*) in the Gulf, they represent an important bycatch and occasional target species. Commercial longliners concentrate effort near thermal fronts where it is believed that bioaccumulation of prey occurs, and therefore the potential for higher catches is increased. To accomplish this, they often use *in situ* water temperatures and SST derived from satellites. The Loop Current is a very important dynamical feature in the Gulf of

Mexico and the majority of the vessels set their gear in the northeastern Gulf along this frontal region, and in the northern central Gulf where the dynamics are affected by the Loop Current and shedding of eddies or rings from this feature.

The Gulf of Mexico (Figure 3.2) is a semi-enclosed sea that is connected in the east to the Atlantic Ocean through the Straits of Florida, and in the south to the Caribbean Sea through the Yucatan Channel.



The Gulf is about 1,800,000 km² and stretches about 1770 km east to west. The bathymetry of the Gulf of Mexico includes major oceanic inflow and outflow paths in the south and the southeast, respectively, with most of the river inflow occurring along the northern boundary. Wide shelves are found along the Florida and Campeche banks. The

shelves around the western Gulf of Mexico are narrower, with a very narrow shelf along the northwestern coast of Florida, where the De Soto Canyon penetrates almost to the shoreline.

During the summer, the temperature of the surface waters of the Gulf of Mexico is quite homogeneous, and chlorophyll levels are high. In contrast, in the winter, warmer Caribbean waters entering the Gulf create sharp temperature gradients with the seasonally cooled surface waters of the Gulf, especially in relation to the Loop Current, the dominant feature of the circulation of the eastern Gulf. It is in this region that the Florida Current originates. The western inflow of the Loop Current begins in the Yucatan Channel with the Yucatan Current. The flow into the Gulf through the Yucatan Channel is approximately 23-27 Sv (Johns *et al.*, 2002). The flow along the western boundary of the Loop Current can reach peak speeds of 1.5 to 1.8 ms⁻¹ in the surface waters (Nowlin, 1972; Schlitz, 1973 and Carder *et al.*, 1977 from hydrography; and Sheinbaum *et al.*, 2002 from ADCP measurements).

The Loop Current is variable both in its north-south extent and its east-west width. The gradients that develop from the inflow of warm Caribbean waters with the Loop Current are also known as temperature fronts, and are important for their ability to aggregate debris and small fish. It is likely due to this higher productivity and persistence of prey items that larger pelagic species are often found along frontal boundaries. Thus, a combination of chlorophyll pigment or ocean color and sea-surface temperature data from satellites provides a year-round look at the large-scale, surface processes occurring in the Gulf of Mexico that may be affecting the distribution of large pelagic species.

Data Processing

In order to be able to address the question of spatial autocorrelation in the catch rates of dolphinfish and swordfish, it was necessary to parse the logbook dataset down to sets that were primarily targeting pelagic species using only longline gear within the Gulf of Mexico. This helped to ensure that no biases were introduced to the analysis due to gear or targeting differences and it was hypothesized that issues with spatial trend would be reduced within a limited area like the Gulf of Mexico. The entire logbook database consisted of records from June 1986 through December 2005. To keep the seasons uniform, the data from 1986 was dropped as it was an incomplete year. Only those records within the Gulf of Mexico were selected, defined as north of 18°N and west of 81.5°W. Analysis was restricted to pelagic longline sets only. All other gear types (i.e., bottom longline, gillnet, bandit or otter trawl, harpoon, rod and reel, handline, greenstick tuna fishing, etc.) were removed. Additionally, if a trip recorded more than one gear type, these records were removed. In order to distinguish between trips that may have been using bottom longline gear or targeting sharks on the shelf, and to remove obvious outliers such as points recorded on land, only records that were recorded in waters deeper than the 25 meter isobath were kept. Depth isobaths were constructed from ETOPO2 gridded 2' elevation data (Version 2). To remove outliers and ensure that catches were consistent, the dataset was truncated by the 2.5% (200 hooks) and 97.5% (1000 hooks) quartiles of number of hooks. CPUE for the logbook records was defined in number of fish caught and discarded alive or dead divided by the number of hooks used per set. Any CPUE greater than one was removed as it was highly unlikely to get more than one fish per hook and this was indicative of an incorrectly reported number of hooks. Lastly,

it was necessary to project the latitude/longitude coordinates to an equidistant coordinate system in order to conduct spatial statistics. While one degree of latitude along a meridian always measures the same distance (i.e. about 111.1 km), one degree of longitude is a different distance at every latitude (about 55.6 km at 60° north or south; and zero at either pole). An Albers equidistant conic projection was used for the logbook data. With this projection, the direction, area, and shape of the map are slightly distorted away from the standard parallels. This projection is commonly used for areas near to, and on one side of, the equator.

Geostatistical Analysis

The abundance of a species as estimated from CPUE measured at discrete spatial points may be suitable for geostatistical analysis. This type of data can exhibit small-scale variability that can be modeled as spatial correlation. This information can then be incorporated into estimation procedures to predict abundance and create maps of spatial distribution (Cressie, 1993; Webster and Oliver, 2001). The variability in space can be modeled as a function of the distance between measurement locations. In other words, measurements that are made closer together are more likely to have similar data values than those that are far apart. This relationship is described by the variogram, which provides a measure of spatial autocorrelation by describing the relationship of the sampled data with distance and direction (Kanyerere, 2000; Kaluzny *et al.*, 1998).

Exploratory Data Analysis

As mentioned before, the logbook data contained a sampling location that was defined by a latitude and longitude. The assumption made when modeling an underlying random spatial process is that:

- i) the spatial distribution is stationary (i.e., the mean and variance do not vary significantly in space over the sampling period).
- ii) the spatial pattern is isotropic (uniform in all directions)

The first assumption pertains to the need to have all CPUE observations within a time step reflecting the same underlying spatial process (Pelletier and Parma, 1994). The fact that dolphinfish are a migratory species makes the first assumption difficult to satisfy. Typically, the spatial process being modeled is composed of a large-scale deterministic component and a small-scale stochastic component. The variogram models the random component after the large scale deterministic pattern has been removed. To test that there are no violations of the first assumption, plots of the CPUE versus the latitude and longitude are explored. The indication of trend would be if there was a linear relationship between the two variables. Trend was tested for and deemed not to be a factor in this analysis. However, if trend were determined to be a confounding factor, it would be necessary to first remove this trend from the data before using the variogram to estimate the underlying random process. Procedures for removing trend include:

- i) rotation of the longitude and latitude axes to analyze the directionality in the spatial domain,
- ii) using a GAM to model the logged data as a smooth function of the longitude and latitude, or
- iii) fitting a local regression model (loess) to the whole trend surface.

To test the second assumption, variogram models were calculated in various directions. An indicator of anisotropy would be if there were significantly different variograms between directions. Variograms were computed for all year-seasons in

several directions (0°, 45°, 90°, 135°, and 180°) and visually evaluated for differences. No dominant patterns in directionality were observed, and therefore only zero degree variograms were used in the following analyses. An additional issue arose when a variogram could not be obtained for a specific year-season. When exploring the range for a particular species, those year-seasons for which no variogram could be obtained were excluded from the analysis.

Two-stage Variogram Analysis

The empirical or theoretical variogram $2\gamma(x,y)$ is the basis for understanding how the data are correlated in space and the degree of spatial dependence of a spatial random field $Z(x)$. It is described by the equation:

$$2\gamma(x,y) \equiv E(|Z(x) - Z(y)|^2) \quad (1)$$

which is the expected squared increment of the values between locations x and y (Cressie, 1993). The semi-variogram $\gamma(x,y)$ or $\gamma(h)$, is defined as half the average squared difference between points separated by a distance h (Kaluzny *et al.*, 1998). The empirical semi-variogram is described by the equation:

$$\gamma(h) = \frac{1}{2|N(h)|} \sum_{N(h)} (Z_x - Z_y)^2 \quad (2)$$

where $N(h)$ is the set of all pairwise Euclidian distances $h = x - y$, $|N(h)|$ is the number of discrete pairs in $N(h)$, and z_x and z_y are data values at location i and j , respectively. The semi-variogram can be called $\gamma(h)$ only when the process is stationary and isotropic (i.e., independent of direction) (Cressie, 1993). We can determine the variogram for different directions, allowing us to find whether spatial continuity shows preferred axes (anisotropy). Often, anisotropy is weak or of secondary interest, and an omnidirectional

variogram $2\gamma(|h|)$ is all we need. The variogram is called isotropic if it only depends on the distance and not on the direction of the lag, that is, $2\gamma(h) = 2\gamma(|h|)$. The h represents a distance measure that has magnitude only. The assumption of isotropy will be addressed in the subsequent section.

The variogram or structure function itself has three main parameters. These are the nugget, the sill, and the range. The nugget is also referred to as the nugget effect and is representative of the sub-grid scale variation or measurement error in the system, and is visualized on the variogram as the intercept of the variogram. For values of $h = 0$, the nugget effect is estimated from the empirical variogram as the value of $\gamma(h)$. The sill is the limit of the variogram tending to infinite lag distances. It represents the variance of the random field. The range is the distance at which the data are no longer autocorrelated (i.e., the difference of the variogram from the sill is negligible).

There were several other parameters that were necessary to customize the individual variograms for each year-season: maximum distance, lag, and number of lags. The maximum distance of analysis is the point at which the number of pairs of points begins to decline. For 92% of the variograms, this distance was 200 km. The reliability of the variogram reduces beyond this point. The lag distance is the interval over which the search for neighbors is conducted, 30 km in this study, and the number of lags is determined by the number of lags within the maximum distance. No minimum number of pairs needed to be specified for the variogram as the sample number of pairs of location points was adequate within each bin.

The variograms were estimated using the robust variogram method estimation as suggested by Cressie and Hawkins as it has the advantage of reducing the effect of

outliers without removing specific data points from a data set (Cressie and Hawkins, 1980). The robust estimation method is based on the fourth power of the square root of absolute differences as follows:

$$\bar{\gamma}(h) = \frac{\left\{ \frac{1}{2|N(h)|} \sum N(h)^{|z_i - z_j|^{1/2}} \right\}^4}{0.914 + (0.988/|N(h)|)}. \quad (3)$$

Because dolphinfish is not a target species of the longline fleet, there are a greater proportion of zeros than for standard analyses of this sort. Additionally, the positive catches of both dolphinfish and swordfish follow a lognormal distribution. The common method for dealing for zero-inflated, lognormal distributions, when standardizing abundance, is to separate the positive catches from the proportion of positives (Maunder and Punt, 2004). This is known as a two-stage modeling process. In order to approximate a normal distribution when data is lognormally distributed, the log of the positives is used. The catches of dolphinfish were determined to be zero-inflated, and a histogram of the positive catches resembled a lognormal distribution. Therefore, it was assumed that there would be different processes described by the positive catches and the proportion positive and it would be advantageous to model these processes separately. Variograms were computed for each year and season for the logged positive catches and the indicator (i.e. zero or positive catch) data. Variogram models based on the logged positive catches will be referred to as lognormal variograms and the variogram models of the proportion positives will be referred to as indicator variograms for this analysis.

Removing Trend Due to Gear Usage from the Swordfish Data

Dolphinfish, a surface-dwelling species is not influenced by gear modifications such as the use of light sticks or different bait type. The amount of variance explained by

these factors was 2.9% and 0.9% respectively. Typically factors are included in the GLM when they account for more than 5% of the variability in the model. A step-wise regression test of swordfish catch reveals that these factors do have a significant effect and account for 7.1% and 59.2% of the variance of the model respectively. In order to level the playing field and enable a comparison of the two species, it is necessary to remove the trend associated with these effects from the swordfish data through a linear regression. The residuals of this regression represent the removal of this trend, and therefore, the variograms for the lognormal positive and the indicator swordfish data are calculated using these residuals instead of the raw CPUE data as was the case with the dolphinfish data. Variogram modeling was performed on the raw CPUE data and a comparison between these variograms and those computed from the residuals show similarities. The main difference is an increase in the range parameters of the residual variograms.

Theoretical Variogram Modeling

Once the parameters of the empirical variogram have been estimated, the next step is to fit a theoretical model to the variogram. To ensure that the assumption of isotropy was met, focused variograms were generated in each orthogonal direction to observe whether or not there were significant differences in the resulting variograms. No significant directionality was observed, and as a result, there was no need to correct for anisotropy before fitting a theoretical variogram model to the empirical one. A significant directionality could be corrected by a linear transformation of the lag vector h . The theoretical variogram model used in this study was the spherical model. Other models, such as the exponential and Gaussian model were tested, but the spherical model

appeared to provide the best fit to the empirical variogram. Apart from possible *a priori* knowledge about the process and the user's subjectivity, there is no standard methodology for quantitatively choosing among valid variogram models (i.e. spherical, exponential, or Gaussian). Recently, Gorsich and Genton (2000) have described a nonparametric variogram derivative estimator tool to aid the determination of a variogram model. Their technique draws on the fact that although variogram models look similar, their derivatives are often quite different. A MATLAB® (2007, The MathWorks) program was used to nonparametrically determine estimates for both the variogram and its derivative for a selection of year seasons for this study (Gorsich and Genton, 2000). It was determined that the spherical model most closely fit the derivatives estimated from the estimated nonparametric model. Qualitatively, the spherical model is preferable as it is most commonly used in geostatistical analysis of biological populations (Freire *et al.*, 1992). The spherical model (Cressie, 1993) is described by the following series of equations:

$$\gamma(h; \theta) = \begin{cases} 0, & h = 0 \\ C_o + C_s \left\{ \frac{3}{2}(\|h\|/a_s) - \frac{1}{2}(\|h\|/a_s)^3 \right\}, & 0 < \|h\| \leq a_s \\ C_o + C_s, & \|h\| \geq a_s \end{cases} \quad (4)$$

where $\theta = (C_o, C_s, a_s)$, $C_o \geq 0$, $C_s \geq 0$, $a_s \geq 0$, and C_o is the nugget effect. The nugget effect exists due to the variability between samples, or errors in measurement or location. C_s is representative of the sill-nugget effect, where the sill is the asymptotic value of semivariance, which is reached with a value of $h = a$. This value corresponds to the range, which is representative of the maximum distance at which spatial effects are detected.

In order to fit this model to the empirical variogram, the residual sum of squares between the theoretical and empirical model is minimized by a weighted least-squares estimation procedure (Cressie 1993):

$$\sum_{y=1}^K |N(h(y))| \left| \frac{\bar{\gamma}(h(y))}{\gamma(h(y); \theta)} - 1 \right|^2 \quad (5)$$

where K is the number of lags, $\theta = (C_o, C_s, a)$, $\gamma(h(y))$ is the spherical variogram model and $\bar{\gamma}(h(y))$ is the empirical variogram.

Tests for Statistical Differences Between Theoretical Variograms

There are no formal methods developed for testing for differences between variograms. The variogram parameters describe the shape of the variogram and therefore reflect differences between the variograms. Of the three parameters, range, sill, and nugget, range is perhaps the most indicative of a biological difference behind any observed variation in the variograms. The range of the variogram is related to the patch size of the animal (Rossi *et al.*, 1992). A shorter range indicates that the organism is spatially autocorrelated at close distances up to the range of the variogram, and a longer range indicates autocorrelation over a larger patch size. Analysis of Variance (ANOVA) was used to test for differences in the ranges of the variograms for a given year/season combination without replication, and between species. All statistical tests were conducted using SAS (SAS Institute Inc., 1999). Of interest in this analysis was whether there were significant differences in the variograms across years and seasons and between dolphinfish and swordfish. The ANOVA tests were constructed separately for the lognormal positive and the indicator portion of the data. The range of the variogram was used as the dependent variable in separate ANOVA tests.

3.3 Results of Spatial Analysis

Variograms

The variograms of dolphinfish (Appendix B), show generally strong patterns of spatial autocorrelation. In general, the shape of the variograms displays a “typical” shape with a well-defined range. The variogram parameters for the logged positive dolphinfish data are summarized in Table 1 in Appendix A. The ranges of the variograms are very similar between seasons. In the spring, the range parameters fall between 25.5 and 110.5 km with an average of 65.5 km. The summer ranges from 15.3 km to 113.57 km, and has an average range of 52.2 km. The fall has the greatest variance in the range parameters with a low of 25.8 km and a high of 147.0 km. The average for this season was 63.2 km. Winter had the lowest average range of 44.4 km and ranged from 15.6 km to 121.7 km. Figure 3.3 displays the lognormal positive variograms for each season in 1989 for example.

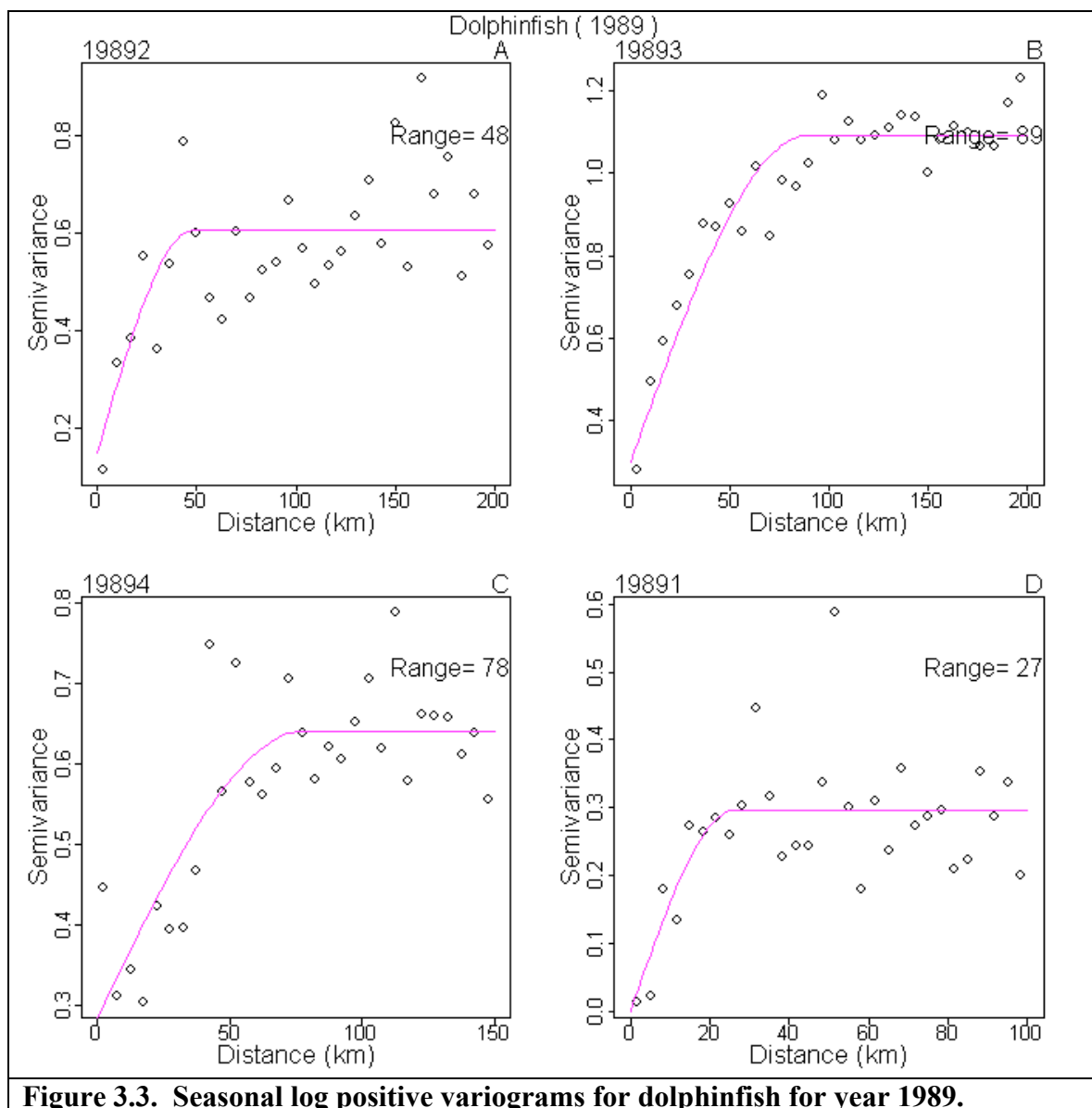


Figure 3.3. Seasonal log positive variograms for dolphinfish for year 1989.

The indicator variograms for dolphinfish exhibited a similar pattern (Appendix B, Figures 5-8). As with the log positive variograms, the average sill was highest in the summer and lowest in the winter. For all seasons the ranges were slightly greater for the indicator variograms than the log positive variograms. This was likely due to the fact that the indicator variograms incorporated data from areas where the fleet was fishing, but not catching dolphinfish. The longest range, 83.4 km, was in the summer, and the shortest

range was 61.8 km in the winter. Figure 3.4 displays the indicator variograms for each season in 2000 for example.

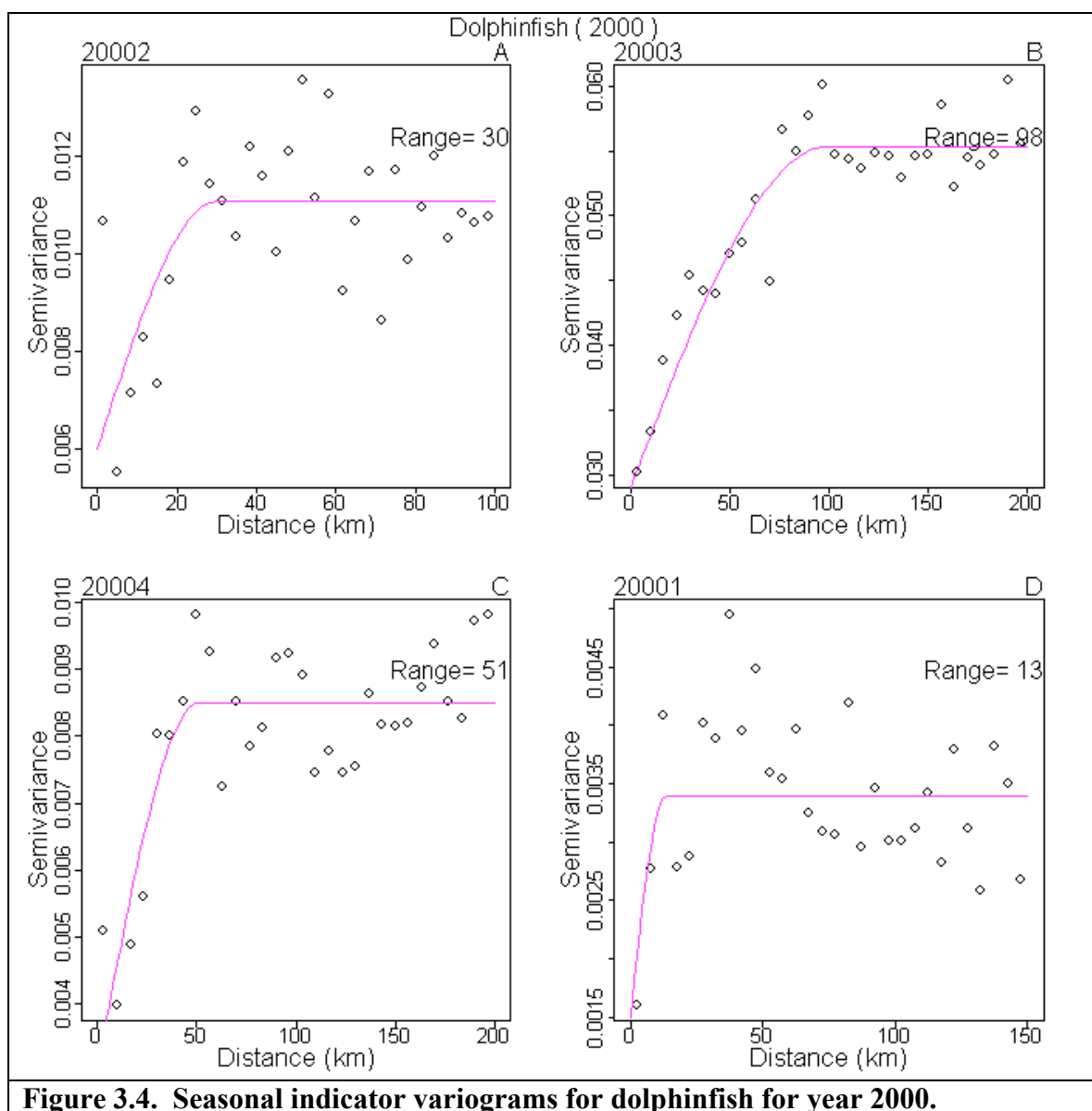


Figure 3.4. Seasonal indicator variograms for dolphinfish for year 2000.

Histograms of the variogram parameters by season are helpful in understanding some of the patterns between species and between the indicator data and the lognormal positive data (Figure 3.5a-f).

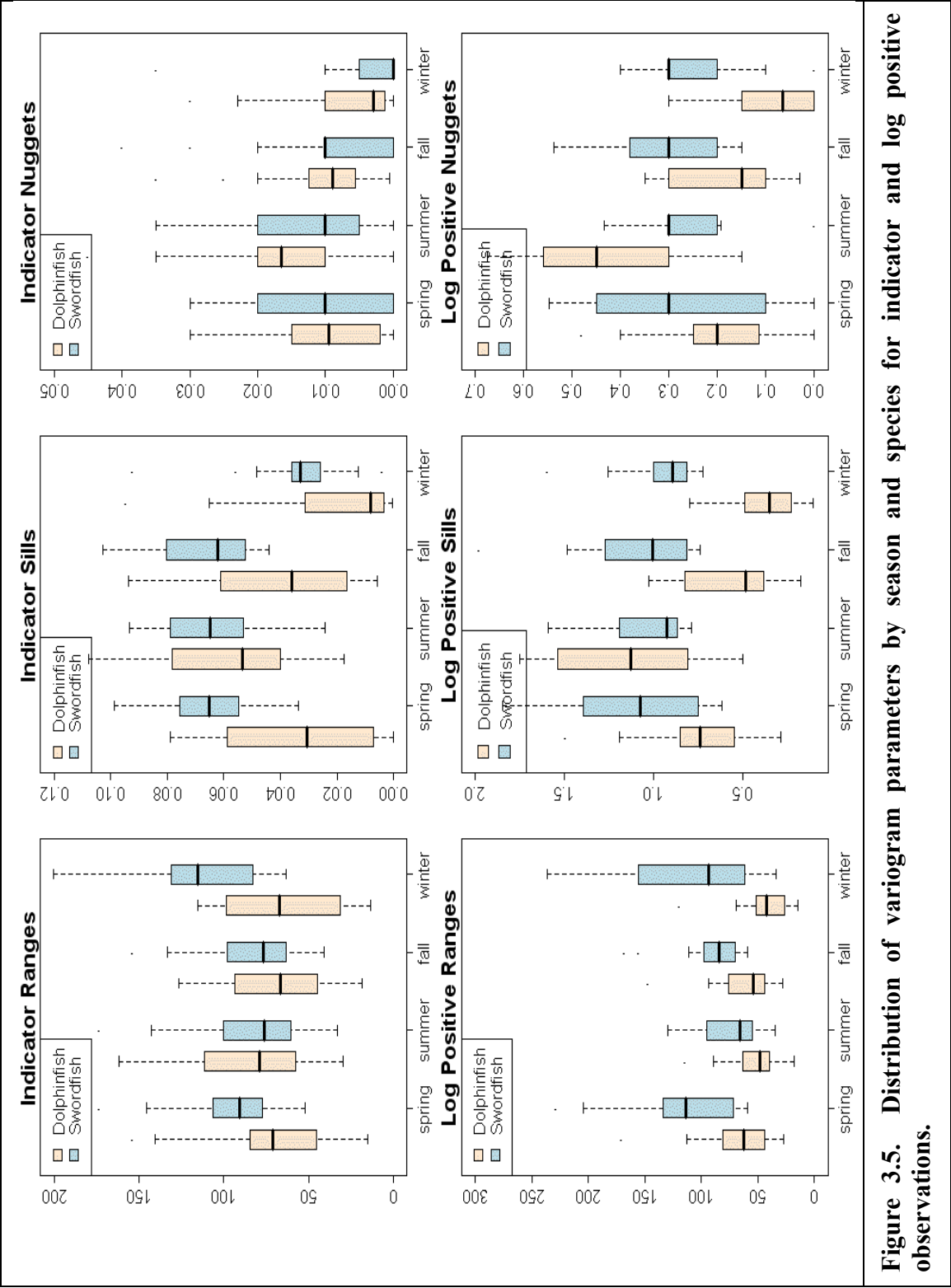
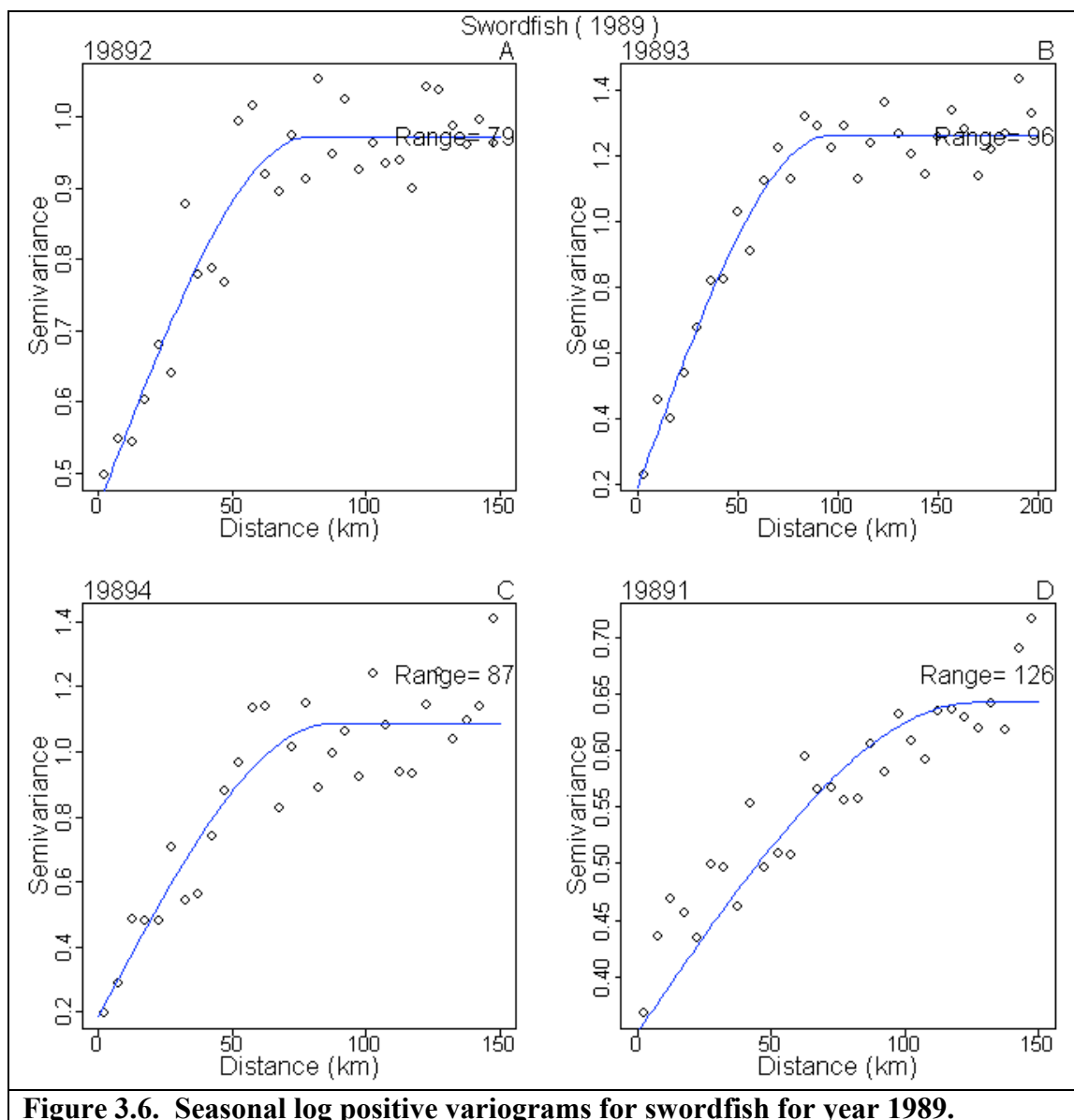


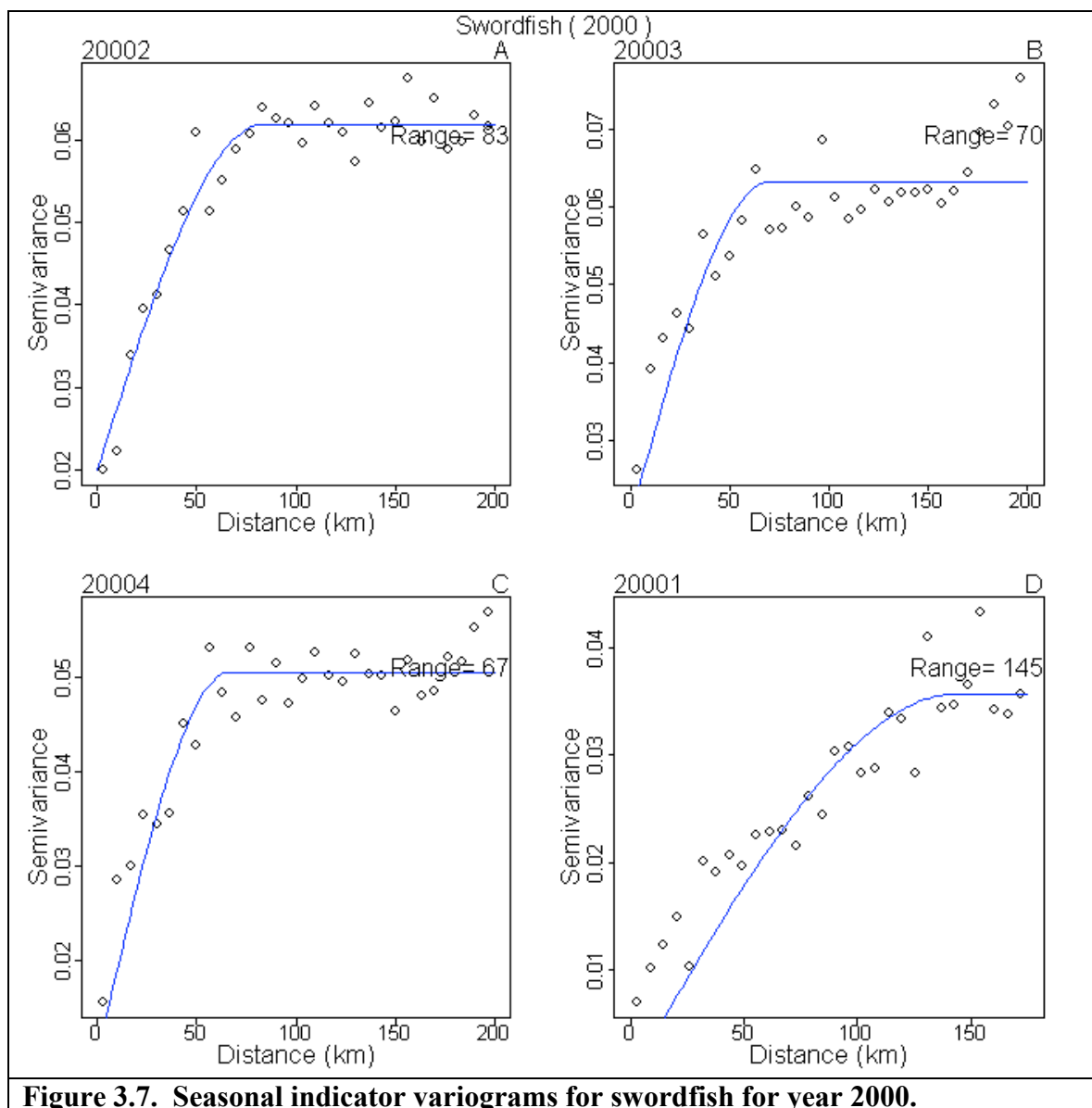
Figure 3.5. Distribution of variogram parameters by season and species for indicator and log positive observations.

The ranges of lognormal positive swordfish were generally consistent across seasons (Figure 3.5a). The median range was around 100 km for all seasons, but there was variation in the spread of the ranges across years. The ranges of lognormal positive dolphinfish were significantly lower, around 50 km. There is variation between seasons in the ranges for both swordfish and dolphinfish for the proportion positive catch (Figure 3.5d). The ranges of swordfish are only significantly higher than dolphinfish in the spring and winter and slightly higher in the fall. The sill, which is indicative of the variance of the system, is influenced by the amount of catch of the species. Since the catch of swordfish is much higher than dolphinfish, it was expected that the sills for swordfish would also be higher (Figure 3.5b). In general, the sills of swordfish are consistent across seasons. There is a deviation from this pattern in the winter for the proportion positive swordfish catch (Figure 3.5e). Dolphinfish show a distinct seasonal pattern with the highest average sill in the summer and lowest in winter following the seasonality in the catch of this species. In the winter, the fleet fishes less and in general exhibits lower catch. This same pattern is observed for the proportion positive dolphinfish catch (Figure 3.5e). The nugget effect, which is related to the amount of measurement error, was generally consistent between seasons for lognormal positive dolphinfish, except in the summer when it was higher (Figure 3.5c). This same pattern is found with the proportion positive dolphinfish catch (Figure 3.5f) and is likely attributed to the fact that there is higher catch in the summer and therefore likely to be more error associated with the increased yield. The nugget effect for swordfish for both types of data was in general consistent across seasons (Figure 3.5c and 3.5f). The observation

error can be attributed mainly to errors in the recording of the positional information, errors in the recording of the catch, and discrepancies in the number of hooks.

The average variogram parameters by season for swordfish for both types of data were significantly higher than for dolphinfish (Appendix B, Tables 3 and 4). Spring and winter had the highest average ranges for both the lognormal data (132 km and 124 km, respectively) and the swordfish indicator data had very similar average ranges across seasons (107km, 107km, 105km, and 112km for spring through winter). The swordfish catch rates also displayed the greatest amount of variability within years over a season. For example, in summer of 1988, the range of the variogram of the lognormal positive data is 218 km. This is in contrast to summer of 2001 where the variogram using the same type of data is 32 km. Figures 3.6 and 3.7 display examples of variograms in a single year for lognormal and indicator swordfish data respectively.





Using the Average Variogram

In general, for both species and both data types (the lognormal positive data and the indicator data), a pattern of relatively strong autocorrelation could be determined. In particular, for dolphinfish, the winter season displayed the weakest autocorrelation with both types of data. No variogram could be fit for the lognormal positive dolphinfish catch from winter 1998, 2000, and 2003-2005. A pattern of autocorrelation could not be

determined for the indicator dolphinfish catch from winter 1988, 1998, 2001, and 2003. When no such pattern of autocorrelation was detectable (Figure 8), the average variogram parameters of all of the years in a given season would be used for prediction.

In contrast, variograms for swordfish were typically well-resolved except in the case of winter 1990 with the lognormal positive data and winter 2005 with the indicator data. This may perhaps be due to the significantly higher number of records of positive catch of swordfish than dolphinfish in the winter seasons.

ANOVA Results

The tests for differences in the variogram ranges of the lognormal positive data revealed significant differences annually ($p=0.0226$) and between the species ($p<0.001$) (Table 2). However, no significant seasonal differences were found ($p=0.5100$). There were significant differences between the variogram ranges for all factors for the proportion positive data: year ($p=0.0144$), season ($p<0.001$), and species ($p<0.0024$).

3.4 Discussion of Spatial Patterns

Most ecological factors display some level of geographical patchiness. Legendre (1993) has found this to be the case at a variety of spatial scales—from the Petri dish to the continental and ocean basin scale. This patchiness in the environment implies that most variables of interest will be spatially autocorrelated. The question then becomes, what is causing this patchiness? Although classical statistics assumes the independence of observations, field ecologists have determined that biological organisms are neither distributed at random nor uniformly. This has also been found to be the case with abiotic phenomena such as ore or mineral deposits (Journel and Huijbregts, 1978). The direct

causes for this patchiness may be attributed to environmental physical processes that constrain the phenomena.

The concept of scale plays an important part of this analysis. It is necessary to consider the scale of fishing effort of the fleet, the patchiness of the fish species, and the scale of the oceanographic features in the ocean. Each factor contributes to the spatial autocorrelation present in the catch rates being modeled. From the perspective of the fisherman, there are many factors influencing where to set the fishing lines. These include knowledge of where higher catches occur (i.e., from satellite information, historical perspectives, or communication with other fishermen), the distance a captain is willing to travel to find the fish, and whether the climate allows the captain to make the fishing trip. The fish themselves are optimizing their location based on prey availability, presence of predators, and optimal oceanography. This last factor could pertain to an optimal temperature range, or an oceanographic feature that serves to aggregate prey or offer protection from predators. Understanding what is influencing the distribution of a pelagic species is not straightforward. It is simpler to consider a benthic oriented species such as a reef fish whose distribution is directly linked to the presence of the coral habitat. Even in this type of system, the presence of the coral habitat follows a patchy distribution that is linked to the particular physical processes—currents, depth, temperature—that allow it to exist. In the open ocean it is more difficult to define what may be constraining a species to a particular region or creating patchiness. In addition these patches are transient, unlike patches associated with most benthic structures. There are many factors to consider, among them, surface and deep water currents, temperature, water clarity, and salinity. The longline dataset used in this analysis can be considered a

sort of “dream dataset” in that there is a large quantity of data available with spatial information that we can use to address some of these questions. Additionally, the availability of satellite derived oceanographic data allows for some interpretation of the spatial patterns detected.

In this study, the ability to obtain clear variogram models affirms that there is spatial autocorrelation occurring in the process under study. Nonetheless, this technique has limitations. The main hindrance was determining whether the range of autocorrelation described by the models was, in fact, due to the biology of the species in response to environmental constraints on its habitat, or simply an artifact of the sampling construct. Determining the spatial autocorrelation of a species from catches from a longline has several issues that must be addressed. The first is that the exact location of the catch on the longline is not known. This contributes to poor sample resolution where the position of the catch has a margin of error on the scale of the longline length. In other words, we can only accurately attribute what is going on in the ecosystem to the spatial scale of the longline set, not to the scale of the individual fishing hook. The second is that catches do not follow a normal distribution and are zero-inflated. It is therefore appropriate to partition and transform the data in a manner similar to a delta lognormal method used with GLMs. In spite of these limitations, it is possible to spatially predict abundance using these methods as the main goal of geostatistics is to better explain variability due to spatial differences. Sampling by fishing gear is never going to give you the perfect picture of the environment or the state of the species, but the level of spatial resolution of this type of data is leaps and bounds ahead of the more typical 10x10 degree

blocks that are typically reported in fishing data. The question that must be asked is whether this resolution is enough?

The fact that there are significant differences in the range parameters between two species with very different life histories is evidence that the observed spatial autocorrelation does reflect some of the biological characteristics of the species. With a pelagic species in particular, the biology and physiology of the animal is closely linked to the oceanography of the system in which the animal is found. A significant amount of work has linked the distribution of pelagic species to temperature gradients and fronts (Uda, 1973; Laurs *et al.*, 1984; Power and May, 1991; Andrade, 2003). As dolphinfish is a surface dwelling species, it is likely that its distribution is closely related to the temperature fronts in the upper layer of the water. Swordfish, on the other hand is a deeper dwelling species, and therefore will be constrained by fronts both at the surface and at depth. This analysis could be enhanced by testing these hypotheses regarding the range of autocorrelation with other species that are associated with different depth distributions such as the deeper diving bigeye tuna or the more epipelagic cobia.

To relate the spatial structure of a population in the Gulf of Mexico to the oceanography of the region at varying depths, it is useful to have some idea of the first-mode (baroclinic) Rossby radius, Ro . In atmospheric dynamics and oceanography, the Rossby radius of deformation is the length scale at which rotational effects become as important as buoyancy effects in the evolution of the flow about some disturbance. It is described by the equation:

$$Ro = \frac{NH}{f_0} \quad (6)$$

where N is the Brunt-Väisälä frequency (the frequency at which a vertically displaced parcel will oscillate within a statically stable environment), H is the scale height or depth (distance over which a quantity decreases by a factor of e), and f_o is the Coriolis parameter at some latitude. Teague et al. (1990) used calculations based on Generalized Digital Environmental Model (GDEM) climatology to determine an Ro of approximately 30 km in the Gulf and in the northwest Caribbean. Comparatively, the Ro in the central and eastern Caribbean Sea was found to be approximately 40-50 km, and about 10-20 km over the shelf break. These calculations are for surface waters. Because Ro is proportional to depth, it is intuitive that at a deeper depth, the Rossby radius will be greater. Therefore, a species that dwells in the surface layers of the water will be subject to greater heterogeneity of the water masses than a species at depth. If two adjacent water masses have very different temperatures, as is often the case in the winter months, this variation will serve to constrain a species that is temperature-dependent within a particular water mass. This calculation is important for understanding the resolution of any spatial autocorrelation (i.e., the resolution of the spatial scale should only be as fine as the most energetic scale). The Rossby radius of deformation emphasizes the fact that oceanography is more consistent at depth than at the surface and that it is important to account for the 3 dimensional nature of patches (both physical and ecological). Therefore, a species like swordfish that spends time at deeper depths should in theory be less constricted in its habitat range because the water masses are more homogeneous over a larger horizontal extent. They also are adapted to a wider range of tolerable temperatures and are therefore less constrained in both the horizontal and the vertical directions. In other words, if we presume that a fish is constrained by temperature, it

follows that a fish at depth would remain in the same temperature water for a longer range and would be more widely distributed.

Satellite tagging studies of swordfish depth distributions reveal that swordfish routinely spend a good deal of time in deeper depths between 500-600m during the day and at depths above 200m during the night (Brill, *pers. comm.*). This is in stark contrast to dolphinfish, which spend the majority of their time above 50m during both the day and night (Hammond, 2006). It is typical to think of patch sizes as a surface characteristic. However, it is important to remember that patches are 3-dimensional and to consider that the depth that these species are occupying has a direct relationship to the oceanography at that depth.

As previously mentioned, it is expected that there will be a seasonal variation in the range of a species. The proportion positive variogram ranges illustrate this variability. In the winter the frontal regions where this species is likely to be located are more well-defined and therefore more easily assessable to the species. Therefore, it would be expected that a surface-associated species like dolphinfish may exhibit a shorter range as they are more concentrated in an area of higher frontal energy (Kleisner *et al.*, 2007). Indeed, with this analysis, dolphinfish do exhibit a shorter average range in the winter than in any other season. The constraint in the range of the dolphinfish is likely twofold due to the heterogeneity of the temperature fronts and the fact that dolphinfish are a surface species. This is in contrast to swordfish, which are displaying an opposite pattern with longer ranges in the winter months. Again, it is important to remember that these species are moving in a 3 dimensional environment. Since swordfish is spending a majority of the time at depth and is less constricted to warmer waters at the surface due to

its physiology, it would make sense that it would utilize a greater portion of the ecosystem than would dolphinfish, whose 3 dimensional habitat is much shallower.

As there is a movement towards spatial management of fish stocks (i.e., seasonal closures of fishing grounds, MPAs, etc.), it is important to determine whether the incorporation of spatial autocorrelation into a stock assessment is in fact possible and whether it confers enough of an improvement to warrant the inclusion. In this analysis, variogram models were useful in describing the spatial autocorrelation patterns of catches of dolphinfish and swordfish from the U.S. pelagic logbook data from the Gulf of Mexico and provide the basis for further geostatistical predictions of abundance. In general, both dolphinfish and swordfish catches showed strong spatial autocorrelation as evidenced by fits of the spherical empirical variogram models to the theoretical variograms derived from the data. The scale of this correlation is considerably smaller than that of the statistical grids typically used in the standardization of CPUE for the US longline. What this implies is that for a species such as dolphinfish, which has a shorter range of autocorrelation, we may be justified in using a model such as a GLM that assumes samples are independent because other than at very close range, samples *are* independent (i.e., at distances greater than the range of autocorrelation). However, for species with a longer range of autocorrelation, there will be more CPUE samples that are actually dependent. This can lead to an underestimation of the variability when we use a model such as a GLM rather than a geostatistical index.

Additionally, advancements were made in dealing with data that is plagued by a high number of zeros and is not normally distributed. While these factors are usually considered a problem, the methodology outlined here represents a small step towards

developing techniques where zeros no longer pose a detriment, but provide extra information about the biology of the species and also provide a basis for spatial prediction. Ultimately, the explicit incorporation of spatial autocorrelation in the standardization of CPUE may help reduce the unexplained variance and provide more precise estimates of abundance.

CHAPTER 4: PREDICTION OF ABUNDANCE BASED ON SPATIALLY AUTOCORRELATED CATCHES

4.1 Spatial Variability and Determining Abundance of a Pelagic Species

The distribution in time and space of biotic and abiotic factors in the environment is influenced by major forces such as global energy inputs and their impacts on climate change, regional and local wind patterns, and variations induced by factors such as plankton blooms and mesoscale physical motions (Rohde, 1992; Shukowsky and Mantovani, 1999; Olson *et al.*, 2005). These distributions affect the harvest of a fishery resource by influencing the distribution and catchability of target species. Environmental conditions may also influence what people target and how species are targeted (Olson *et al.*, 2004). Therefore availability of the fish is dependent on oceanographic and environmental conditions (Fleming, 2000) as well as factors such as market effects that can influence fishing effort (Miller, 2007). While the potential causal factors involved are varied, they typically include spatially continuous changes in ocean conditions (i.e., water temperature, large and small-scale currents, climatic patterns, bathymetry) and general migration patterns (i.e., food supply, spawning locations). Additionally, some of these changes are readily perceived by the fishery and therefore influence the behavior of the anglers toward the target species (Pederson and Hall-Arber, 1999; ICES, 2003; Bergmann *et al.*, 2004).

Generally, these factors change gradually over the majority of the ocean. In some instances, however, there are distinctly different masses of water that can have a great influence on the distribution of pelagic species, for example in SST frontal regions. These areas where change is more dramatic are areas of aggregation of prey and floating

structures that attract larger pelagics for both food and shelter (Mann, 2000). These spatial changes in ocean conditions and general migration patterns can dictate the spatiotemporal distribution of a species (Carroll and Pearson, 2000) and variations in fishing effort. Due to these influences, data collected from fisheries are likely to display spatial or temporal dependencies induced by a combination of these factors. In spite of this, for many years biologists have relied on statistical methods that were developed for data that conform to rather strict assumptions of independence between ecosystem variations and fishing. One of the most common statistical models used to standardize catch rate data to obtain indices of abundance is the GLM. This model attempts to control for annual, seasonal, vessel, gear, and sometimes environmental effects. Additionally, it is common to address spatial variation at a crude level within the model framework, usually in terms of a relatively large area such as the FAO statistical fishing areas which typically encompass an entire ocean basin such as the Gulf of Mexico. These areas cannot address small scale variation however. Often with these models, a determination of whether the data are actually spatially independent is never made (Carroll and Pearson, 2000). Legendre (1993) has argued that it is necessary to revise our current models and address the spatial and temporal dependence that is present in much of the biological data. On the other hand, Carroll and Pearson (2000) note that there are most likely many cases where the degree of dependence is small to the point of actually being insignificant. When this is the case, traditional statistical techniques that rely on independence are most likely sufficiently robust to make the results from both spatially explicit and traditional analyses similar. When the degree of dependence is high, however, these patterns of spatial correlation are important for many reasons including

the determination of stock structure, understanding the habitat utilization of a species, and determining the influence that the environment has on determining where a species is distributed.

In this chapter the catch of dolphinfish and swordfish from the U.S. pelagic logbook database and lognormal ordinary kriging (Cressie, 1992; Goovaerts, 1997; Chiles and Delfiner, 1999) were used to obtain a spatial mapping of estimated densities for both species in the Gulf of Mexico region. The results were then used to develop a spatial index of abundance that can be used in a stock assessment framework to inform management decisions relative to the status of the stock in the area. As a comparison, the logbook data were also standardized by a more traditional GLM approach and annual indices were developed for both species. It was hypothesized that because dolphinfish catch rates are spatially correlated at shorter ranges than those of swordfish (see Chapter 3), there would be less difference between the geostatistical and GLM indices derived for dolphinfish. In other words, with a smaller range of autocorrelation, more of the observations would be independent, and the GLM approach would be less biased by violations of the assumption of independence. Conversely, swordfish catch rates are correlated over longer ranges and therefore it was expected that there would be significant differences between the indices obtained from each approach. If there are differences in the indices due to spatial variability, this could translate into different predictions of the status of the stock and other biological reference points when spatial indices are incorporated into a stock assessment model.

There are inherent differences between the geostatistical and GLM approaches that must be addressed before comparisons can be made. In order to understand the

nature of the predictions from the two approaches and the extent to which they can be compared, it is necessary to understand the nature of two conceptual frameworks that support inferences on general population characteristics from samples of the population: design-based versus model-based inference (Cassel *et al.*, 1977; Hanson *et al.*, 1983). The design-based approach relies on assumptions made for survey methodology. With this estimation scheme, probabilities are assigned to samples to form the basis for the inferences. For the purposes of this analysis, the samples were the records of catch of dolphinfish and swordfish by the longline fishery. The assumption made was that sampling is random, and for the GLM analysis, that factors are independent of each other. It is because of this independence of the sampling structure that the mean and variance estimates can be calculated directly from the samples without making implicit assumptions about the spatial distribution of the data (Pettigas, 2001). When, as it was hypothesized in this analysis, there is spatial structure to the population and samples are therefore correlated, the ability to make inferences requires a model of the level of spatial autocorrelation in the data (Matheron, 1971; Cochran, 1977), and therefore the estimation of the variance is model-based. Between the two approaches, the unbiasedness and minimum variance in the design-based model will be quite different from that in the model-based approach. It could be argued that if the catch data followed a “true” design-based structure (i.e., fishery independent random survey data), then this approach would be more suitable for developing the confidence intervals of the index because it allows the accuracy of predictions to be assessed objectively (i.e., based on the sample data alone). However, the model-based strategy is useful for local estimation within small blocks provided that there is enough data to estimate the variogram.

Despite the inherent differences in the approaches, it has been shown that model-based and design based approaches can lead to similar results when the same prior information and standardized data are incorporated (Särndal *et al.*, 1992; Stevens and Olsen, 2004). For this reason, the indices derived by both methods in this analysis have been standardized for any extraneous sources of variation such as annual, seasonal, or gear effects. The sole difference between the indices should therefore be due to spatial variability. While the indices themselves may be compared qualitatively, the prediction error from the model-based geostatistical approach is not directly comparable to the more traditional design-based variance (Warren, 1998; Walter, 2006).

There are several physical features in the Gulf of Mexico that would play a role in the aggregation of pelagic species in this region. The main feature is the Loop Current. This is a warm Caribbean-based current that flows northward into the Gulf between western Cuba and the Yucatan peninsula, loops east and south and exits the Gulf through the Florida Straits. This is a dynamic region that varies in its northern-most extent. The Loop Current sheds eddies or rings several times a year that drift westward at speeds of 2-5 km day⁻¹ (Elliott, 1982; Coats, 1992; Shay *et al.*, 1998). It is expected that the energy of the Loop Current is a dominant factor in the level of aggregation of the pelagic species in this area. Indeed, much of the recent work in fisheries has focused on the links between some attributes of a biological stock, such as abundance or recruitment, and the environmental forces that may be driving fluctuations in the attribute (Laurs *et al.*, 1984; Olson and Backus, 1985; Podesta *et al.*, 1993; Bigelow *et al.*, 1999). Since the physical, chemical, and biological characteristics of a particular environment control to a large part fish consumption, growth, mortality, and production, the ability to predict a life history

parameter spatially should greatly aid a stock assessment. The following chapter will explore the implications on the productivity parameter estimations of the different indices when they are used in a surplus production model.

4.2 Methods for Spatial Abundance Predictions from Kriging

Kriging is an interpolation method where the value of an unknown real function f at a certain point is predicted, given the values of the function at some other points (Pelletier and Parma, 1994; Webster and Oliver, 2001). It is linear due to the fact that the estimated values are weighted linear combinations of the available data although it involves implicit nonlinear terms (Journel and Huijbregts, 1978). The theoretical variogram model of the covariance of the random function (see Chapter 3) is incorporated when calculating the predictions of the unknown values. There are three main forms of kriging used in geostatistical analysis: simple kriging, ordinary kriging, and universal kriging. Simple kriging assumes that there is knowledge of the stationary mean of the stationary random function. Because this is a difficult criterion to meet, this technique is not often used in practice but does form the foundation of ordinary and universal kriging (see section 4.2.3). Ordinary kriging is most commonly used, and assumes a constant, but unknown underlying mean. Again the assumptions for this method are that there is intrinsic stationarity (the data do not exhibit a spatial trend) and adequate sample size to calculate a variogram model. This variogram model is used to calculate a weighted linear combination of available samples for prediction of abundance and variance in areas without samples. The objective is to minimize the error variance and to ensure that the average error for the model is zero. Universal kriging is used when there are temporal trends in the data being estimated (i.e., the data is nonstationary).

When this is the case, the stationary condition can be imitated and imposed on the data by a polynomial function known as a drift term that models the average value of the scatter of points. In other words, the temporal pattern is identified and removed. The residuals of the theoretical and empirical variogram model represent the difference between the drift and the actual values of the scatter of points over time. The residuals are assumed to be stationary, and therefore kriging can be performed on these residuals. The interpolated residuals are then added to the drift to compute the estimated values.

In this study, ordinary kriging is used to predict the value of the spatial process $S(x)$ for every location x within a specified grid surface within the Gulf of Mexico from a linear combination of the observed values $\{Z(x_i), i = 1, \dots, g\}$ where fishing occurred. It is assumed that measurement error is the only source of difference between $S(x)$ and $Z(x)$ and therefore the spatial covariance of $Z(x)$ can be modeled directly. The main assumption in ordinary kriging is that the first differences of $Z(x)$ are stationary. This means that the expected value of $Z(x)$ is the same over the whole area regardless of location. This is represented by the equation for the expected value of Z at different points:

$$E(Z(x+h) - Z(x)) = 0 \quad (1)$$

where h is a vector representing the distances and directions between individual data points. Additionally, the variance of the difference is also a function of h . This is represented by the equation:

$$V(Z(x+h) - Z(x)) = 2\gamma(h). \quad (2)$$

where $2\gamma(h)$ represents the variogram model.

It is typical to assume second-order stationarity in kriging such that:

$$\text{Cov}(Z(x+h), Z(x)) = C(h) \quad (3)$$

and the covariance between two points is only related to their position. In this way, it is possible to express the covariance in terms of the semivariogram:

$$\gamma(h) = \delta^2 - C(h) \quad (4)$$

where δ^2 is the sill and is representative of the variance of $Z(x)$ (Pelletier and Parma, 1994). An example of a variogram model showing the three parameters is displayed in Figure 4.1.

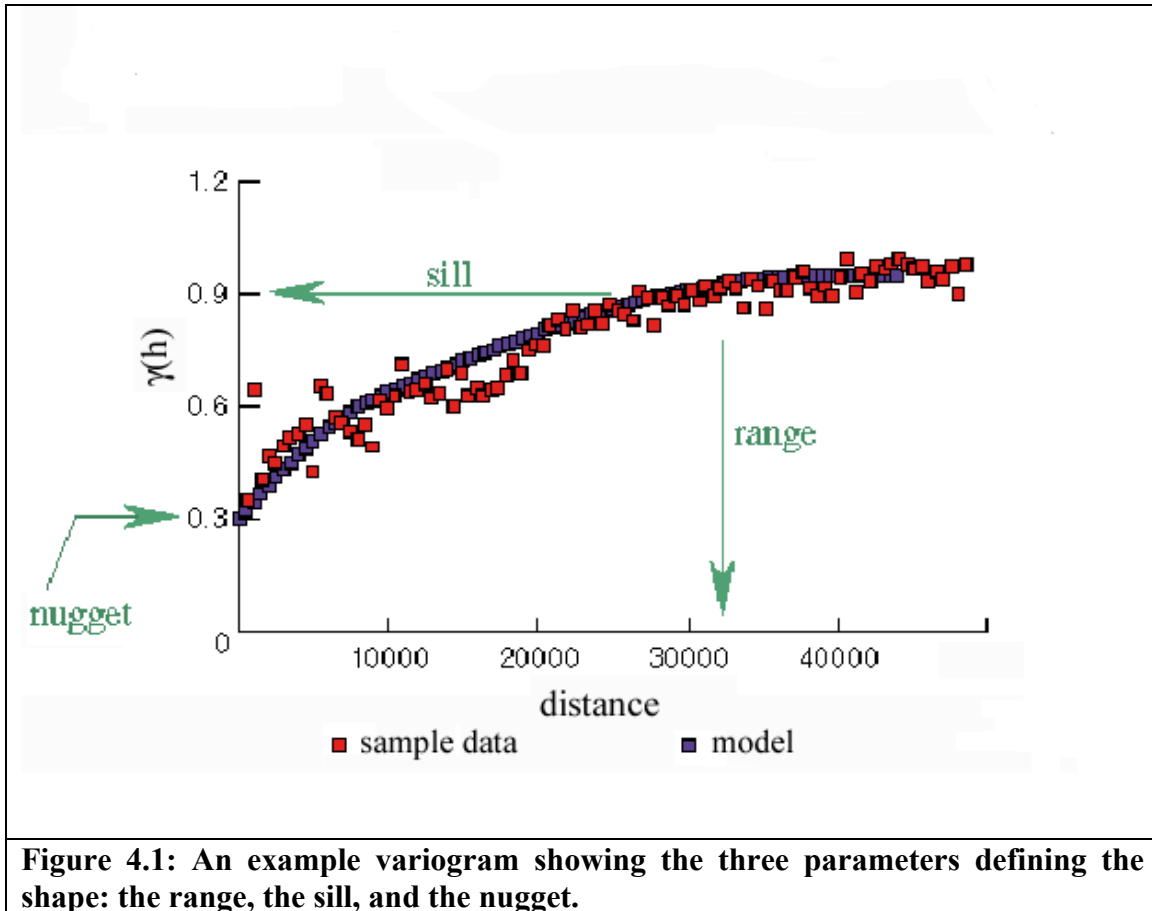


Figure 4.1: An example variogram showing the three parameters defining the shape: the range, the sill, and the nugget.

All geostatistical analyses were performed using functions modified from the S-PLUS spatial statistics package in R (Kaluzny *et al.*, 1998; R Development Core Team, 2007).

As stated in Chapter 3, an additional issue arose when a variogram could not be obtained

for a specific year-season. In this case, the average variogram parameters for that season were used for kriging purposes.

Constraining the Prediction Area

Since the goal of this study was to determine an index of abundance for the area fished, it was necessary to krig only within the sampling area. A caveat to this approach is that if constriction of the fishing area is due to serial depletion, this will introduce bias into the index of abundance. Two separate methods were used to obtain grids upon which predictions can be made. One index was based on a grid of locations restricted to 95% of the kriging variance or the sill as a measure of sample coverage for each year-season. This index will be referred to as the KV index (where KV refers to the kriging variance). The second index was based on the 95% kernel or utilization distribution that was common among seasons. This method was adapted from the home range calculations of Worton (1995) where the home range is defined as the minimum area in which an animal has some specified probability of being located. In this case, the grid is calculated by using the kernel method to estimate the utilization distribution for each year-season. A kernel density estimate (Worton, 1995) is calculated from n locations at points (x,y) by the equation:

$$\frac{1}{2\pi n h^2} \sum_{i=1}^n \exp\left[-\frac{d_i^2}{2h^2}\right] \quad (5)$$

where h is the specified value of a smoothing parameter and d_i is the distance of the i th observation from the point at (x,y) . The best estimate of the smoothing parameter h is given by:

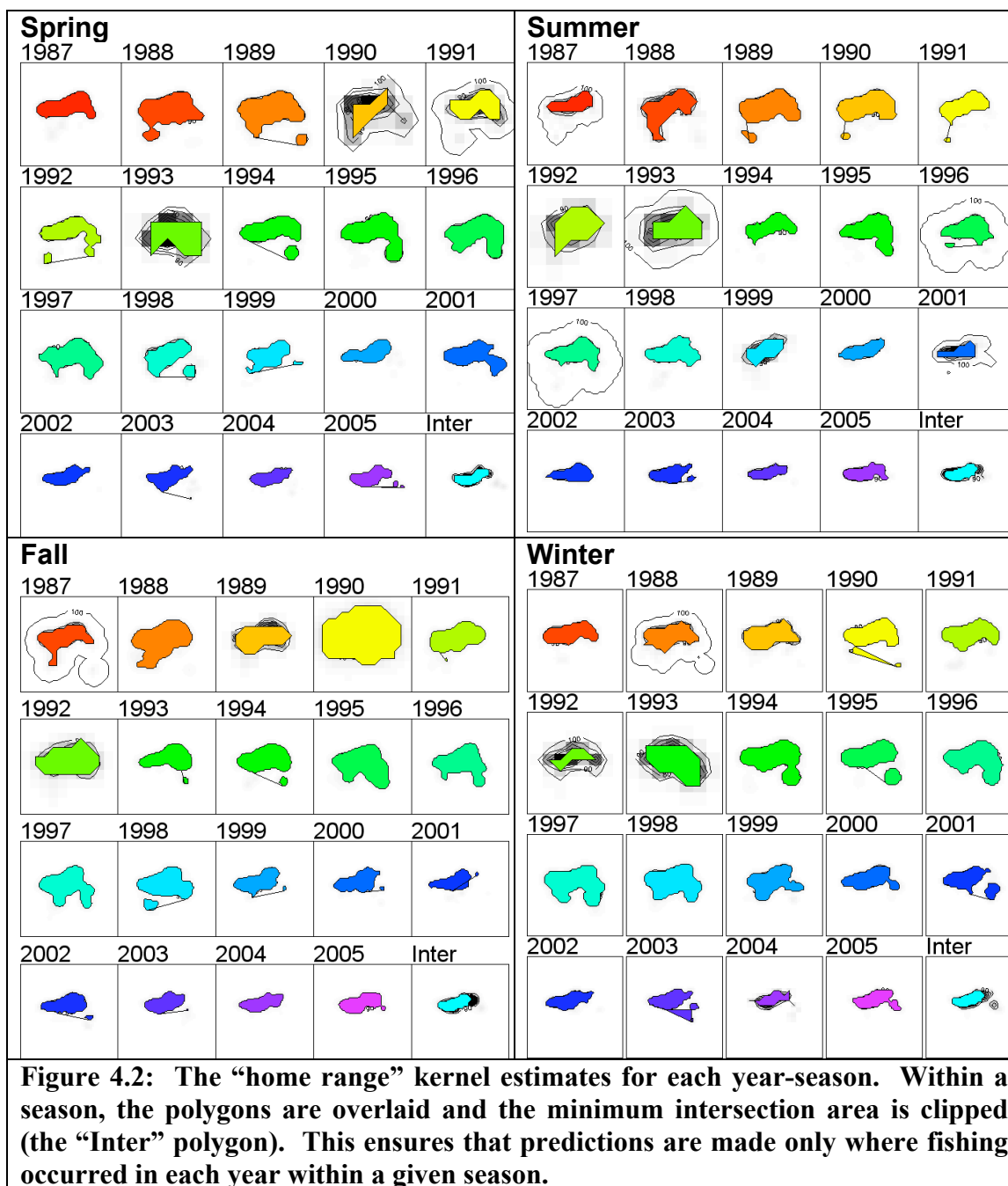
$$h = \theta(n^{-1/6}) \quad (6)$$

where θ is given by:

$$\theta = ([s_x^2 + s_y^2]/2)^{1/2} \quad (7)$$

and s_x^2 and s_y^2 are the estimates of the variances of the x, y locations, respectively.

Within a season, the kernel-based distributions for each year were overlaid, and the union of the polygons was selected as the area where fishing occurred consistently over all years during a season. This step ensured that during a single season, all predictions would be made for each year over the same grid. The polygons for each year by season are illustrated in Figure 4.2.



For each season, the annual polygons are overlaid and the minimum area is clipped (the “Inter” polygons in Figure 4.2). This index is referred to as the HR index (HR=home range). Each of these methods produced geostatistical abundance indices that were

nearly identical. Therefore, only the most constrained abundance indices (the HR indices) are presented and discussed for both dolphinfish and swordfish.

Calculating the “Unbiased” Lognormal Predictions and Associated Variance

The kriging predictions were calculated for the proportion of positive records and for the logarithm of the positive records. Lognormal kriging is a technique that was developed in the field of mining geostatistics as a probabilistic approach to determine the distribution of precious metals and ores using experimental mining data that was often skewed (Journel and Huijbregts, 1978; Goovaerts, 1997). There are several caveats to this method that will be outlined in this section.

To understand lognormal ordinary kriging, first consider a lognormal simple kriging example. To begin, if we consider the lognormally distributed, stationary random function:

$$Y(x) = \log(Z(x)) \quad (8)$$

where $Z(x)$ represents the raw data with the following parameters:

$$\begin{aligned} \square \text{mean} &= E\{Z(x)\} = M \\ Z(x) \square \text{cov} &= E\{Z(x), Z(x+h)\} - M^2 = C(h) \\ \square \text{var} &= C(0) = C^2 \end{aligned} \quad (9)$$

and $Y(x)$ represents the transformed data with

$$\begin{aligned} \square \text{mean} &= E\{Y(x)\} = m = \log M - \sigma^2 / 2 \\ Y(x) \square \text{cov} &= \text{Cov}\{Y(x), Y(x+h)\} = \sigma(h) = \log \left\{ + [C(h) / M^2] \right\} \\ \square \text{var} &= \sigma(0) = \sigma^2 \end{aligned} \quad (10)$$

If $Y(x)$ is *multivariate* normally distributed, then the mean of the conditional distribution of predictions, Y_{SK}^* , is normal:

$$mean = Y_{SK}^* = m + \sum_{\alpha=1}^N \lambda_{\alpha} (y_{\alpha} - m) \quad (11)$$

and the N coefficients, λ_{α} , are solutions of the linear simple kriging system:

$$\sum_{\beta=1}^N \lambda_{\beta} \sigma(x_{\alpha} - x_{\beta}) = \sigma(x_{\alpha} - x), \forall_{\alpha} = (1, N). \quad (12)$$

The variance of the system is represented by:

$$\sigma_{SK}^2(x) = \sigma^2 - \sum_{\alpha=1}^N \lambda_{\alpha} \sigma(x_{\alpha} - x). \quad (13)$$

Predictions, Z^* , are represented by:

$$Z_{SLK}^*(x) = \exp[Y_{SK}^*(x) + [\sigma_{SK}^2(x)/2]] \quad (14)$$

and the prediction variance is represented by:

$$Var = [Z_{SLK}^*(x)]^2 [\exp(\sigma_{SK}^2(x)) - 1]. \quad (15)$$

These calculations are relatively straightforward if the mean is known. As mentioned previously, the mean is often not known, and therefore the technique of ordinary lognormal kriging must be used. In this case, again assume that $Y(x) = \text{Log } Z(x)$ is multivariate Gaussian, and that there is no knowledge of the stationary mean (m). The application of the condition of

$$\sum_{\alpha=1}^N \lambda_{\alpha} = 1 \quad (16)$$

to the kriging system ensures unbiasedness whatever the unknown mean m . $Y(x)$ and $\text{Log } Z(x)$ from the simple kriging example can be replaced by ordinary kriging estimators. However, there is a problem because the ordinary kriging estimators are not identical to the conditional expectations. The prediction term for ordinary kriging is then represented by:

$$Y_{OK}^*(x) = \sum_{\alpha=1}^N v_{\alpha} Y(x_{\alpha}) \quad (17)$$

where the N coefficients, v_{α} , are solutions of the linear ordinary kriging system of order $N+1$:

$$\begin{aligned} \sum_{\beta=1}^N v_{\beta} \sigma(x_{\alpha} - x_{\beta}) - K &= \sigma(x_{\alpha} - x) \\ \forall_{\alpha} &= (1, N) \\ \sum_{\beta=1}^N v_{\beta} &= 1 \end{aligned} \quad (18)$$

and the prediction variance is represented by:

$$\sigma_{OK}^2(x) = \sigma^2 - \sum_{\alpha=1}^N v_{\alpha} \sigma(x_{\alpha} - x) + K. \quad (19)$$

The K in equations 18 and 19 is the Lagrange multiplier parameter. Lagrange multipliers are used when there is a need to maximize the magnitude of a function that is subject to fixed outside conditions or constraints. The Lagrange multiplier provides a means for solving problems of this type without the need to explicitly solve the conditions and use them to eliminate extra variables. This technique is useful here because the mean of the estimated values, Z^* , can differ noticeably from the expectation m estimated from the available data (Journel and Huijbregts, 1978). There must be a way to determine the extent of the variation and use this constant (the Lagrange multiplier, K) to reign in the predictions. Determining the constant K is relatively straightforward and can be solved by considering the estimator:

$$Z_0^* = K \exp[Y_K + \sigma_K'^2 / 2] \quad (20)$$

where the corrective factor, or Lagrange multiplier, K is determined by equating the arithmetic mean of the estimated values, K^* , to the expectation or mean, m (Journel and

Huijbregts, 1978). The explanation given by Journel and Huijbregts (1978) for the divergence of the estimator from the mean is that the exponential expression is not robust with respect to the multivariate lognormal hypothesis. The fact is that although the univariate distribution of $Z(x)$ can approximate a lognormal distribution, the multivariate distribution may not also be lognormal. Journel and Huijbregts determined that the “unbiased” or corrected estimate gave a lower experimental estimation variance than the classical linear kriging estimators. In addition to correcting for bias in the predictions, it is also necessary to correct the prediction variances. Journel (1980) provides the methodology outlined here. If the distribution of $Y_{OK}^*(x)$ is normal with:

$$\begin{aligned} Y_{OK}^* \begin{cases} \text{mean} = E\{Y_{OK}^*(x)\} = m \\ \text{var} = \text{Var}\{Y_{OK}^*(x)\} = \sum_{\alpha=1}^N \sum_{\beta=1}^N v_{\alpha} v_{\beta} \sigma(x_{\alpha} - x_{\beta}) = \sigma^2 - \sigma_{OK}^2(x) + 2K \end{cases} \end{aligned} \quad (21)$$

then the distribution of $\exp[Y_{OK}^*(x)]$ is lognormally distributed with a mean of $e^{(m+\sigma^2/2)} \cdot e^{K-\sigma_{OK}^2(x)/2} = M \cdot e^{K-\sigma_{OK}^2(x)/2}$. The unbiased prediction estimation variance is then:

$$E\{[Z(x) - Z_{OLK}^*(x)]^2\} = M^2 e^{\sigma^2} [1 + e^{-\sigma_{OK}^2(x)+K} (e^K - 2)] \quad (22)$$

Construction of the Geostatistical Abundance Index

Lo *et al.* (1992) outline a method for combining indices for lognormally distributed data where the analysis has been made on the positive portion of the data separately from the proportion of positive data. This work focused on the calculation of indices of relative abundance from fish spotter data based on delta-lognormal models. The final index is a simple product of the predictions from each portion of the analysis. The formula for obtaining the index variance is as follows:

$$\begin{aligned} \text{Variance} = & (INDvar) * (UBBTpred)^2 + (UBBTvar) * \\ & (INDpred)^2 + cor((INDpred) * (UBBTpred)) * \sqrt{(INDvar) * (UBBTpred)} \end{aligned} \quad (23)$$

where UBBTpred is the unbiased back transformed predictions from the lognormal observations, UBBTvar is the unbiased back transformed variance associated with the predictions from the lognormal observations, INDpred is the prediction from the indicator kriging, and INDvar is the variance associated with the indicator index. The term “cor” represents the correlation between the positive CPUE predictions and the proportion positive CPUE predictions. This correlation is calculated using Spearman’s correlation.

Modification for Swordfish

To test the hypothesis that a species with a shorter range of autocorrelation will have a geostatistical index that is similar to that from GLM standardization, a geostatistical index and a GLM standardized index were constructed for both dolphinfish and swordfish. A typical GLM standardization will account for such effects as number of light sticks used on the longline and bait type (Dead or Alive). These factors are gear effects. While these factors were significant in the swordfish GLM, they do not influence the catch rates of dolphinfish. As noted in Chapter 3, the swordfish catch rates were standardized for gear effects (logCPUE/success= light sticks, bait type). The residuals from this standardization were used to calculate variograms for each year-season.

The “fishing power” effort standardization of Robson (1966) was employed in order to standardize the catch data to make predictions through kriging. This is a traditional fisheries method (Gulland, 1956; Beverton and Holt, 1957; Ricker, 1975) whereby catch C in number of animals is related to the average population abundance \bar{N} in a specified time interval by:

$$C = F\bar{N} = qf\bar{N} \quad (24)$$

where F is the instantaneous rate of fishing mortality, defined as the product of nominal fishing effort f and catchability coefficient q , the fraction of the stock removed per unit of nominal fishing effort. CPUE, a relative index of abundance, is given by

$$\frac{C}{f} = q\bar{N} \quad (25)$$

When dealing with several different types of gear fishing the same unit of stock, fishing mortality for each gear type j can be described as:

$$F_j = q_j f_j \quad (26)$$

with the overall fishing mortality described as:

$$F = \sum_j q_j f_j . \quad (27)$$

Because catchability can differ substantially between different gear types, Robson's fishing power method serves to estimate the relative catchability among different gears, fleets, or vessel types. In the fishing power model, variation in CPUE is usually attributed to two main factors: timing and location of sampling effort and the type of gear or vessel that is taking the samples. This can be expressed for time-location i and gear type j by the following model:

$$CPUE_{ij} = \alpha + b_i + g_j = \varepsilon_{ij} \quad (28)$$

where α is a constant, b_i is a time-location coefficient, g_j is a gear coefficient, and ε_{ij} is an additive error term. There is an assumption that for a given species or life stage of fish, the ability of the gear to capture the fish (g_j) is constant for each gear type j . Robson (1966) outlines a general linear model for estimating the parameters of equation 28 for time-locations $i=1, 2, \dots, q$ and gears $j=1, 2, \dots, k$ as:

$$y = \alpha + b_1 X_1^{(b)} + \dots + b_{q-1} X_{q-1}^{(b)} + g_1 X_1^{(g)} + \dots + g_{k-1} X_{k-1}^{(g)} + \varepsilon \quad (29)$$

where the parameters that are estimated are the intercept (α), time-location coefficients (b_i 's), and the gear coefficients (g_j 's). The independent variables (X 's) are discrete categorical or “dummy” variables for time-locations ($X_i(b)$'s) and gear types ($X_i(g)$'s).

The standard ANOVA restrictions:

$$\begin{aligned} \sum_{i=1}^q b_i &= 0 \\ \sum_{j=1}^k g_j &= 0 \end{aligned} \tag{30}$$

are applied to the parameters. There are $q - 1$ time-location parameters and $k - 1$ gear parameters estimated from equation 29. Equation 30 allows the estimation of the remaining parameters $b_{i=q}$ and $g_{j=k}$ by imposing the following constraints:

$$\begin{aligned} b_q &= - \left[\sum_{i=1}^{q-1} b_i \right] \\ g_k &= - \left[\sum_{j=1}^{k-1} g_j \right] \end{aligned} \tag{31}$$

These parameters are used to standardize the raw swordfish CPUE observations. The coefficients b_i 's are incorporated into equation 30 in order to correct for temporal and spatial variation in CPUE. The model-predicted CPUE for gear j is estimated by:

$$CPUE_j = \alpha + g_j. \tag{32}$$

Fishing power, which is also referred to as the Gear Calibration Factor for gear j (GCF_j), is calculated as the ratio of the model-predicted CPUE for gear j to the model-predicted CPUE of a standard gear ($j = S$):

$$GCF_j = \frac{CPUE_j}{CPUE_S}. \tag{33}$$

Although any gear can be selected as the standard, for this analysis, the most common gear was selected as the standard. The standardization of the raw swordfish CPUE was done by dividing each CPUE value by its associated GCF_j .

Construction of GLM Abundance Index

The Delta approach of Lo *et al.* (1992) was used to model the probability of obtaining a zero catch and the catch rate, given that the catch is non-zero, separately (Maunder and Punt, 2004). A GLMM approach in SAS 9.0 was used to estimate relative indices of abundance for the U.S. pelagic longline data from the logbooks in the Gulf of Mexico (Littell *et al.*, 1996). A binomial distribution was used for the analysis of the presence of dolphinfish and a lognormal distribution was used for the analysis of catch rates from positive trips (trips that land dolphinfish). This type of combined model is a standard analysis tool for evaluating datasets where there are a large proportion of zero catches (i.e. the species is not the main target of the fishing fleet) (Ridout *et al.*, 1998; Ortiz and Arocha, 2004).

The following factors were examined as possible influences on the proportion positive trips, and the catch rates on positive trips:

- Year (1987-2006),
- season (Dec-Feb; Mar-May; Jun-Aug; Sep-Nov),
- light sticks (number used: 0-3),
- bait type (Dead, Alive, Unknown),
- SST.

SST was derived from the MODIS and AVHRR satellite imagery. The daily SST data for the region was converted in ArcGIS 9 to raster data and individual daily rasters were

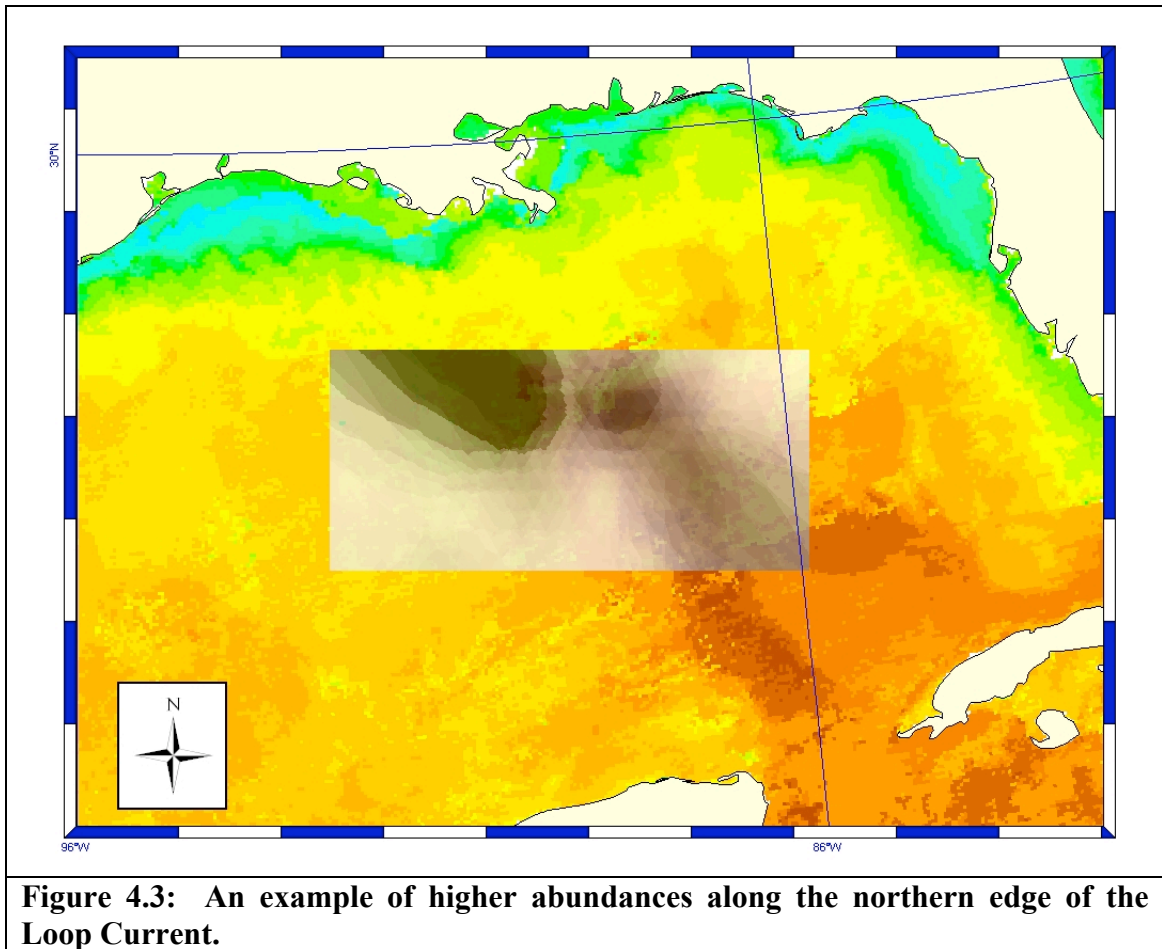
overlaid to create a weekly composite because cloud cover left gaps otherwise. These weekly composites were then temporally linked to the average CPUE data point in a particular week. When SST could not be obtained from the satellite, usually as a result of cloud cover, the ship board sea surface temperature measurements were used. The temperature readings from the ship were not used explicitly because for many of the records, the information was missing, or the entry was not accurate and had to be discarded. A forward stepwise regression procedure was used to determine the set of fixed factors and interaction terms that explained a significant portion of the observed variability. Factors and interaction terms were selected for final analysis if: 1) the percent reduction in deviance per degree of freedom explained by adding the factor exceeded five percent, 2) the χ^2 test was significant and 3) the Type-III test was significant for the specified model. In addition, a χ^2 analysis was performed to test the significance of the reduction in deviance between each consecutive set of nested models (McCullagh and Nelder 1989).

Once a set of fixed factors was identified, the influence of the YEAR \times FACTOR interactions was examined. YEAR \times FACTOR interaction terms were included in the model as random effects. Because the goal of this analysis is to compare the geostatistical index to the GLM index, every attempt was made to ensure that corresponding standardizations were made for each index. This was done so that any apparent differences in the indices could be attributed to spatial differences and not to trends due to gear or temporal effects. In the case of dolphinfish, the GLM was straightforward. The model for both the proportion positives and the positive observations included only year and season. Therefore, the geostatistical index was

constructed from the raw data and variograms computed for each year-season. Swordfish on the other hand had an added layer of complexity. The significant factors were year, season, bait type, and light sticks. Additionally, the interaction terms of YEAR×LIGHT STICKS, YEAR×BAIT type, SEASON×LIGHT STICKS, and SEASON×BAIT TYPE were significant and these interactions were added to the model because the GCF employed to construct the geostatistical index is accounting for annual and seasonal gear effects in the same manner as the interaction terms do in the GLM. The final delta-lognormal models were fit using the SAS macro GLIMMIX and the SAS procedure PROC MIXED (SAS Institute Inc., 1997) following the procedures described by Lo et al. (1992).

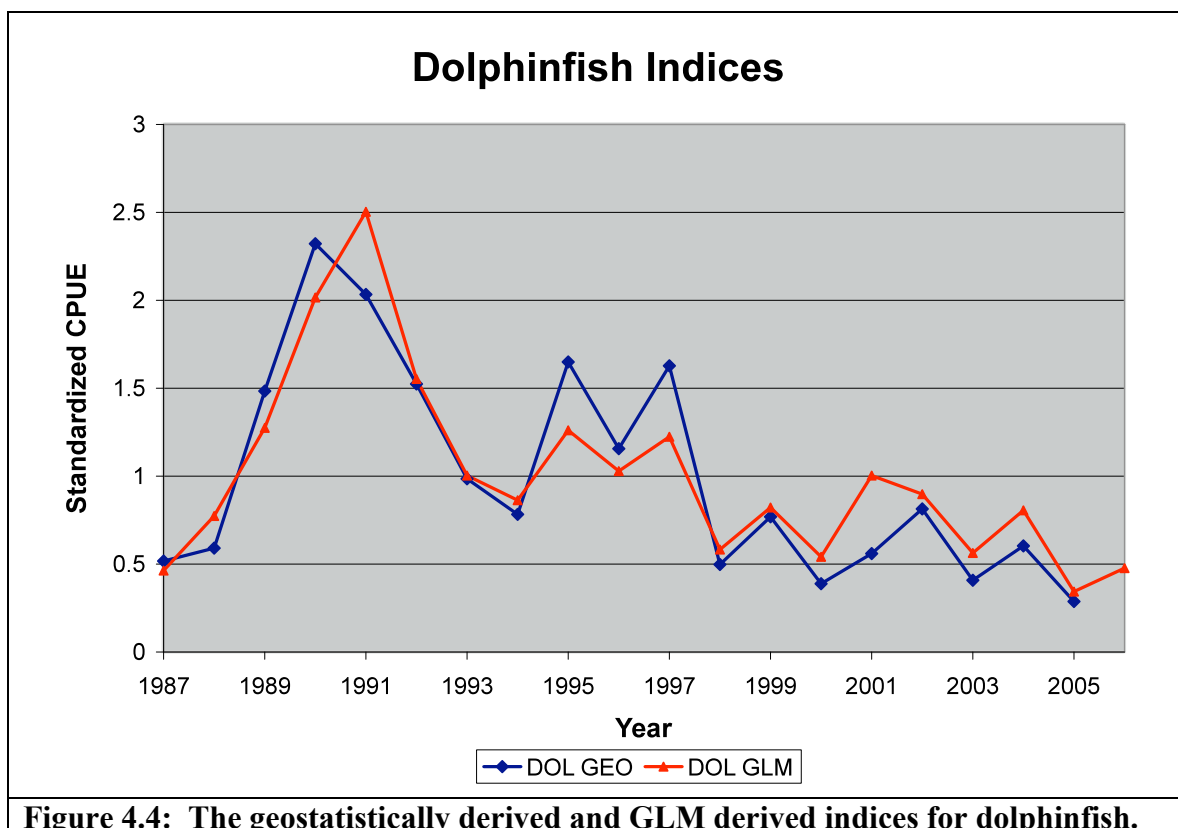
4.3 Index Calculation Results

One of the outputs of this analysis is a set of maps of the abundance of dolphinfish and swordfish in the Gulf of Mexico for the period 1986-2005 (Appendix C). These maps are seasonal and allow a comparison of the high and low abundance areas both seasonally and annually and between species. Some of the major patterns are a high peak fishing area off of the Loop Current extension, and a shelf break fishing area. An example of a high abundance patch off of the northern tip of the loop current is displayed in Figure 4.3.



This image has the map of abundance for a given year-season overlaid transparently on a composite image of SST for the same season. The fact that the prediction area for kriging was constrained to a “home range” area that was a consistent 95% kernel over a season ensures that predictions are only made where fishing has occurred continuously.

As hypothesized, the GLM index followed the geostatistical index for dolphinfish very closely (Figure 4.4).



The GLM index was standardized for annual and seasonal effects. The geostatistical index was also corrected in a similar way since it was based on variograms that were calculated for each year-season. Slight differences in the trend could be due to the fact that including spatial variation in the geostatistical index of abundance will reduce bias due to autocorrelated samples, but since the range of autocorrelation is small, the predictions will revert to the arithmetic mean, which will be similar to the GLM index. Overall, the trend of both indices shows a decline in relative abundance from about 1990 to 2005/2006. The abundances in 1987 and 1988 are low, but this could be due to the fact that dolphinfish were not targeted in the early years of the longline fishery. A more realistic abundance trend may begin in 1990, and for the purposes of the stock assessment

model, separate model runs will be made with an index that includes the early years and an index that begins in 1990.

Swordfish, as expected, shows some differences between the GLM and the geostatistically derived indices (Figure 4.5).

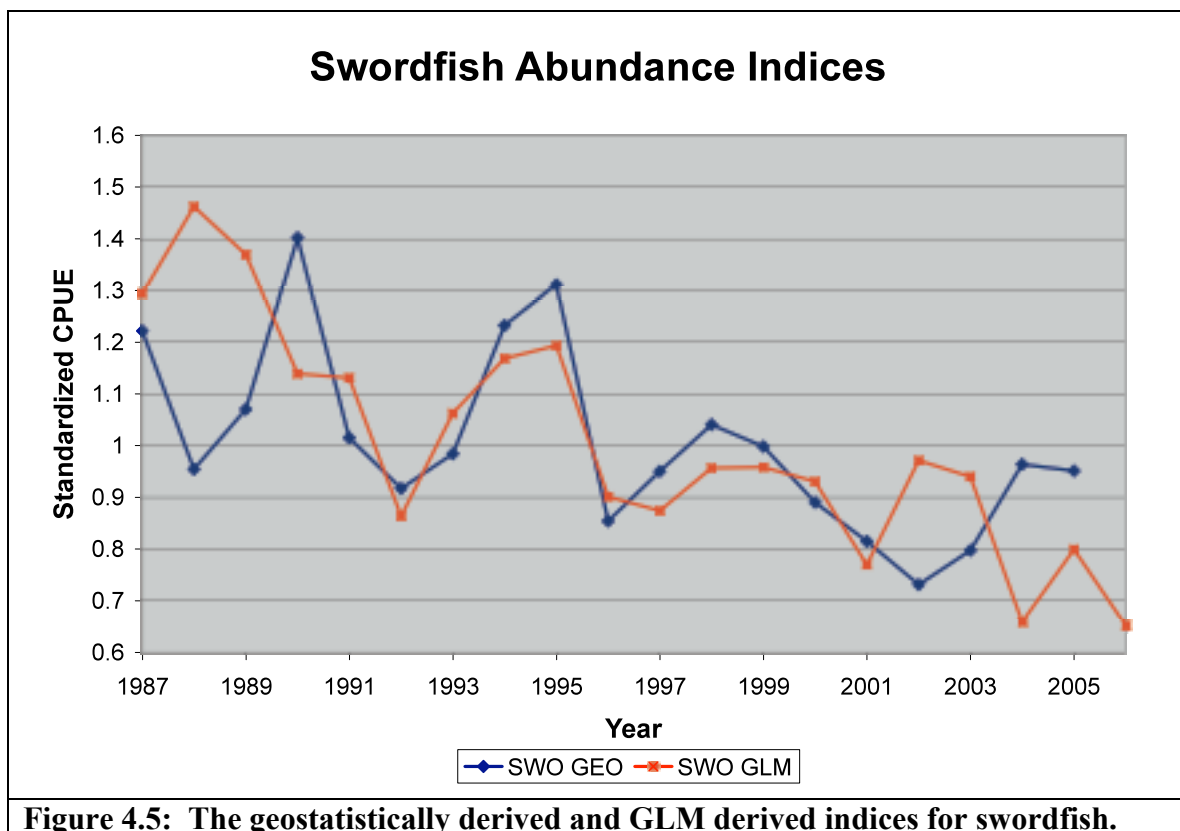
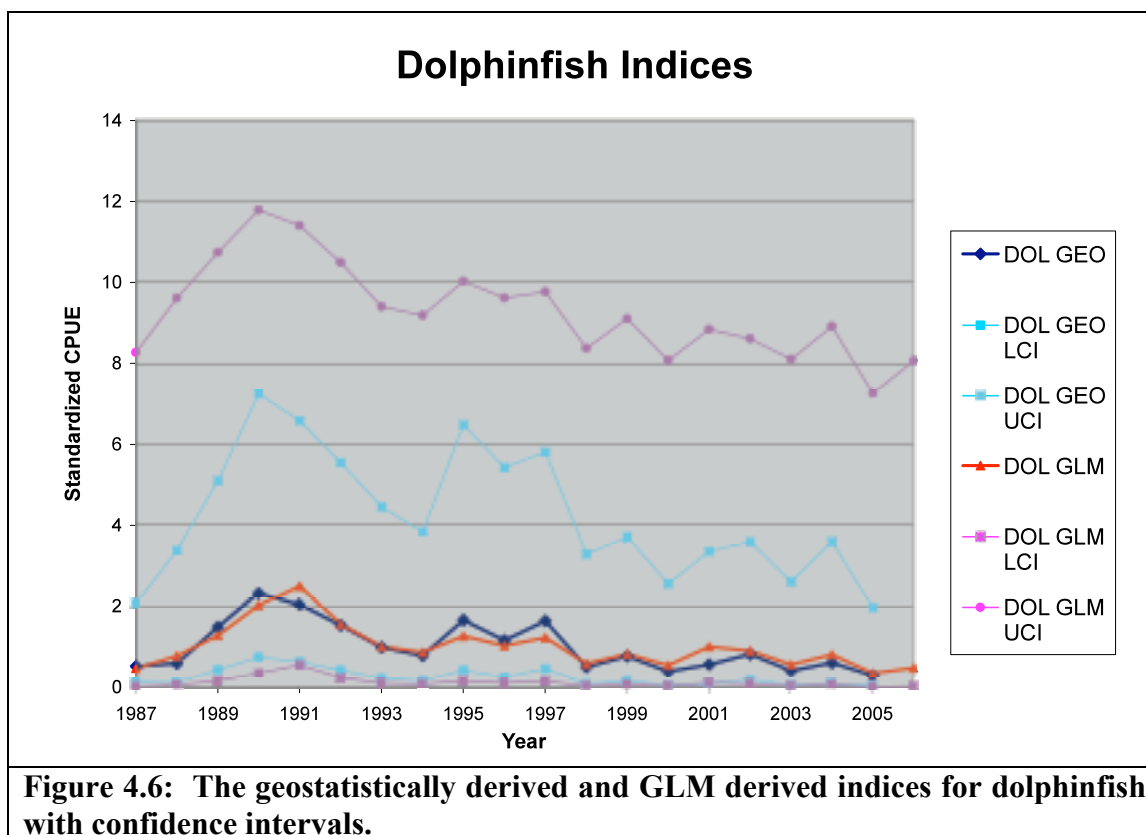


Figure 4.5: The geostatistically derived and GLM derived indices for swordfish.

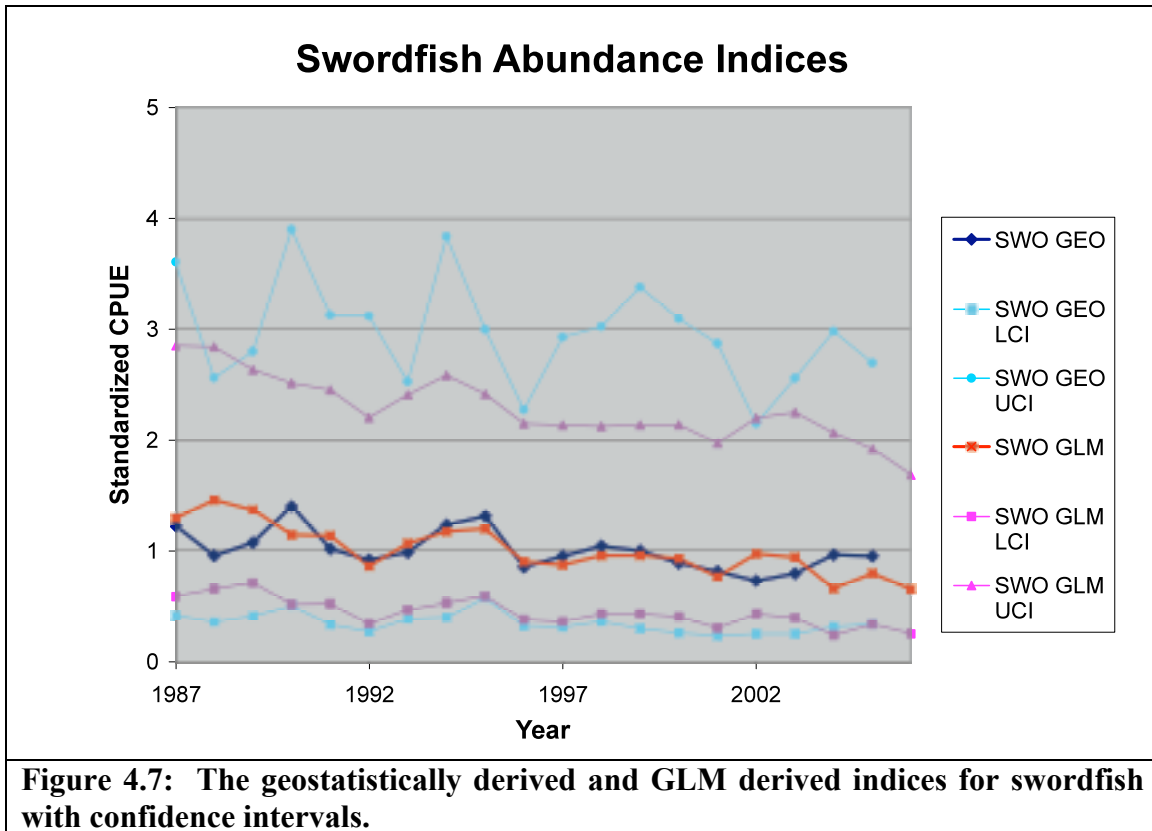
While the overall trend is the same, there are differences annually where the pattern is either offset, or completely opposite between the approaches. For example, in 1988-1990 and in 2002-2005, when there are peaks in CPUE in one index, there are valleys in the other index. Since it is especially evident that patterns in abundance are different in the later years, one could expect that the biomass ratio estimates from a stock assessment model may be different if the index was the main input to a stock assessment model. The effect of this difference may, of course, be diluted if there are many other indices added

to the stock assessment model that have differing trends, which in effect may negate the trend of the geostatistical index. For example, the ICCAT assessment of swordfish in 2006 included indices from the U.S., Japan, Brazil, and Spain (ICCAT, 2006). If the trends of any of these indices are pulling in different directions, the result will be a biomass trend that is averaged between the CPUEs.

An examination of the variance of the indices is somewhat problematic since the variance of the GLM index is design-based and the variance of the geostatistical index is in effect model-based. Design-based estimators model the status and trend of the observations, but do not model the underlying stochastic process. They have the benefit of avoiding selection bias and controlling for sample process variance. Model-based predictions on the other hand model the stochastic behavior of the response and the forecasting or predictions are conditional on the observed data. Walter (2006) addressed this issue in an examination of classical design-based and model-based approaches for incorporating space into a stock assessment of a benthic species. He noted that due to the fact that the kriging prediction variances rely on the weights assigned to sample values based on the variogram model, variances obtained from these methods can not be interpreted the same way as a design-based variance where the variance is based on samples of an assumed fixed process. One way of looking at this is that for design-based inference, the samples are random and the process is fixed so repeated “samples” can be obtained. Conversely, with model-based estimation, the samples are fixed and the process is random (Walter, 2006). However, a visual comparison of the variance of dolphinfish indices shows that although the indices are quite similar, there is a distinct tightening of the confidence intervals of the geostatistical index (Figure 4.6).



This is to be expected as the geostatistical index incorporates an additional layer of variance that can be attributed to spatial differences. The swordfish indices actually display an opposite pattern with a decrease in the variance of the GLM index (Figure 4.7).



An explanation for this difference might be due to the fact that the GLM implicitly accounts for temporal and gear effects. The data for the geostatistical index has also been standardized for these effects *a priori*. However, it is important to realize that the variance of the geostatistical index is a measure of the quality of the prediction at a given grid point, and therefore encompasses only the spatial variability at a given location, not the variance attributed to other factors.

4.4 Discussion

One of the goals of geostatistics as applied to fisheries is to determine the spatial structure of the processes involved. These are the population dynamics in the target ecosystem and the action of the fishery itself. As modeled here this involves the size of patches in space and the pattern of these patches coupled to the distribution of fishing

effort. The methods introduced here use fishery-based information to build a map of the density of a species in an area. Additionally, if the spatial structure can be determined for individual temporal units, this can provide the means for constructing an annual or seasonal index of abundance. Geostatistics provides a unique opportunity to estimate density in locations that are not sampled (Rufino *et al.*, 2005). This therefore allows for more realistic representations of the population distribution and a smoothed effect. Kriging allows for the removal of spatial variation in the data due to sampling or search techniques, and to some extent patterns of environmental heterogeneity that are influencing the presence of a species in an area (Rufino *et al.*, 2005). This work indicates that spatial patterns can be determined for dolphinfish and swordfish and patterns of abundance for this species may be tied to variation in the local environment.

Several conclusions may be drawn from this study. First, there are several oceanographic features within the Gulf of Mexico that may, in conjunction with physiological adaptations of swordfish and dolphinfish, be contributing to the spatial patterns observed in the catch rate data. Within the region, the oceanography is variable mainly due to the fluctuations in the Loop Current and eddies produced by this dominant current regime. This variability in the physical environment will affect a pelagic species that is dependent on optimal temperature zones and frontal regions for both efficient biological function and for effective resource utilization (Olson, 2001; 2007) leading to spatial autocorrelation in the catch rates. A similar “patchy” effect will also be observed in the case of schooling species (Conan, 1988; Pettigas, 1993; Freon and Misund, 1999). In most cases, it is likely that pelagic schooling fish or pelagic fish that are aggregated along a frontal feature may show little or no decline in catch rates as effort increases due

to the fact that the patchiness ensures high densities even when the total population abundance may be reduced (Hilborn and Walters, 1992). In this instance it would be very important to remove the effect of patchiness by explicitly addressing the spatial variability in a system before attempting to determine a pattern of abundance. This may also be true for a species that is less restricted in its habitat usage such as the swordfish. Swordfish is a deep-diving species that spends a good deal of time at depths of up to 800 meters (Carey and Robison, 1981; Brill and Lutcavage, 2001). The baroclinic Rossby radius of deformation, describes the horizontal scale at which rotational effects become as important as buoyancy effects (Rossby, 1938). It is an important measure of oceanographic dynamics and describes the horizontal scales of mesoscale processes. In general, as the depth increases, there is an increase in the Rossby radius. This means that at the surface of the ocean, eddies and current structures are much smaller than at depth. For a species that is constrained by a particular temperature regime this translates into a more constricted habitat at the water surface than at depth. One might therefore expect that a deeper diving species such as swordfish would have a longer range of autocorrelation and would be subject to greater spatial variability than a surface species such as dolphinfish. Additionally, dolphinfish distribution is known to be influenced by floating objects in the water such as *Sargassum* or other debris (Dempster, 2003; Taquet *et al.*, 2000). Wind strength has also been shown to have an effect on fish distribution and abundance. Winds create currents which influence prey distribution. Both swordfish and dolphinfish tend to associate with areas of convergence and divergence because there is a higher frequency of both plankton and smaller fish species (Olson and Backus, 1985). This is true during moderate wind events, and may cause the catch rates to be inflated.

Conversely, strong winds tend to have a negative effect on swordfish catch because swordfish will remain at deeper depths below the range of the longline gear (Bigelow *et al.*, 1999).

The second conclusion is that the approach of using log-transformed abundances and modeling lognormal positive CPUE separately from proportion positive CPUE resulted in higher spatial dependency and more precise range estimates than modeling the spatial structure of the whole dataset. This separation is convenient because you can separate and analyze each component of the data with different error structures and then recombine the pieces to obtain the final index. By incorporating different model structures to the slightly different systems, the underlying process is modeled more accurately. Although the models are representing portions of the same dataset, there may be differences in what is revealed about the system by looking at the pieces. The positive catch data addresses patchiness in the catch data and may point to a level of patchiness of the species. The proportion positive data may actually reveal a slightly different view of the data structure since the fact that fishing occurred, but no catch was made (the zeros) is indicative of areas that may not be suitable for the capture of the species.

Third, the GLM derived index of abundance assumes that the un-fished areas are the same as the areas that are fished. In other words, across a fishing area, the GLM index assumes a mean CPUE. In contrast, the geostatistical index of abundance assigns a value based on the spatial autocorrelation in the data to an area where fishing is occurring. This means that there will be estimates of CPUE in areas where fishing has not occurred within the range of autocorrelation. Outside of the range, in an un-fished area, the kriging GLM assumes a mean CPUE value. Intuitively, this means that the

geostatistical index will revert to the GLM index when the range of autocorrelation is small enough that it becomes insignificant. This was the case with the indices for dolphinfish. The indices were quite similar because the range of autocorrelation was small and therefore most samples were uncorrelated and estimates reverted to the sample mean. The true power of the geostatistically derived index was seen in the case of swordfish, where the range of autocorrelation was significantly greater than the length of the longline gear. This resulted in differences between the indices because fewer of the observations regressed to sample mean. The end result was that the kriging forced a definition of the spatial extent of the CPUE that was reflected in the geostatistical index.

A benefit of geostatistically derived indices of abundance is their applicability in spatially explicit stock assessment models, which are becoming increasingly popular (Hilborn, 2003). Incorporating information on the distribution of a species aids in the biological understanding of a species and can reduce the uncertainty surrounding parameter estimates from stock assessment models. Additionally, as the use of Marine Protected Areas (MPAs) expands, the need to examine the effectiveness of existing MPAs demands the use of spatially explicit observations of catch rates. This is especially important in areas where closures have been established for pelagic species such as in the De Soto Canyon in the northeastern Gulf of Mexico. A spatial map of the high and low abundance of a species may be a useful tool for delineating areas that could have potential as MPAs. Furthermore, these maps may identify whether areas currently designated as MPAs are sufficient in both a spatial and a temporal sense. For example, if a pelagic species is not found in an area other than the specified MPA during critical periods such as spawning, then the MPA may be failing to protect the species during a

period that it may be most vulnerable to fishing pressures. Or, perhaps an MPA or restricted fishing zone should move according to season in order to protect a greater majority of the species in question. Identifying critical “pelagic habitat” is a very important consideration when considering MPAs for a pelagic species that is not restricted to a particular benthic habitat. The drawbacks of accommodating spatial correlation are that estimation of the model parameters is more complex and that estimation of the model-based predictions is computer intensive. In addition, prediction estimates can be sensitive to the parameters of the fitted semi-variograms, and there are no stringent guidelines for obtaining a “best fit” of the variogram model to the data.

Related to the idea of identifying areas that are consistent “hotspots” for species in an MPA context is the idea that geostatistics can be used to account for large differences in the spatial distribution of a fishery from one year to the next. Walters (2003) addresses this issue by pointing out two potentially serious flaws in the analysis of spatial catch rate data. The first he describes as the “folly” of incorrectly assuming that when you sum catch and effort over large spatial strata you achieve a balanced design. In actuality, you place a greater emphasis on cells where fishing was most prevalent and therefore assume that the picture in the heavily fished areas is the same as in the unfished or lightly fished areas. A geostatistical approach would, in a sense, decluster these heavily fished areas and weight them appropriately so that the pattern is statistically uniform. An added layer of complexity is found in a fishery where heavy fishing was concentrated in a few strata and then over time the fishery expanded. Walters argues that it is often the case that catch rates will decline in the original fishing area before fishers reallocate effort to new fishing grounds. This will cause bias in the estimator when the

assumption is made that these catch rate declines are directly related to decreases in the overall stock. The effect of both of these errors would be taken into account in a geostatistical analysis such as the one presented here because the data is spatially detrended at a seasonal level within the Gulf of Mexico.

The methods presented here also address the second problem presented by Walters (2003) that he describes as the “fantasy” of stock assessment: when areas that are unfished are ignored in the analysis. For this study, careful consideration was given to the area that was used for predictions. Because geostatistical inference results in maps of abundance over the area of prediction, this allows predictions for a given time strata over areas where fishing (i.e., sampling) did not occur. The constraints that were made in this study were to relegate predictions to an area that was fished consistently over time (i.e., the home range of fishing). Walters argues that when faced with many missing entries there are three choices: (1) to only predict abundance for strata that are fished every year, (2) to plug in the mean catch rate when faced with an area for which there is no data, and (3) to fill the empty cells with an estimate of what catch rates would be if fishing had occurred. The first point would yield an abundance index that was not appropriate for stock assessment of the stock as a whole. The second makes an assumption that is similar to what a GLM assumes: that a mean abundance value is applied across the spatial domain. The third point requires the assumption that the stock size in each strata was stable over time (i.e., that current biomass is equal to initial biomass before fishing occurred). It is Walters’ assumption that the best option is to fill in the gaps using knowledge of the temporal or spatial autocorrelation structure if available. The geostatistical analysis presented here ensures that a robust estimate is provided for areas

that are not fished in a certain season. The constraining of the prediction grid to areas that are fished in at least one season means that unlike the GLM, a mean value is not used in an area where there is absolutely no information.

Finally, there are several theoretical and practical tradeoffs to consider when deciding between geostatistical model-based approach and traditional GLM design-based estimation. Although the traditional GLM standardized index, a design-based approach, is more familiar and more straight-forward, it has drawbacks related to determining the exact CPUE in an area. If the question being asked is, “where are the animals located”, the design-based approach fails to address this. Also statistically, the design-based approach requires the assumptions of random, uncorrelated samples, and it is necessary to keep this in mind when making predictions from this technique. Despite these caveats, the increase in complexity of the geostatistical modeling may be unnecessary in the case where the range of autocorrelation is only slightly greater than the spatial resolution of the sampling framework. In these cases, there will be little difference between the indices because the geostatistical index will revert to the sample mean for a majority of the data points that are a greater distance apart than the range of autocorrelation.

CHAPTER 5: ACCOUNTING FOR SPATIAL VARIABILITY IN A STOCK ASSESSMENT MODEL.

5.1 Background of Stock Assessment Models and Role of CPUE Indices

While biomass dynamics models may be considered inferior to age-structured models because of their simplicity, they are often considered the most appropriate stock assessment approach when data are limited to landings and relative abundance time series (Hilborn and Walters, 1992). Such data-limited situations are common in tropical fisheries (Caddy, 1992; Sadovy, 2005) and many minor pelagic fisheries. Comparisons of biomass dynamics and age-structured models have demonstrated that when the main assumptions of the models are satisfied, both types of models can perform equally well, giving similar management recommendations (Punt, 1994). In some cases, biomass dynamic models may provide better estimates of management parameters and are thus more robust (Hilborn and Walters, 1992; Punt, 1995; and Abuanza et al., 2003). Additionally, when age-structured analysis is not feasible, the simpler biomass dynamic models are a time-saving and cost-effective alternative (Punt, 1994). In certain cases, it is difficult or impossible to obtain a CPUE index or catch series that is age-structured, necessitating the use of an aggregated biomass dynamic pool model. In this instance, an age-structured analysis would not be a feasible option.

Dolphinfish is a species for which catch-at-age data do not exist. Similarly, swordfish are notoriously difficult to age, and in the Atlantic, a surplus-production model has been used to assess the status of this species. For this study, the dynamics of dolphinfish and swordfish were accounted for by fitting surplus-production

models using catch and landings records and several CPUE time series from the Gulf of Mexico and wider Caribbean within a Bayesian state-space modeling framework. This framework allows observation error to be accounted for, as well as our prior knowledge of the demography of the dolphinfish (Millar and Meyer, 2000).

Bayesian modeling of fisheries allows assessment scientists to more accurately portray the variability and uncertainty that is inherent in a dynamical system such as the marine environment (Punt and Hilborn, 1997). The highlight of Bayesian methods is that they provide a formal means of making inferences on parameters of interest (usually life history parameters) that are based on any observed data and background information on the parameter (Gelman *et al.*, 1995). The uncertainty surrounding the parameter value given the prior knowledge is expressed in terms of a probability density function (PDF). This method, often referred to as the Bayesian inference approach, allows the incorporation of prior knowledge of a species' demography into the model to supplement the information available for the stock. Additionally, the Bayesian approach allows for the accounting and partitioning of the uncertainty in the model parameters and the variability due to temporal changes in the abundance data.

Because CPUE indices must represent the relative abundance of the stock, it is important that indices are first standardized for any extraneous factors that may be contributing to the annual variation in the CPUE trend so that the final index is representative of the fluctuation in the abundance of the species. Therefore, it is not typically the nominal CPUE index that is input to the stock assessment, but a standardized version. Typically this standardization is done using a model such as a GLM whereby explanatory variables are added to the model via a selection criterion such

as a forward or stepwise selection procedure based on the amount of variance they explain. The indices derived for dolphinfish and swordfish in Chapter 4 have been subject to similar standardizations for annual and seasonal variability, and specifically for swordfish, gear effects. Additionally, the effect of spatial autocorrelation was explored with a geostatistical model. The main differences between the nominal CPUE, the GLM standardized CPUE index, and the full geostatistical CPUE index are summarized in Table 5.1. It was found that for swordfish, a species that displayed a longer range of autocorrelation, the spatial variability was significant enough to lead to major qualitative differences between the spatially explicit (geostatistical) and non-spatial (GLM) indices. Dolphinfish exhibited spatial autocorrelation on a shorter range, and this was likely the reason that there were smaller differences between the geostatistically-derived and GLM-derived indices. The question addressed in this chapter is whether the differences between the spatial and non-spatial indices would contribute to significant differences in the biological reference points and management criteria within a stock assessment framework.

Index	Method	Pros	Cons
Nominal	<ul style="list-style-type: none"> Ratio Estimator 	<ul style="list-style-type: none"> Simplicity 	<ul style="list-style-type: none"> Does not include space No standardization No attempt at removing sources of bias Does not deal with issue of serial depletion
GLM	<ul style="list-style-type: none"> Delta Lognormal Design based 	<ul style="list-style-type: none"> Standardization Separation of LN positives and zeros (method for handling zeros) 	<ul style="list-style-type: none"> Does not include space usually Does not deal with issue of serial depletion
Geostatistical (1): Kriging Variance	<ul style="list-style-type: none"> Area of prediction constrained to 95% of the kriging variance Model based 	<ul style="list-style-type: none"> Delta Lognormal method of dealing with zeros Reduces bias of clustered observations Allows spatial prediction 	<ul style="list-style-type: none"> More complicated to implement than other methods Does not deal with issue of serial depletion

Table 5.1. A comparison between the nominal, GLM, and geostatistical indices and approaches used to derive each index.

With this question in mind, the purpose of this analysis was to address the importance of the CPUE index as a driving force in the stock assessments. Specifically, the CPUE indices that accounted for spatial patterns and those CPUE indices that ignored spatial autocorrelation are input separately to a Bayesian Surplus Production (BSP) model in order to qualitatively compare the productivity parameters from the models. It was hypothesized that there would be some variation in the results from the swordfish model due to the differences between the indices that stem from spatial variability. Conversely, because dolphinfish was autocorrelated on a short range (see Chapters 3 and

4), there was little difference between the geostatistical and the GLM indices. Therefore there should be no difference between assessment models that incorporate these indices separately. Given the lack of information on stock status for western Atlantic dolphinfish, a second objective of this chapter was to use a Bayesian surplus production model to re-evaluate whether standardized CPUE and catch data provide information on productivity parameters and current stock status for dolphinfish.

This analysis incorporates recent developments in Bayesian stock assessment and its applications to data-limited situations. These adaptations provide a theoretical framework for incorporating externally available information on stock assessment in order to reduce the uncertainty that is inherent with uninformative data series or data that alone does not have enough information to resolve the trends in biomass and fishing mortality in the stock assessment model (Punt and Hilborn, 1997, Hilborn and Liermann, 1998, McAllister and Kirkwood, 1998 and McAllister et al., 2001).

5.2 Modeling Methodology

Data Series

The main data collated in previous chapters for the models of dolphinfish and swordfish consist of the reported annual landings in the western Atlantic (1950-2005), and two relative abundance indices from the U.S. longline operations in the Gulf of Mexico (1987-2005): a GLM standardized index and a geostatistical index. Additional sources of data used, are the relative abundance index for swordfish for the Japanese longline fleet and the r prior used in ICCAT's assessments of North Atlantic swordfish. Finally, we conducted a meta-analysis of biological parameters for pelagic species that helped us obtained a prior for r for dolphinfish.

Each Gulf of Mexico relative abundance index was added to the model by itself in a separate model run to evaluate what information the series contains regarding life history parameters and biomass trends. Differences between the current biomass and fishing mortality estimates from the initial values were used to determine if the status of the stock was overfished (a measure of relative abundance) or experiencing overfishing (a measure of fishing pressure). If there were differences in the predictions of the models when different indices were used, it would serve as a cautionary example of the need to address spatial autocorrelation appropriately.

For both the nominal and the GLM standardized index, the abundance index represents the number of fish of the species caught (alive, dead, and discarded) per hook per trip. Because the length of the U.S. time series was relatively short (1986-2005), additional models were run that incorporated the Japanese standardized CPUE index (JLL) (1967-2005) from the western Atlantic (Yokawa *et al.*, 2003). The effect of

overlap between the U.S. and Japanese index was explored by using the full Japanese series with the U.S. indices, and by using a truncated Japanese index (1967-1998) (Figure 5.1).

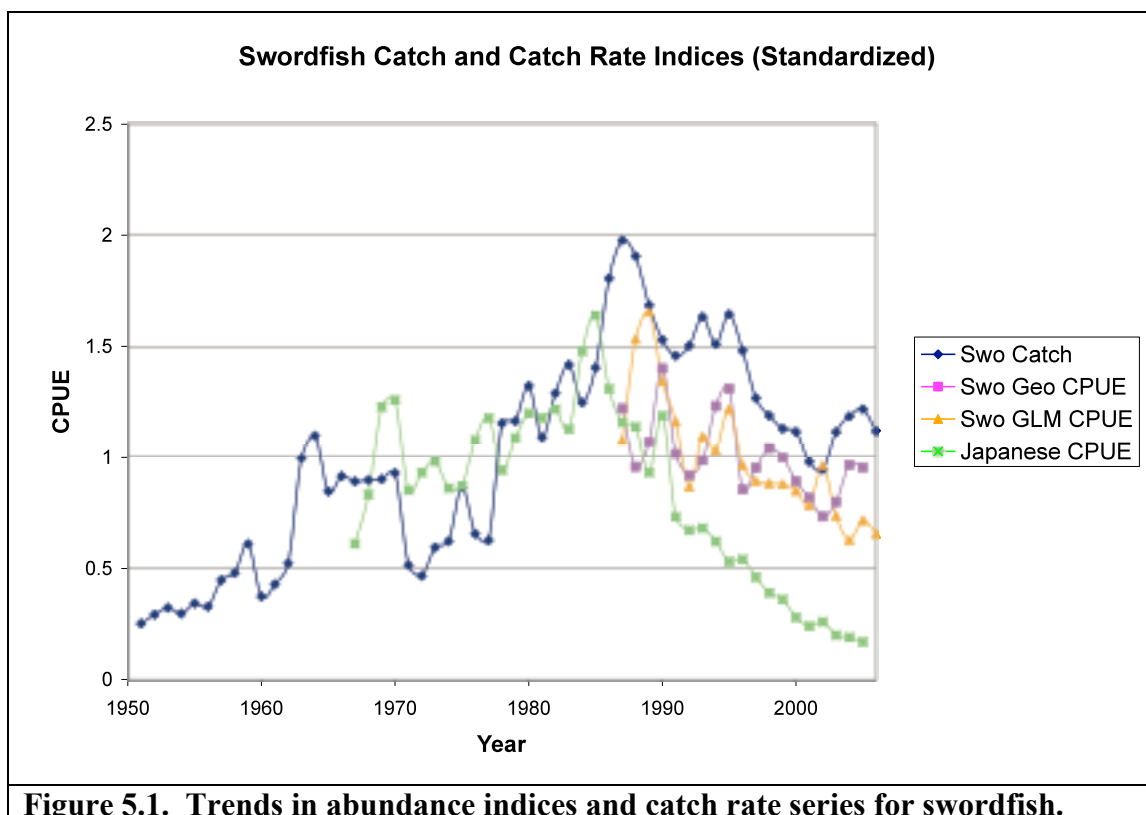


Figure 5.1. Trends in abundance indices and catch rate series for swordfish.

This allowed the current years in the model to be driven by the U.S. indices to highlight any differences between the trends in the geostatistical and GLM indices. Finally, a model was run for swordfish that only used the Japanese index for comparison purposes. Table 5.2 lists the components involved in each of the BSP model runs. For all models, when more than one index was incorporated into the model, an equal weighting was applied to all points in both indices.

Species	Model Indices	Model ID
Dolphinfish	U.S. GLM	D1
Dolphinfish	U.S. GEO	D2
Swordfish	U.S. GLM	SS1 and SF1
Swordfish	U.S. GEO	SS2 and SF1
Swordfish	Full Japanese Index Only (1961-2005)	SS3 and SF3
Swordfish	U.S. GLM (1987-2005) and Truncated Japanese Index (1961-1998)	SS4 and SF4
Swordfish	U.S. GEO (1987-2005) and Truncated Japanese Index (1961-1998)	SS5 and SF5
Swordfish	U.S. GLM (1987-2005) and Full Japanese Index (1961-2005)	SS6 and SF6
Swordfish	U.S. GEO (1987-2005) and Full Japanese Index (1961-2005)	SS7 and SF7

Table 5.2. A summary of the BSP models and the abundance indices incorporated in each. The first letter of the ID refers to the species and the second letter refers to whether the model run was the Schaefer or Fletcher model.

BSP Model Formulation

The models were developed using the BSP model program, which can fit either a Schaefer model or a generalized Fletcher/Schaefer model (hereafter referred to as the Fletcher model) to CPUE data using the Sampling/Importance Resampling algorithm (McAllister and Kirkwood, 1998; McAllister and Ianelli, 1997; Gelman *et al.*, 1995; McAllister *et al.*, 1994). The Schaefer approach was used for the dolphinfish models and both the Fletcher and Schaefer models were used for swordfish following the 2006 assessment by ICCAT in order to explore whether there were significant differences between the outputs from either model type. With this approach, we used a logistic difference equation to model changes in the population biomass B in year t according to Equation 1:

$$B_{t+1} = B_t + rB_t \left(1 - \frac{B_t}{K}\right) - C_t \quad (1)$$

where r is the intrinsic rate of population growth, K is the carrying capacity, and C is the total harvest in year t (Hilborn and Walters, 1992; Quinn and Deriso, 1999). The model allows several parameters to be fit, and priors can be estimated for all of these parameters for a Bayesian fit of the model. The Fletcher modification of the model represented in equation 1 allows B_{msy}/K to vary by including a shape parameter, n , as well as the parameters K (carrying capacity) and m (maximum sustainable yield) and is given by (Fletcher 1978):

$$\frac{dB_t}{dt} = gm \frac{B_t}{K} - gm \left(\frac{B_t}{K} \right)^n - F_t B_t \quad (2)$$

The parameters that the model estimates are K , r , the Fletcher model shape parameter (n) if applicable, the biomass in the first modeled year over K ($\alpha.b0$), the average annual catch prior to years when catch was recorded ($cat0$), parameters for the variance of each CPUE series depending on how the CPUE series are weighted, and catchability for each CPUE series (q) (McAllister and Babcock, 2008).

In order to analyze a system in a Bayesian framework for decision-making purposes, it is necessary to make probabilistic statements about model parameters that are conditional on information available for the species (Gelman *et al.*, 1995). This entails evaluating $P(\theta|data)$ in terms of the prior distributions for all of the estimated model parameters and the unobserved system states $P(\theta_i)$ and sampling distributions or likelihoods for the observed data $P(data|\theta_i)$ (Meyer and Millar, 1999). Using Bayes theorem, the posterior distribution $P(\theta_i|data)$ is:

$$P(\theta_i|data) = \frac{P(\theta_i)L(data|\theta)d\theta}{\int P(\theta)L(data|\theta)d\theta} \quad (3)$$

where $P(\theta_i)$ is the prior probability distribution for state of nature i and $L(data|\theta_i)$ is the likelihood function for the data evaluated at θ_i (McAllister and Ianelli, 1997).

Sampling Importance Resampling Algorithm

This posterior distribution is approximated by the sampling importance resampling (SIR) algorithm, which is a numerical integration method (McAllister and Babcock, 2008). The basis of this algorithm is that a posterior distribution for a parameter, $g(\theta)$, can be redefined in terms of the expected value of the probability density function, $E^{h(\theta)}$, which is the importance function (McAllister *et al.*, 1994; McAllister *et al.*, 2002). Sampling of a larger number of draws (m) from the importance function ($>20,000$) approximates the expected value so that the marginal posterior of $g(\theta)$ is defined as:

$$E^{P(\theta|y)}(g(\theta)) \cong \frac{\sum_{k=1}^m g(\theta_k) w(\theta_k)}{\sum_{k=1}^m w(\theta_k)} \quad (4)$$

where:

$$w(\theta_k) = \frac{L(y|\theta_k) p(\theta_k)}{h(\theta_k)} \quad (5)$$

represents the weight of draw k or the importance ratio. When there are enough samples taken, equation 3 should converge on the posterior distribution of $g(\theta)$ for any importance function that allows a non-zero probability of sampling each point in the posterior distribution (McAllister and Babcock, 2008). The models for dolphinfish used an importance function that was a multivariate t-distribution with 0.01 degrees of freedom, the means at the mode of the posterior, and variances that were calculated from the Hessian matrix at the mode with an expansion factor of 100. The caveat to using a

multivariate t-distribution is that one must make sure that the importance function is wide enough that it does not underestimate the variance of the parameters (McAllister *et al.*, 2002; McAllister and Babcock, 2008). This is a diagnostic that must be met by checking that the CV of the weights is less than the CV of the likelihood times the priors. If this condition is not met, then that importance function must be expanded by decreasing the degrees of freedom, setting the covariance of the t-distribution to 0, using an expansion factor, or a combination of all three. The swordfish models used draws from the priors as the importance function. The caveat to this function is that one must make sure that the limits for the parameters are not too far outside the possible values of any of the parameters that have been assigned a uniform distribution. If this criterion is not met, then sampling will be very inefficient and many of the draws will be discarded as they will be outside the boundary conditions.

Starting Parameter Value Estimation

Dolphinfish Models

Preliminary attempts at modeling biomass dynamics of dolphinfish in the western Atlantic using an ASPIC surplus production model were unsatisfactory for developing management metrics (Prager, 2000). Parameters of the Schaefer model were ill defined, resulting in large uncertainty around parameter estimates and reference points for management. This was due to lack of contrast in the CPUE time series. Despite these issues, the r and K parameters from Prager's model were useful as starting r and K parameter guesses for the dolphinfish models for this analysis because they are reasonable parameter estimates for a fast growing, short lived species (Table 5.3).

Parameter	Formula	Value
Y_{MSY}	$rK/4$	12,241 mt
F_{MSY}	$r/2$	0.49
r	$2*F_{MSY}$	0.98 / year
K	$MSY*4/r$	49,963 mt

Table 5.3. Estimates of MSY , F_{MSY} , r , and K from an ASPIC Schaefer surplus production model (Prager, 2000).

Using parameters from an ASPIC model is identical to running the BSP model with completely uninformative priors when F is iteratively estimated. ASPIC, which was used as the preliminary model, is based on the original, continuous time version of the Schaefer model and relates biomass, B , in the following year as a function of current biomass through the following non-linear relationship:

$$B_{y+1} = \frac{(r - F_y)B_y \exp(r - F_y)}{(r - F_y) + (r/K)B_y(\exp(r - F_y) - 1)} \quad (6)$$

where F is the fishing mortality coefficient. The Schaefer model assumes that the instantaneous rate of variation of the unexploited biomass is linear to the actual biomass.

Parameters for this model are estimated using non-linear least-squares with log-normally distributed observation errors in the effort. Sensitivity of the model to starting values in the estimation procedure is often a problem with ASPIC. Therefore, Prager (2000) made an assessment of this sensitivity by fitting the model with different initial guess values for B_0 , K , r , and q . The reference points, F_{MSY} (the fishing mortality at MSY) and Y_{MSY} (the catch at MSY) of the Schaefer model are calculated as:

$$F_{MSY} = \frac{r}{2} \quad (7)$$

$$Y_{MSY} = \frac{rK}{4} \quad (8)$$

Prager (2000) assessed the precision of the key parameter estimates of the MSY reference points by calculating confidence intervals using bootstrapping (Efron and Tibshirani, 1993). Bootstrapping is carried out in ASPIC by randomly sampling the CPUE data to create new datasets. Residuals from the original fitted model are added to the predicted CPUE dataset. The model is refit using the new CPUE data and new estimates of K , r , and q are obtained and new biological reference points are calculated. This procedure is repeated 1000 times. Often, the empirical distributions adopted from bootstrap analyses are skewed (Efron and Tibshirani, 1993). Therefore, the 50% confidence intervals are used as bias-corrected percentiles. Despite the bootstrapping, the values of r and K were not reported in the stock assessment because the estimates of r and K from ASPIC are typically quite imprecise—more so than the estimates of MSY or stock status. For this reason, and because uncertainty about stock structure was a strong theme in the assessment, it is not recommended to put much weight on the values of r and

K from the ASPIC model, but to use them as guidelines or starting parameters for the BSP model (Prager, *pers. comm.*).

Swordfish Models

There have been more attempts at assessing Atlantic Swordfish stocks than dolphinfish stocks, because swordfish is one of the species regularly assessed by ICCAT. The last assessment of the northern Atlantic swordfish stock by ICCAT was conducted in 2006 using an updated version of the dynamic (non-equilibrium) ASPIC model (v5.05) and for sensitivity analyses, a BSP model. The BSP model used was a discrete time-step model with harvest estimated at the beginning of the year. The prior distribution for the r parameter from SCRS/1999/085 was applied as the baseline prior for the Northern stock for the ICCAT model with a median value of 0.42 and a CV of 0.49. This distribution was used as the prior distribution for r for this analysis. Additionally, the parameters from the ICCAT assessment were used as starting parameter values for this analysis (Table 5.4).

Parameter	Mean	CV
K	1.33E+05	0.19
R	0.43	0.24
MSY	1.37E+04	0.04
B2005	6.52E+04	0.18
B2005/K	0.5	0.15
B1950	1.16E+05	0.25
B2005/B1950	0.58	0.23
C2005/MSY	0.89	0.04
F2005/Fmsy	0.92	0.19
B2005/Bmsy	1	0.15
C2005/rep-y	0.9	0.05
Bmsy	6.64E+04	0.19
rep.yield	1.35E+04	0.05

Table 5.4. Means and CVs of the marginal posterior distributions of management parameters from the BSP model for the Northern stock of Atlantic swordfish. Values for K, MSY, B. and yield are in metric tons.

It is very important to ensure that the BSP model converges on the mode of the posterior. This is accomplished by running the “estimate modes” component of the model with different starting parameter values. If the model has converged on the mode, then the estimated most likely values will not depend on variations in the starting parameters. This is unlike the ASPIC model and if there are different estimates obtained from BSP, then the model has not converged on the mode. Running the “estimate modes” component with different starting values ensures that the model has converged on the global mode, which can sometimes be difficult if the input to the model is uninformative (i.e., a lack of contrast between the landings data and the abundance indices) (McAllister and Babcock, 2008). Additionally, it is important to check the Hessian covariance matrix for negative values on the diagonal, which is an indication that the model has not converged to the mode of the posteriors, and that none of the parameters are highly correlated ($> 99\%$) as this will lead to inefficient importance sampling. The final models for swordfish were run using a starting value of r of 0.4 and a value of 150,000 for K . For the Fletcher model runs for swordfish, the starting value of n was 0.5. The catchability coefficient q was not estimated as a free parameter for either species, rather it was calculated numerically (McAllister and Babcock, 2008).

Bayesian Prior Development

Ideally, demographic information may be available for a species allowing calculation of a prior distribution for the parameter r . Additional methods for developing a prior for r consist of correlating r with other biological parameters, or assessing the likelihood of a certain species having an r parameter that is similar to other species that have similar life histories (Punt and Hilborn, 1997; Myers *et al.*, 2002). This latter

methodology was adopted by Babcock and McAllister (2003) and forms the basis for the prior development of r for the dolphinfish model in this study as it is useful for species for which little or no demographic information exists. This methodology was used only for the dolphinfish models as no other information on r was available. The swordfish models closely followed the ICCAT stock assessment models for prior inputs for the various parameters of the model.

The key to the use of demographic information for developing a prior for a species with little information is the ability to estimate r from the slope of the stock recruitment relationship (Myers *et al.*, 1997; Myers *et al.*, 1999):

$$(e^{r_m})^a - p_s (e^{r_m})^{a-1} - \tilde{\alpha} = 0 \quad (9)$$

where r_m is the maximum population growth rate at low population size (which can be substituted for the r from the surplus production model), p_s is the annual survival of spawners, a is the age of first maturity, and $\tilde{\alpha}$ is the maximum annual reproductive rate. Myers *et al.* (1999) provides a table of $\tilde{\alpha}$ for a number of teleost species. Because of the lack of information for dolphinfish, this list was assumed to encompass the full range of values that this parameter could take. To narrow the distribution of the parameter to values that more closely represented dolphinfish, the list was subset by removing any anadromous or benthic species (Table 5.5).

Species	Scientific Name	n	log alpha~	SE	Sigma ²	Alpha	z20	zmed	z80
Clupeiformes									
Atlantic menhaden	Bevoortia tyrannus	1	2.20	0.12		24.8		0.86	
Blueback herring	Alosa aestivalis	3	2.60	0.55	0.81	31.9	0.71	0.84	0.92
Gulf menhaden	Brevoortia patronus	1	1.25	0.16		5.3		0.57	
Atlantic herring	Clupea harengus	18	0.73	0.28	1.31	22.1	0.52	0.74	0.88
Pacific sardine	Sardinops sagax	2	0.66	0.89	1.56	12.7	0.34	0.59	0.81
Spanish sardine	Sardina pilchardus	1	-0.56	0.75		2.1		0.34	

Table 5.5 cont.									
Species	Scientific Name	n	log alpha~	SE	Sigma²	Alpha	z20	zmed	z80
Northern pike	Esox lucius	2	0.51	0.19	0.03	6.1	0.57	0.6	0.64
Ayu	Plecoglossus altivelis		1.00	4.73	0.16	123.5		0.97	
Scorpaeniformes									
Sablefish	Anoplopoma fimbria	1	-2.35	0.47		1.4		0.26	
Atka mackerel	Pleurogrammus monopterygius	1	1.13	0.49		12		0.75	
Chilipepper	Sebastes goodie	1	-0.85	0.57		2.1		0.35	
Pacific ocean perch	Sebastes alutus	3	-1.93	0.18	0	3		0.43	
Deepwater redfish	Sebastes mentella	1	-1.08	0.18		3.6		0.47	
Swordfish	Xiphias gladius	1	1.70	0.05		30.1		0.88	
Pleuronectiformes									
Northern pike	Esox lucius	2	0.51	0.19	0.03	6.1	0.57	0.6	0.64
Ayu	Plecoglossus altivelis		1.00	4.73	0.16	123.5		0.97	

Table 5.5. Listed are the empirical Best Linear Unbiased Estimators (BLUE) of the mean value of the log-transformed maximum annual reproductive rate (log-alpha), the standard error (SE) of this estimate, the estimated variance among populations (sigma-sq) (where possible), the estimated expected maximum lifetime reproductive rate for a species, where the expectation is taken over the distribution of the random effects (alpha), the 20th percentile of z (z20)—the steepness parameter, the median of z (zmed), and the 80th percentile of z (z80). Adapted from Myers *et al.*, 1999.

Histograms of the distribution of the remaining values were used to fit a function to $\ln(\tilde{\alpha})$ and 1000 random draws were made from a normal distribution with the mean and variance of the $\ln(\tilde{\alpha})$ values from the list. Values of the age at first maturity were drawn from a uniform distribution ranging from ages 0.5 to 2. Spawner survival (p_s) was calculated as $\exp(-M)$, where M represents natural mortality. Because dolphinfish is a short-lived species, generally believed to live fewer than 5 years, for this study it was assumed that the natural mortality rate (M) would remain constant. Natural mortality is typically a difficult parameter to estimate. Hoenig (1983) developed a linear regression technique to predict the total mortality rate of fish, cetacean, and mollusk stocks from

their maximum age. This tool is based on the assumption that the lifespan of a species should be inversely related to the mortality rate. The predictive equation for teleost species is:

$$\ln(Z) = 1.46 + -1.01 \ln(t_{\max}) . \quad (10)$$

This resulted in values of p_s of 0.24, 0.35, and 0.43 for fish with maximum ages of 3, 4 and 5 years respectively. Values of M were drawn from a lognormal distribution with a median M of 0.35 and standard deviation of 0.4 to allow for variability due to the uncertainty of the maximum age. One thousand draws of each parameter were made, and the corresponding value of r was calculated from the equation. It was necessary to truncate implausibly large or small values of r (<0.2 and >1.5). These truncated values came from the fact that the input parameters to the equation were selected from a distribution and a small number of draws would have come from the tails of the distribution. The mean (0.83) and standard deviation (0.53) of the remaining r values was used to formulate a lognormal prior for r for the Bayesian model (Figure 5.2).

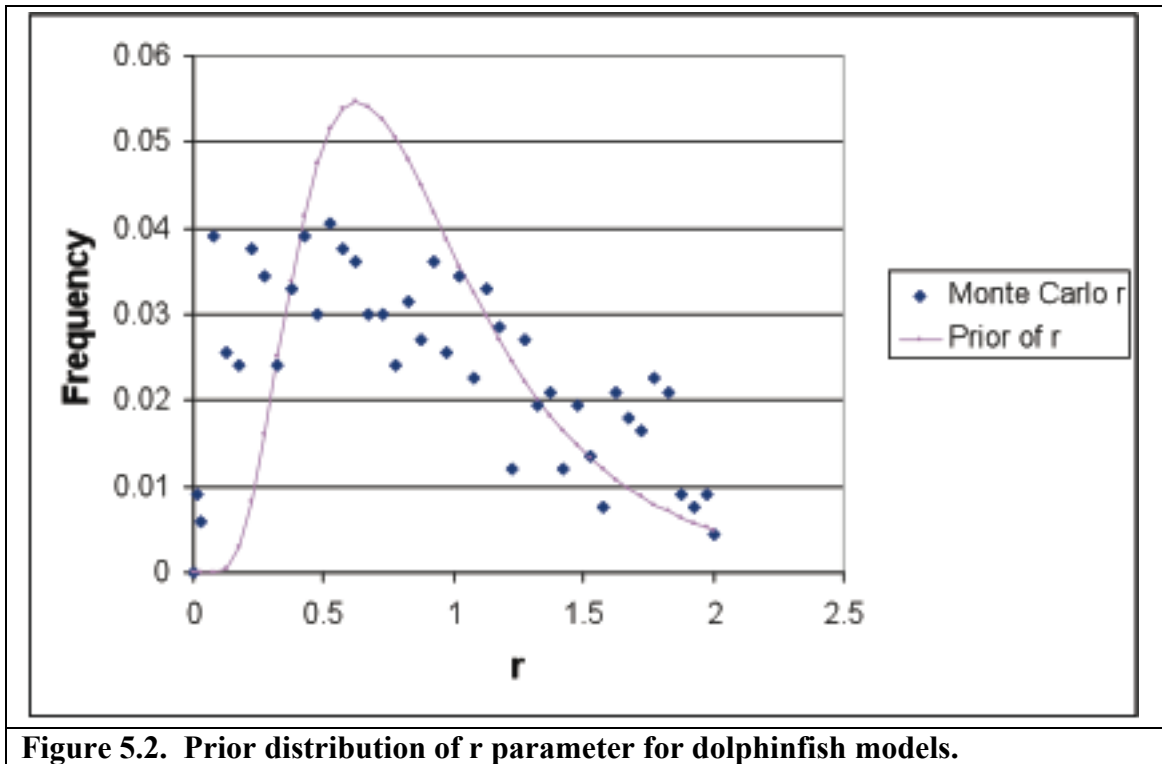


Figure 5.2. Prior distribution of r parameter for dolphinfish models.

The prior displayed in Figure 5.2 does not represent a good fit to the data and looks to be more informative than the actual data. To test the sensitivity of the model output to the prior used for r , a less informative prior was used for separate model runs (Figure 5.3). This prior was also a lognormal fit with a mean of 0.93 and a standard deviation of 1. The less informative prior was used as the prior for r for dolphinfish and results of the BSP models are presented for this species as a better alternative to the original prior.

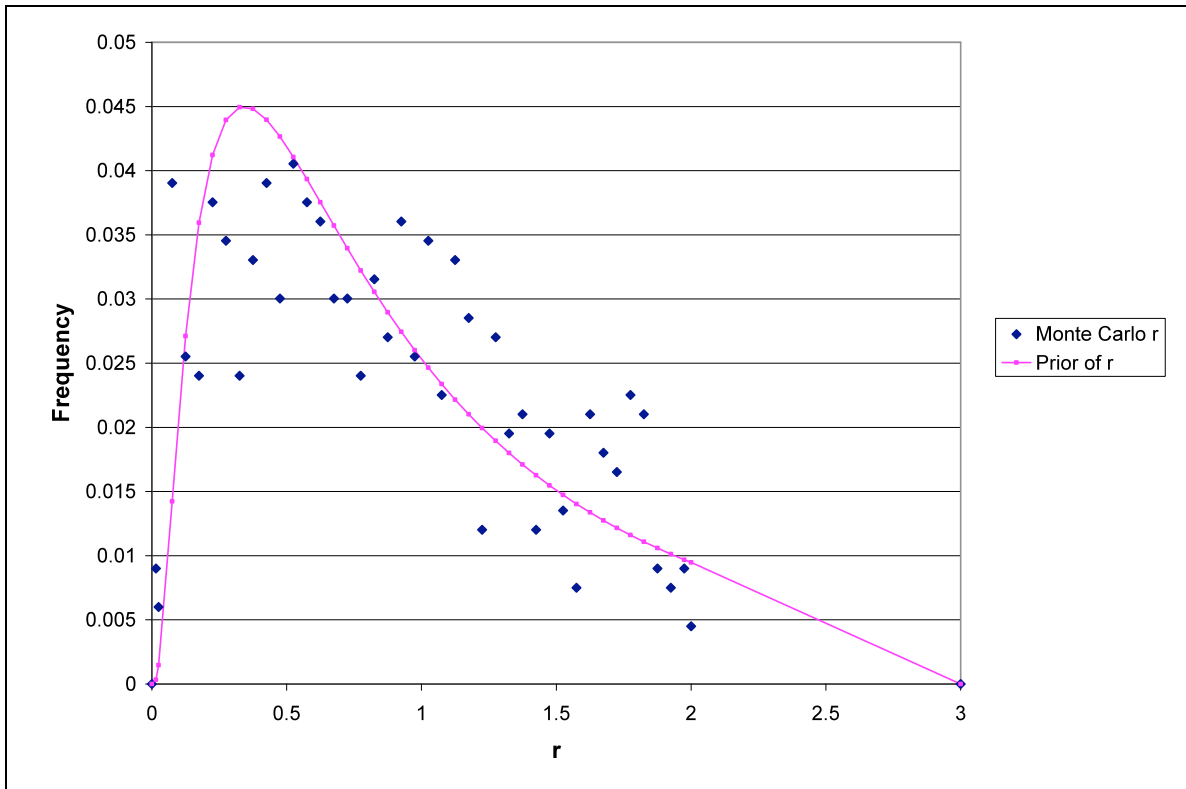


Figure 5.3. Less informative prior distribution of r parameter for dolphinfish models.

The prior for r for swordfish followed that used in the ICCAT assessment model: a median value of 0.42 and a CV of 0.49 (Figure 5.4).

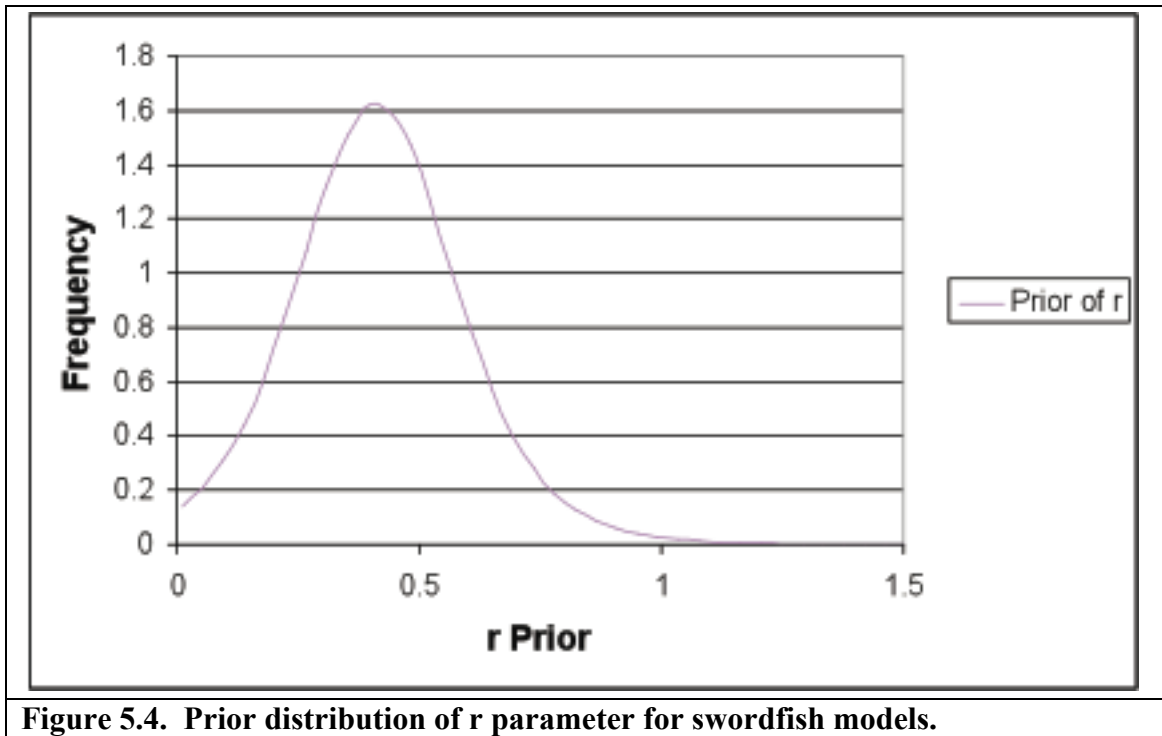


Figure 5.4. Prior distribution of r parameter for swordfish models.

For the dolphinfish parameter $\alpha.b0$, the biomass in the first modeled year expressed as a ratio of the virgin stock biomass (K), a somewhat informative prior with a mean of one and a standard deviation of 0.25 was used. This allowed some flexibility in determining the starting biomass while at the same time holding the parameter within reasonable bounds. This is different than the ASPIC model, which requires that $\alpha.b0$ is either fixed at 1, or estimated by the model. Similarly for the corresponding parameter for swordfish, the prior distribution had a mean of 0.875 and a standard deviation of 0.25 following the distribution used in the ICCAT stock assessment. An informative prior for K cannot be developed because there is no information that is independent of the data used to fit the model. Therefore for both species, an uninformative prior for K was used, which was uniform on the natural log of K . For the generalized Fletcher model for swordfish, it was necessary to set a multivariate t prior for the parameter n , and for the covariance of r and n for the multivariate t prior. The values used were the same as the

values of n used in the ICCAT Fletcher model scenario runs: a mean of 1.382 and a variance of 0.141, -0.000289 for the covariance of r and n , and 6.62 degrees of freedom for the multivariate t distribution. A starting value of 0.5 was used for all runs.

5.3 Bayesian Surplus Production Model Results

For all model runs, tables of the expected parameters are presented with the percentage difference between the values from the models using the U.S. GLM index and the U.S. geostatistical index. The parameters K , r , B_{cur}/B_{init} , B_{cur}/B_{msy} , and F_{cur}/F_{msy} are highlighted in all of the tables. K and r describe features of the biology of the species. B_{cur}/B_{msy} and F_{cur}/F_{msy} are typically used by stock assessment scientists to tell whether a stock is close to a desirable level of productivity (like B_{msy}) or is being overfished. These are important benchmark parameters that are commonly used by stock assessment scientists and managers to summarize the current status of the fishery. B_{cur}/B_{init} is useful for interpreting the amount of depletion of the stock that has occurred since the start of the fishery. The ratios of this parameter are used to compare the fits from the models that only use the U.S. data to those that use only the Japanese data to discuss the importance of having a long time series of both CPUE and catch with large contrast in biomass. Graphs of the posterior distributions of the parameters and the historical trends in biomass and fishing mortality ratios help to clarify the differences in the models. The credibility intervals of the latter evaluate the fit of the models and provide a visual interpretation of the status of the fishery over time. It is important to note that the expected values provided in the tables do not correspond with the mode of the posterior. The values presented in the time series graphs are the medians of the distributions with the 80% credibility intervals. The disparity between the expected

value, median, and mode values can sometimes be attributed to the width of the right tails of the marginal posterior distributions.

Dolphinfish BSP Models

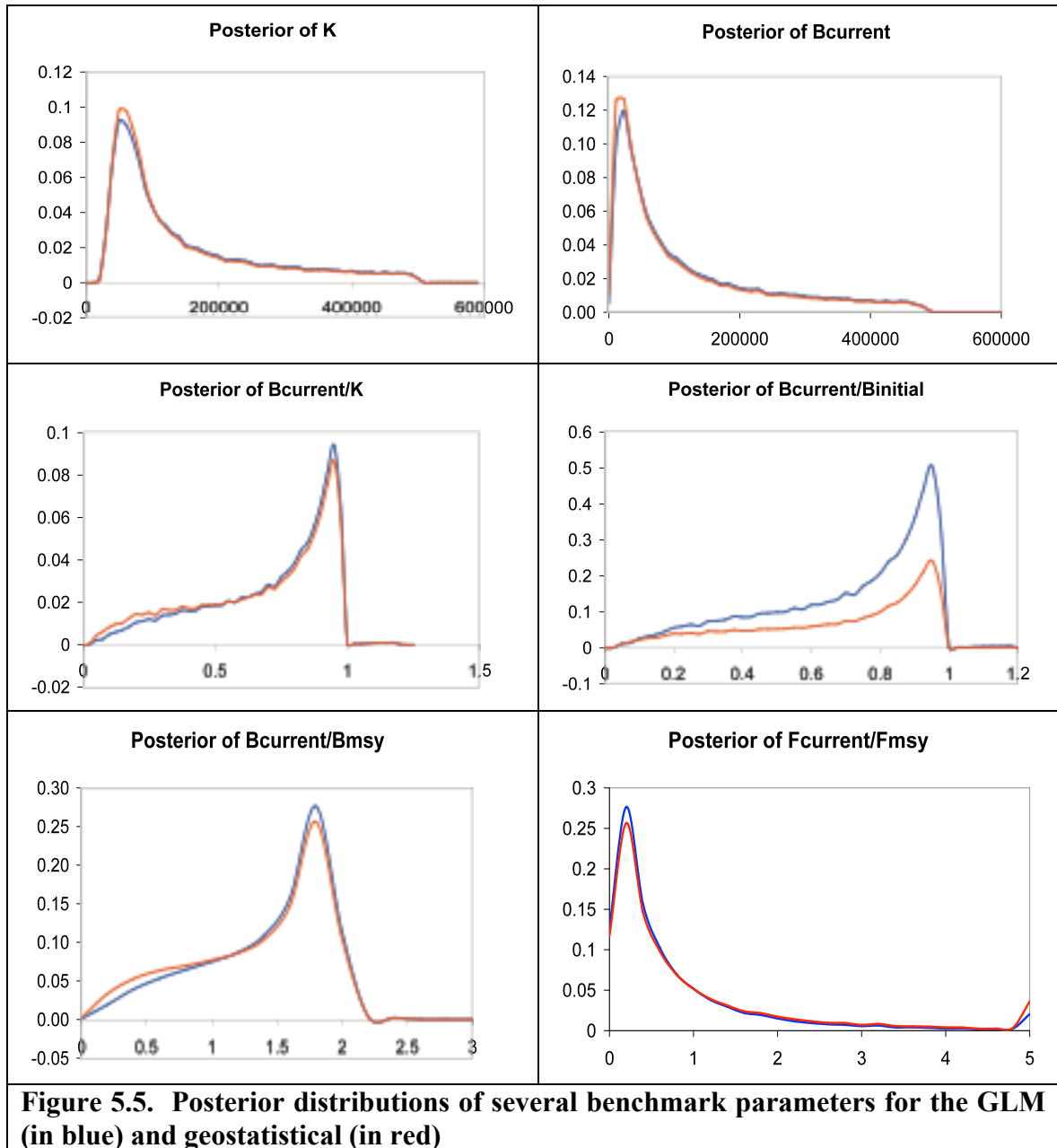
As expected, the dolphinfish models had very similar results due to the fact that there was little difference between the geostatistical and GLM indices (Table 5.6).

Schaefer Model					
Parameter	E(D1)	CV(D1)	E(D2)	CV(D2)	% Difference
E(K)	161513	0.72	156475	0.72	3.12
E(<i>r</i>)	0.74	0.80	0.69	0.84	6.57
E(MSY)	26170	1.27	24110	1.34	7.87
E(<i>B_{cur}</i>)	123451	0.96	113859	1.02	7.77
E(<i>B_{cur}</i> /K)	0.67	0.38	0.63	0.45	6.65
E(<i>B_{init}</i>)	161513	0.72	156475	0.72	3.12
E(<i>B_{cur}</i> / <i>B_{init}</i>)	0.67	0.38	0.63	0.45	6.65
E(<i>C_{cur}</i> /MSY)	0.90	0.75	1.01	0.75	12.05
E(<i>F_{cur}</i> / <i>F_{msy}</i>)	1.47	2.61	2.26	2.78	53.87
E(<i>B_{cur}</i> / <i>B_{msy}</i>)	1.35	0.38	1.26	0.45	6.65
E(<i>C_{cur}</i> / <i>repy</i>)	1.08	54.98	1.21	52.89	12.14
E(<i>B_{msy}</i>)	80756	0.72	78237	0.72	3.12
E(<i>repy</i>)	10602	1.50	10029	1.57	5.40

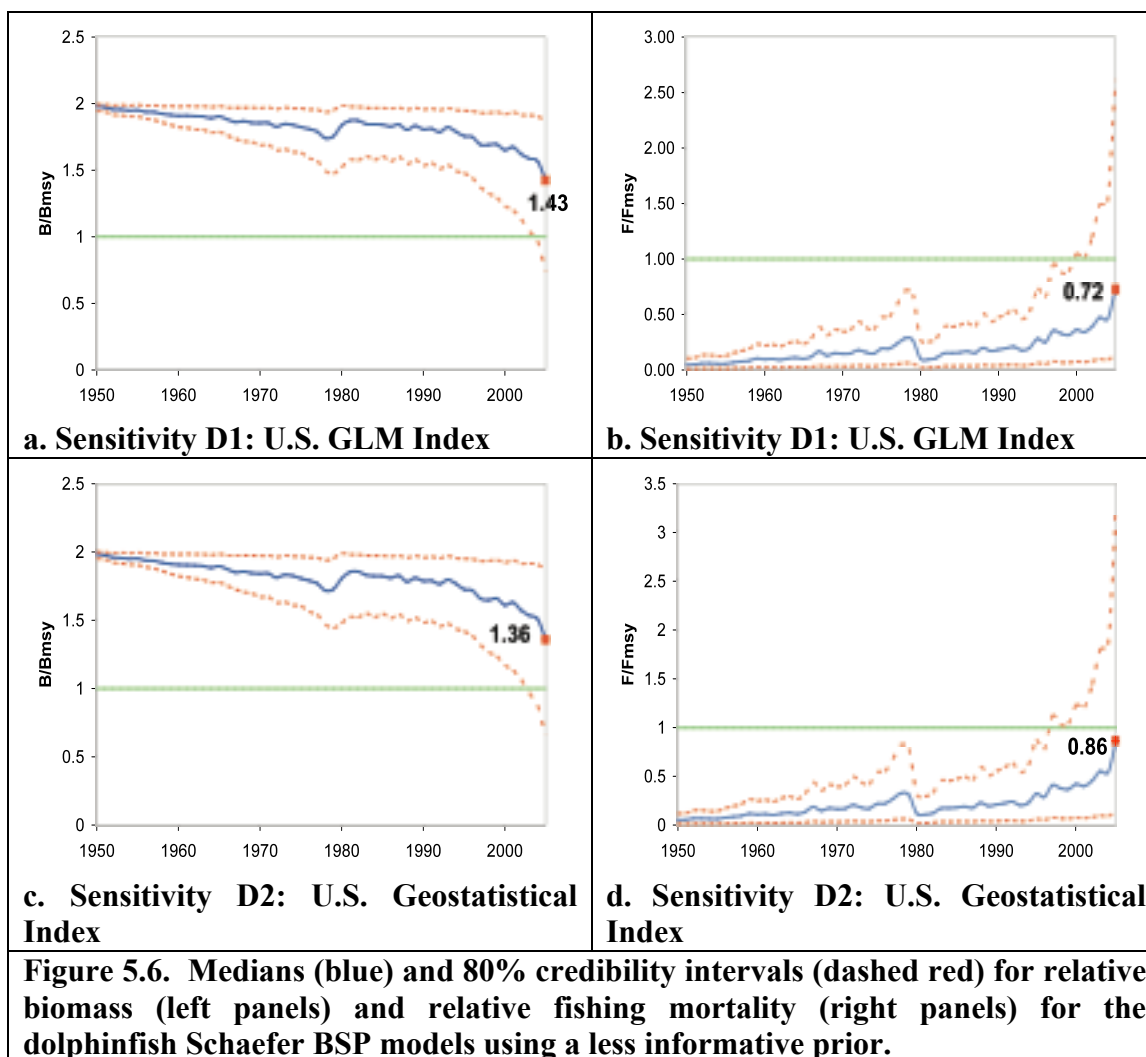
Table 5.6. Expected values (E) and coefficients of variation (CVs) of the posterior distribution of the parameters from model D1 and D2 (refer to Table 5.2 for model specifications). Parameters are defined as follows: *K* is the carrying capacity, *r* is the intrinsic rate of growth, *n* is the shape parameter for the Fletcher model, MSY is maximum sustainable yield, *B_{cur}* is the current biomass, *B_{init}* is the initial biomass at the start of the fishery, *C_{cur}* is the current catch, *B_{msy}* is the biomass at MSY, *F_{cur}* is the current fishing mortality, *F_{msy}* is the fishing mortality at MSY, and *repy* is replacement yield.

For the dolphinfish data, only the Schaefer model was used as there was no information available to parameterize the shape parameter *n* from the Fletcher model and it was likely that the inclusion of the additional parameter would lead to over-parameterization of the model. There were no longer time series of abundance for dolphinfish available to incorporate into the model to aid in the estimation of the productivity in the early years as was the case for swordfish. The expectation however, was that since the U.S.

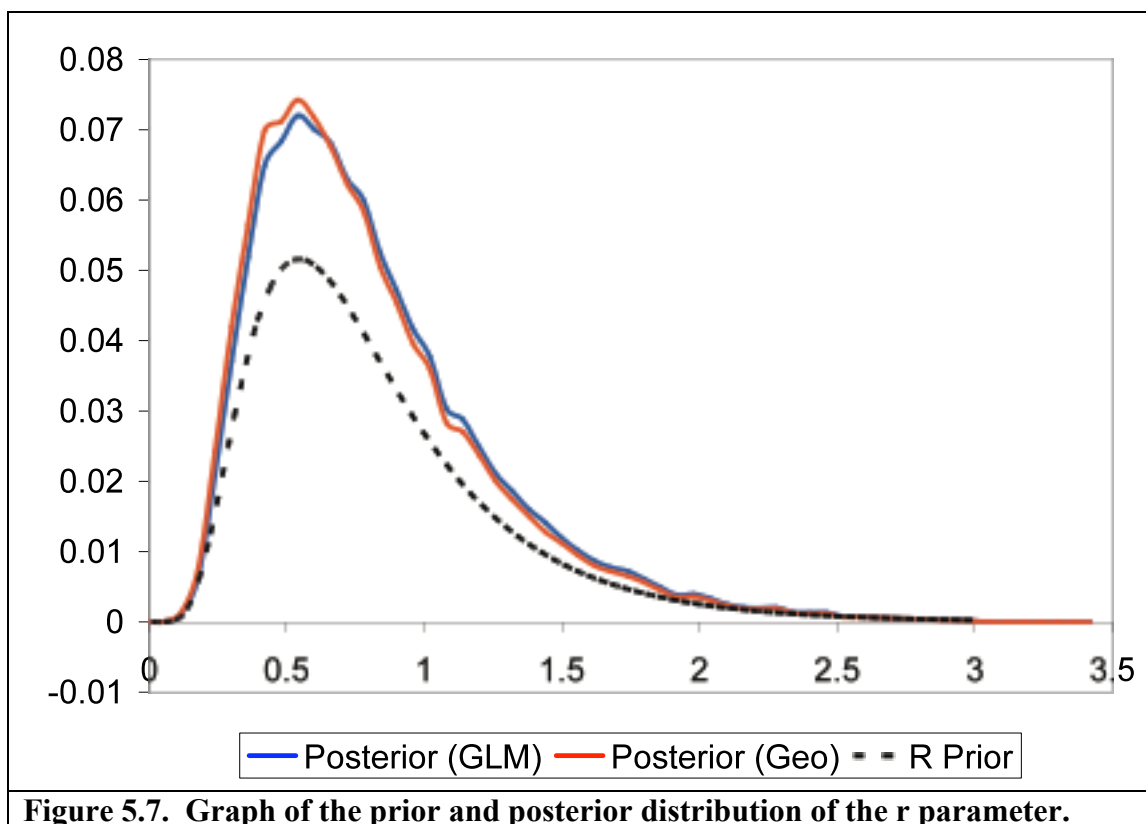
geostatistical and GLM indices had nearly identical trends, there would not be great differences between the models. The expected value of the posterior of K was around 140,000 mt for both models. The expected value of r was 0.82 for the GLM model and 0.80 for the geostatistical model. For both models, the value of the ratio of the current biomass to the initial biomass was around 0.70 suggesting that the fishery has declined roughly 30% from initial, “virgin” conditions. The models do deviate slightly in the estimates of the expected value of the ratio of the current fishing mortality to the fishing mortality at MSY. The GLM model predicts the ratio to be 0.87 whereas the geostatistical model predicts the ratio to be 1.10. In the former case, the interpretation is that the fishery is experiencing a level of fishing pressure that does not exceed the MSY level, and in the latter case the fishery is exceeding the MSY fishing pressure. However, the CVs of these parameters are relatively large suggesting that for both model fits, it is uncertain whether the current fishing mortality rate is above or below F_{MSY} . Therefore, caution should be exercised when interpreting these results. The similarity between the models is readily seen in the distributions of the posteriors of K , current biomass ($B_{current}$), the ratio of current biomass over K , and the ratio of current biomass over initial biomass (Figure 5.5). In each of these plots the shape of the distributions are nearly identical.



Additionally, graphs of the biomass and fishing mortality trends with the credibility intervals show very similar patterns with a relatively constant and high biomass (over MSY) and low fishing mortality (below the MSY level) (Figure 5.6).



The development of the r prior for dolphinfish from information about other species with similar life histories was very useful especially as there is little demographic information available for dolphinfish. The mean r value of 0.83 was very plausible for a fast growing species with a short lifespan. Figure 5.7 shows the distribution of the prior and posterior distributions of the r parameter. The shape of these distributions is very similar implying that the combination of CPUE and catch data available for dolphinfish is not very informative in the estimation of r .



Swordfish BSP Models

U.S. Geostatistical and GLM Indices Only

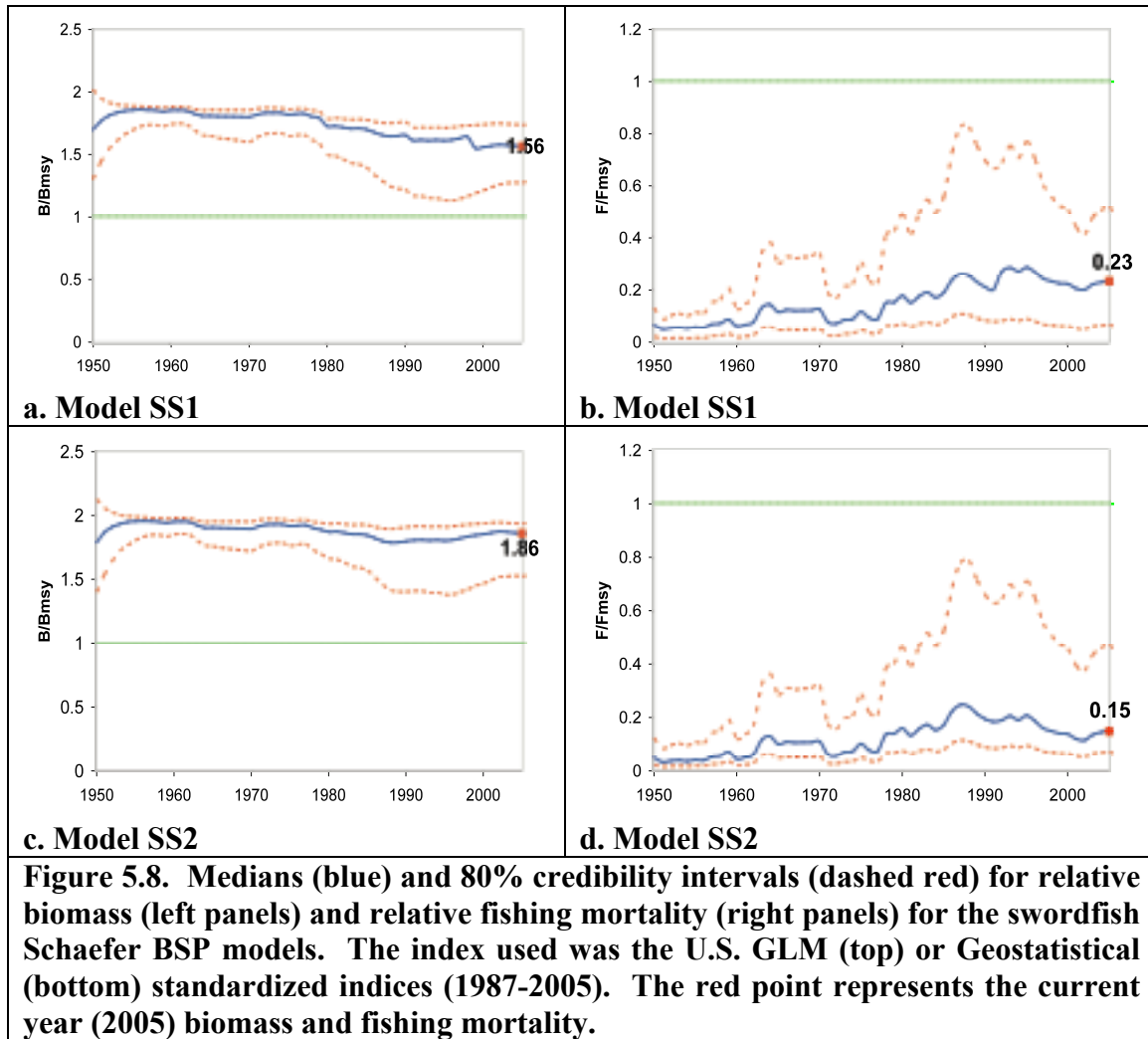
The models that incorporated only the U.S. index and the catch series for swordfish showed very little difference between any of the expected life history or productivity parameters regardless of whether the geostatistical or GLM index was used or whether the model was the Schaefer or the generalized Fletcher version (Table 5.7).

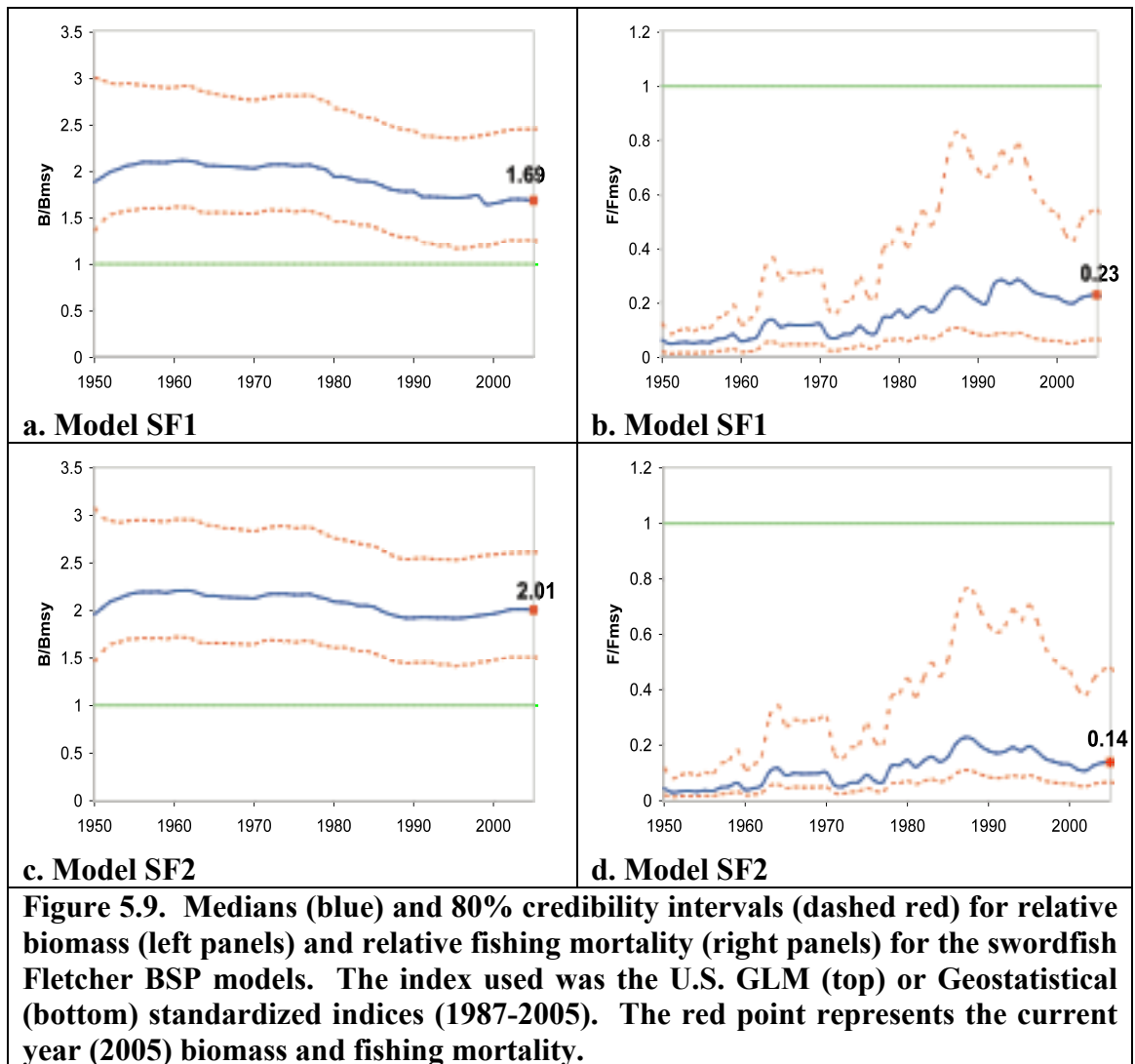
Schaefer Model					
Parameter	E(SS1)	CV(SS1)	E(SS2)	CV(SS1)	% Difference
E(K)	487120	0.38	483920	0.39	0.66
E(r)	0.44	0.48	0.45	0.47	1.53
E(MSY)	52061	0.61	52032	0.61	0.06
E(Bcur)	439859	0.44	439656	0.44	0.05
E(Bcur/K)	0.88	0.15	0.89	0.13	0.81
E(Binit)	428211	0.40	425935	0.41	0.53
E(Bcur/Binit)	1.03	0.23	1.04	0.23	0.77
E(Ccur/MSY)	0.35	0.88	0.33	0.82	3.35
E(Fcur/Fmsy)	0.28	3.78	0.24	2.40	14.94
E(Bcur/Bmsy)	1.77	0.15	1.78	0.13	0.81
E(Ccur/rep _y)	1.00	0.35	0.98	0.31	1.13
E(Bmsy)	243560	0.38	241960	0.39	0.66
E(rep _y)	11734	0.19	11774	0.18	0.35
Fletcher Model					
Parameter	E(SF1)	CV(SF1)	E(SF2)	CV(SF2)	% Difference
E(K)	495284	0.38	494807	0.39	0.10
E(r)	0.44	0.49	0.46	0.49	3.69
E(n)	1.59	0.55	1.65	0.54	3.58
E(MSY)	47620	0.70	49827	0.69	4.63
E(Bcur)	422787	0.46	428979	0.46	1.46
E(Bcur/K)	0.84	0.20	0.85	0.18	1.81
E(Binit)	431910	0.41	427750	0.41	0.96
E(Bcur/Binit)	0.99	0.37	1.01	0.31	2.15
E(Ccur/MSY)	0.39	0.93	0.37	0.89	6.54
E(Bmsy/K)	0.43	0.23	0.44	0.23	1.50
E(Fcur/Fmsy)	0.29	3.66	0.24	2.79	17.33
E(Bcur/Bmsy)	1.72	0.29	2.03	0.27	0.49
E(Ccur/rep _y)	1.00	1.84	0.94	5.87	6.04
E(Bmsy)	209795	0.43	212611	0.44	1.34
E(rep _y)	11429	0.97	11652	1.03	1.95

Table 5.7. Expected values (E) and coefficients of variation (CVs) of the posterior distribution of the parameters from the BSP model run with either the U.S. GLM or geostatistical (GEO) index (1987-2005) (refer to Table 5.2 for model specifications). Parameters are as defined in Table 5.6.

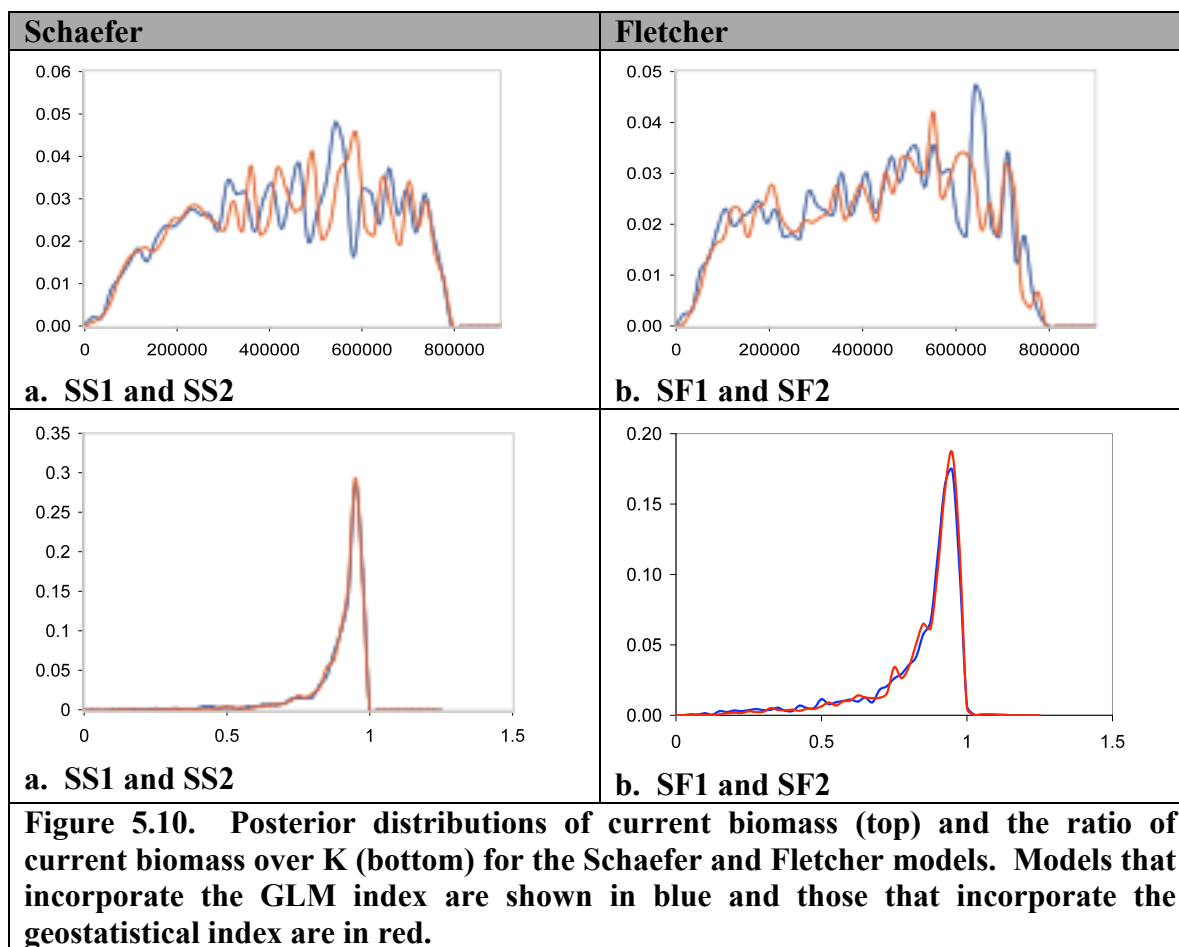
The estimated K for both Schaefer models was approximately 485,000 mt and r was estimated to be 0.44 and 0.45 for the GLM and geostatistical models respectively. The estimated K for both Fletcher models was around 495,000 mt and r was 0.46 for the geostatistical model and 0.44 for the GLM model. The greatest percentage difference

(~20%) in the estimated expected values is for the ratio of the current fishing mortality to the fishing mortality at MSY (F_{cur}/F_{msy}). This difference is seen in the trajectories of F/F_{msy} where the GLM indices for both models show a relatively steeper increase in F_{msy} over time and predict a significantly different current level of fishing mortality (in 2005). Ultimately, regardless of the index used, both estimates describe the stock as experiencing a low level of fishing pressure. There are differences between the trajectories of B/B_{msy} for each model type. In both instances, the GLM index presents a slightly more pessimistic picture with biomass nearer to the MSY level. The graphs of the biomass over biomass at MSY (B/B_{MSY}) and the fishing mortality ratio to fishing mortality at MSY (F/F_{MSY}) suggest that regardless of whether the Schaefer or generalized Fletcher model is used, the trends in both parameters remain fairly constant with biomass above the MSY level and fishing mortality below the MSY level (Figure 5.8 and Figure 5.9). This is consistent with the fact that the expected values of this parameter are nearly identical (Table 5.7). For all models, the ratio of current biomass to biomass at the start of the fishery (B_{cur}/B_{init}) was virtually one suggesting that the fishery is at virgin conditions.





Another difference between the models that use the GLM index and those that incorporate the geostatistical index is that there is a tightening of the credibility intervals of the geostatistical index biomass trajectory for both the Schaefer and the Fletcher models. Additionally, the credibility intervals of B/B_{msy} are greatly tightened in the Schaefer model. The posterior distributions are also similar (Figure 5.10) emphasizing the fact that the models should predict similar results.



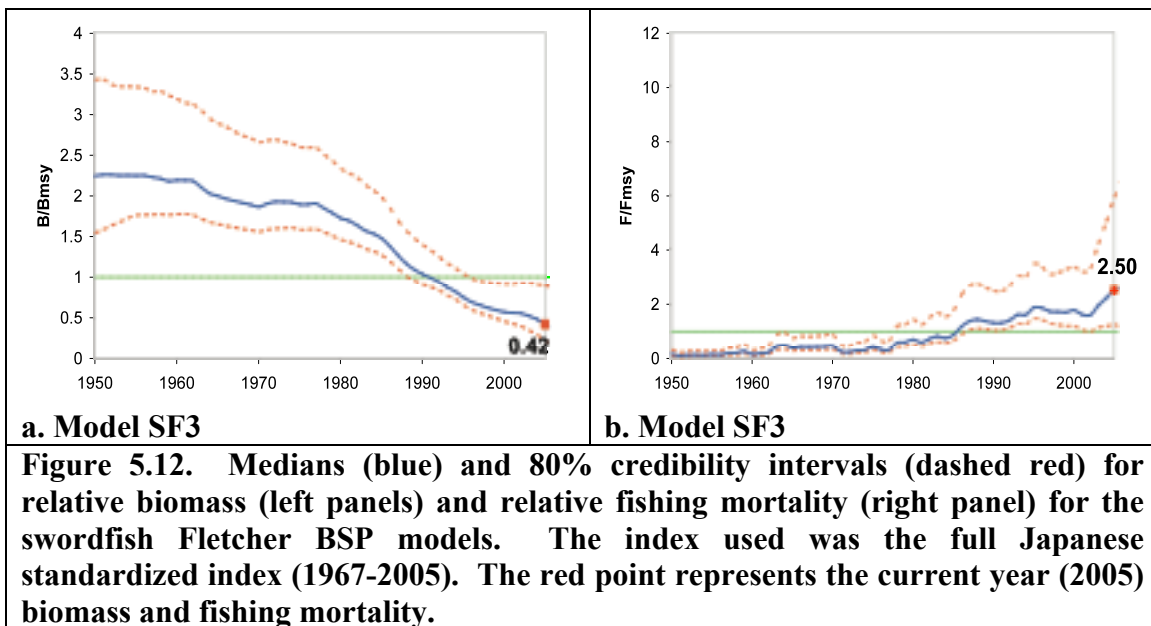
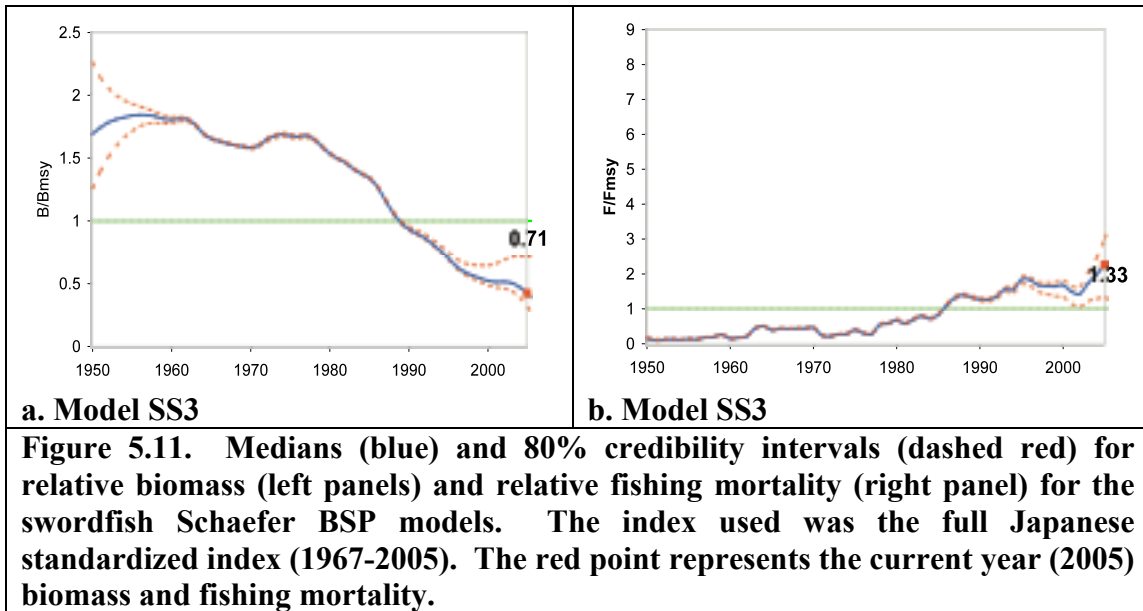
Full Japanese Index Only

In order to estimate the influence of the Japanese index, a model was run using only the Japanese index of abundance and the swordfish catch (Table 5.8) for both the Schaefer model and the generalized Fletcher model.

Japanese Only				
Parameter	E(SS3)	CV(SS3)	E(SF3)	CV(SF3)
E(K)	136479	0.09	288931	0.44
E(r)	0.39	0.10	0.24	0.57
E(n)	-----	-----	1.14	0.42
E(MSY)	13084	0.04	10002	0.29
E(Bcur)	23414	0.83	40859	0.95
E(Bcur/K)	0.17	0.78	0.14	0.74
E(Binit)	118207	0.23	245391	0.49
E(Bcur/Binit)	0.20	0.80	0.17	0.76
E(Ccur/MSY)	0.88	0.03	1.30	0.52
E(Bmsy/K)	-----	-----	0.38	0.22
E(Fcur/Fmsy)	6.05	1.25	7.14	1.31
E(Bcur/Bmsy)	0.34	0.78	0.43	0.93
E(Ccur/rep _y)	3.30	1.14	2.72	0.90
E(Bmsy)	68239	0.09	107059	0.49
E(rep _y)	6538	0.58	6358	0.51

Table 5.8. Expected values (E) and coefficients of variation (CVs) of the posterior distribution of the parameters from the Schaefer and Fletcher BSP model run with only the full Japanese CPUE index (1961-2005) (refer to Table 5.2 for model specifications). Parameters are as defined in Table 5.6.

The Schaefer model suggests a significantly lower carrying capacity with a K of 136479 mt and a higher r of 0.39. In contrast, the Fletcher model suggests a K of 288931 mt and a lower r of 0.24. For both models, the ratios of B_{cur}/B_{msy} describe a fishery that is severely overfished. These parameters show that currently the biomass is about 60-65% below the MSY level. Historically, the B_{cur}/B_{init} ratios for both models suggest that the stock has declined by about 80% from conditions at the start of the fishery. These figures correspond to the higher expected values of fishing mortality and signify that the fishery is experiencing overfishing. The trends in the biomass and fishing mortality ratios and the credibility intervals are shown in Figures 5.11 and 5.12.



The model predictions show that when the Japanese index is used alone, there is a strong decline in biomass from 1950 to the current year. Similarly, there is a relatively steep increase in fishing mortality. The results are more pessimistic about the level of stock decline when the Fletcher model is used. It is interesting to note that the results of the Schaefer model more closely follow the results of the models that incorporate the U.S.

indices, and that the K and r values are similar to those predicted in the north Atlantic ICCAT assessment.

U.S. Indices with Truncated Japanese Index

The runs that used only the U.S. GLM or geostatistical index showed only slight differences. The length of the series is suggestive of the fact that these indices may not be informative enough to show a complete picture of the fishery. Because the indices begin in 1987 and the catch rates extend back to 1950, there is not enough information in these short catch rate series to provide a reliable estimation of productivity parameters of the model. The Japanese index begins in 1967 and provides information on the early years of the fishery. By truncating the series, this allowed the U.S. indices to drive the trends in the current years of the fishery

When the shortened Japanese index was included in models with the U.S. geostatistical and GLM indices, there were significant differences between the parameters, both between the Schaefer and Fletcher versions of the model and between the models that incorporated the GLM or geostatistical indices (Table 5.9).

Schaefer Model					
Parameter	E(SS4)	CV(SS4)	E(SS5)	CV(SS5)	% Difference
E(K)	351260	0.55	453805	0.43	29.19
E(r)	0.28	0.68	0.41	0.53	46.35
E(MSY)	21519	1.07	44549	0.71	107.02
E(Bcur)	201917	0.93	392628	0.52	94.45
E(Bcur/K)	0.53	0.54	0.84	0.21	59.32
E(Binit1)	307408	0.58	398991	0.45	29.79
E(Bcur/Binit1)	0.62	0.58	0.98	0.28	57.54
E(Ccur/MSY)	0.93	0.67	0.44	0.89	52.71
E(Fcur/Fmsy)	1.97	2.00	0.40	2.47	79.43
E(Bcur/Bmsy)	1.05	0.54	1.68	0.21	59.32
E(Ccur/rep _y)	1.43	0.89	1.02	0.41	28.96
E(Bmsy)	175630	0.55	226902	0.43	29.19
E(rep _y)	10085	0.33	11683	0.17	15.85
Fletcher Model					
Parameter	E(SF4)	CV(SF4)	E(SF5)	CV(SF5)	% Difference
E(K)	427970	0.45	437096	0.44	2.13
E(r)	0.33	0.67	0.45	0.66	36.36
E(n)	1.31	0.64	1.46	0.65	11.82
E(MSY)	25304	1.02	40394	1.06	59.63
E(Bcur)	264022	0.73	354710	0.77	34.35
E(Bcur/K)	0.59	0.45	0.78	0.47	33.78
E(Binit)	366296	0.48	385581	0.48	5.26
E(Bcur/Binit)	0.70	0.51	0.92	0.54	31.21
E(Ccur/MSY)	0.83	0.75	0.49	0.77	40.59
E(Bmsy/K)	0.39	0.31	0.42	0.31	9.03
E(Fcur/Fmsy)	0.95	1.53	0.39	2.21	59.54
E(Bcur/Bmsy)	1.64	0.53	1.93	0.54	17.73
E(Ccur/rep _y)	1.20	0.58	1.00	0.85	16.55
E(Bmsy)	161509	0.55	182549	0.56	13.03
E(rep _y)	10671	0.66	11518	0.67	7.94

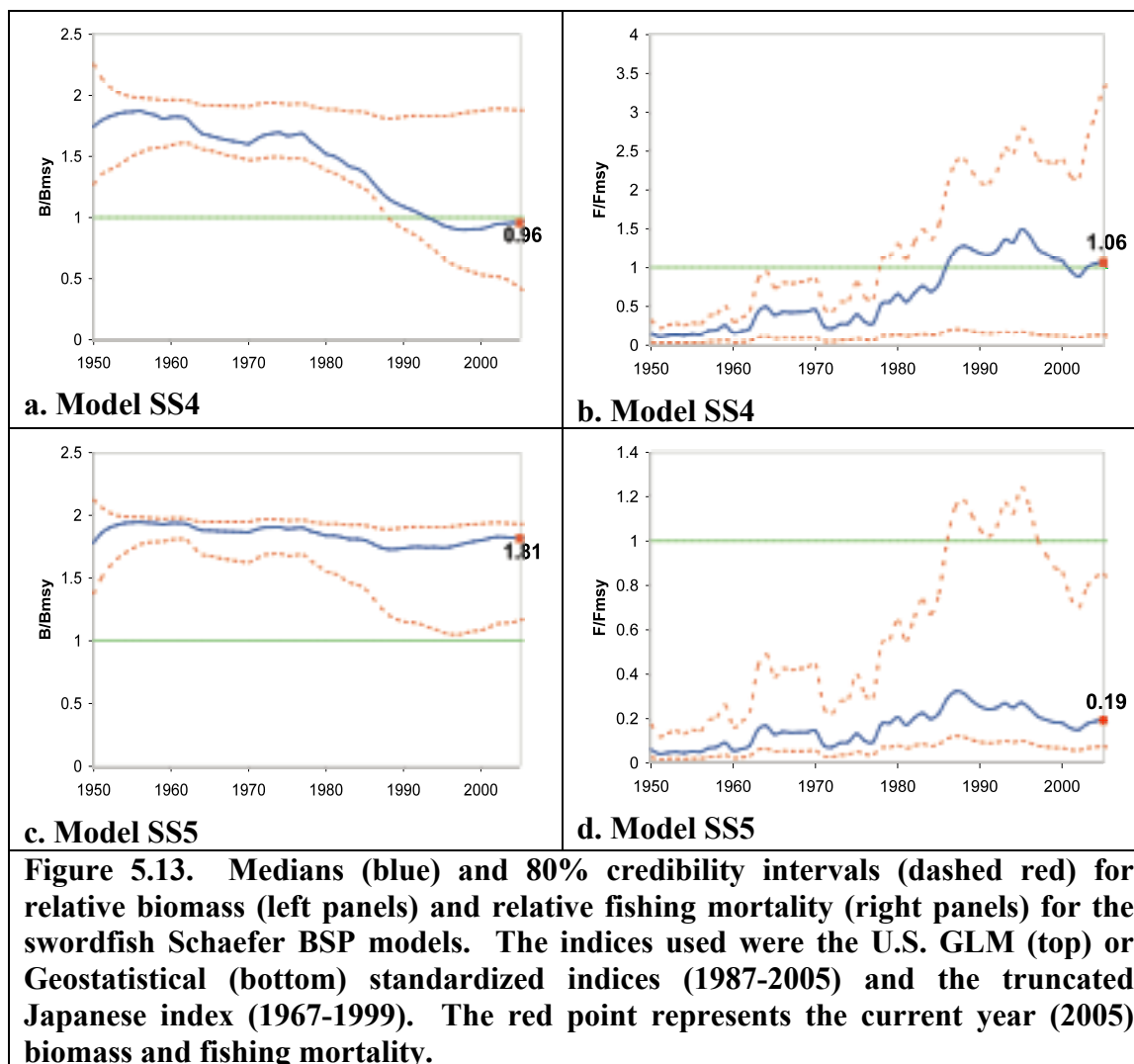
Table 5.9. Expected values (E) and coefficients of variation (CVs) of the posterior distribution of the parameters from the BSP model run with the truncated Japanese CPUE index (1967-1999) and either the U.S. GLM or geostatistical (GEO) index (1987-2005) (refer to Table 5.2 for model specifications). Parameters are as defined in Table 5.6.

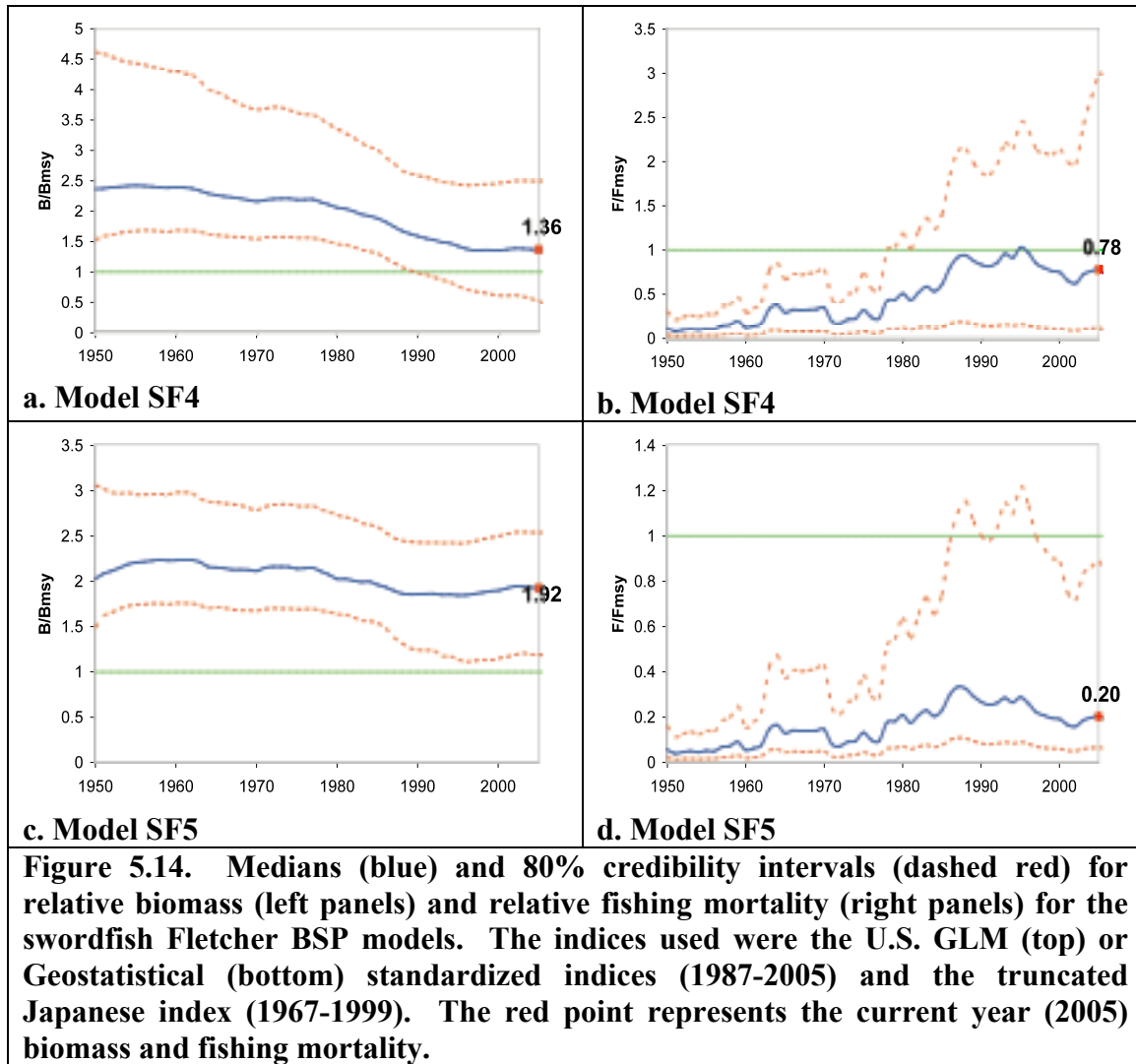
With the Schaefer model, the percentage differences between the GLM index and geostatistical index were greater for all parameters except initial biomass (*binit*). The estimate of *K* from the GLM model was significantly lower by about 100,000 mt.

Interestingly, the productivity parameters of biomass and fishing mortality describe the stock as experiencing overfishing when the GLM index is used and present a more positive picture when the geostatistical index is used. In the former instance, the current biomass is right around the MSY level although the level of fishing mortality is almost double the MSY level. Historically, the expected value of the biomass in the current year compared to the initial biomass at the start of the fishery has declined by about 60%. The expected value of the B_{cur}/B_{msy} parameter suggests that the current biomass is well above the MSY level in the geostatistical model and at a fishing mortality level that is well below MSY. A more benign historical picture is also seen as the current biomass is relatively close to the biomass at the start of the fishery. For both the GLM and the geostatistical Fletcher models, the current biomass is expected to be well above the MSY level at 1.64 and 1.93 respectively. The biomass ratio of current over initial for the geostatistical model describes the stock as slightly below conditions at the start of the fishery (0.92), while the GLM model gives a prediction that is 24% lower (0.70), suggesting that the stock has experienced some decline but is still well above B_{msy} . The expected values of the fishing mortality ratios correspond with this interpretation as the geostatistical model predicts that fishing mortality is about 60% lower than the MSY value, but very close to the MSY value (0.95) with the GLM model. The interpretation of the status of the stock would differ for each of these models. According to the geostatistical model, the stock is not experiencing overfishing. However, the interpretation of the GLM model results would be that the stock is experiencing overfishing and could decline further if fishing mortality rates continue at the same level. Additionally, the estimates of K are much closer than in the Schaefer model runs, but the

r parameter was significantly different (27%) with the geostatistical model predicting an r of 0.45 and the GLM model predicting an r of 0.33.

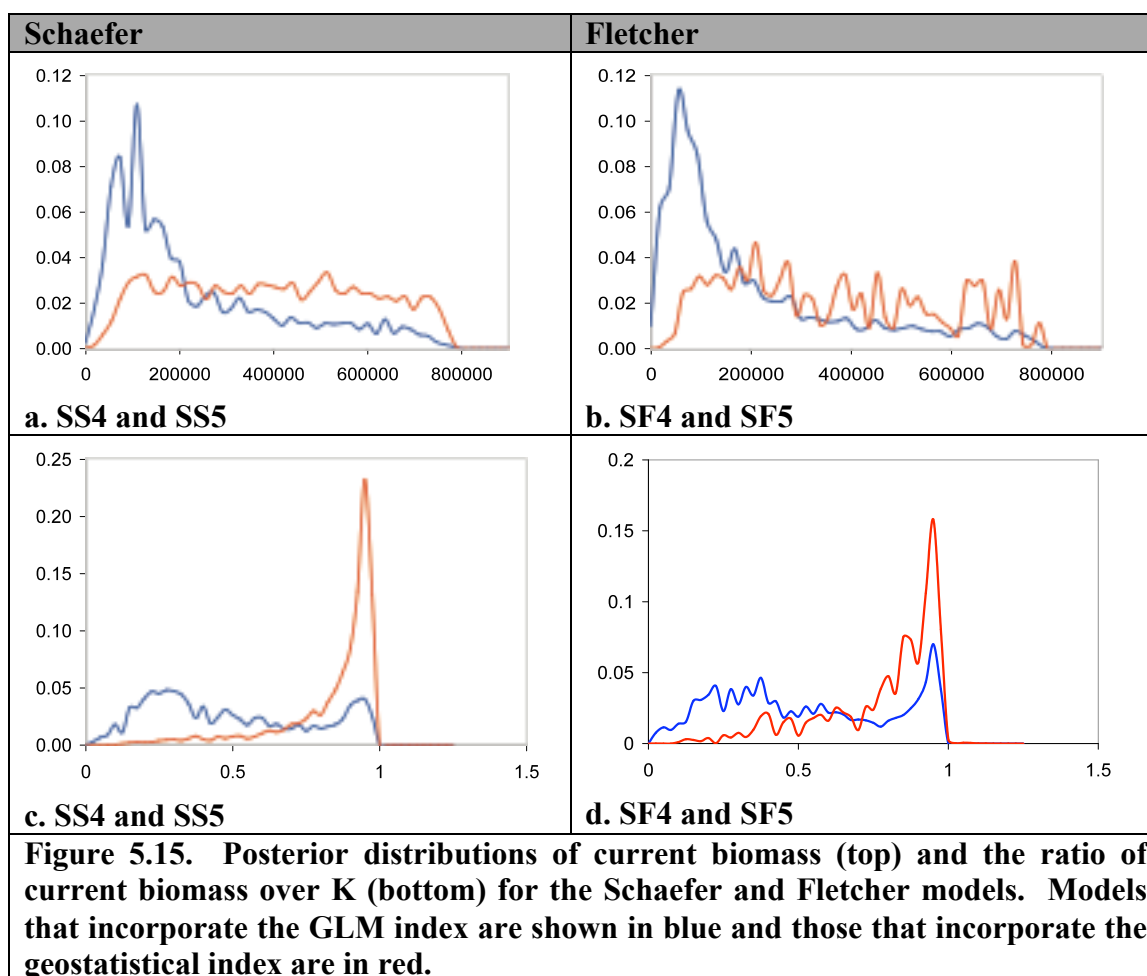
The fits of the biomass and fishing mortality trends are displayed in Figure 5.13 and Figure 5.14.





There are significant differences between the Schaefer models using the GLM index and the geostatistical index. The GLM model shows the biomass declining to just below the B_{MSY} level and fishing mortality increasing to just above the MSY level. In contrast, the biomass and fishing mortality trends as estimated from the geostatistical model remains fairly constant and describe the stock as well above the MSY level and not experiencing overfishing. The Fletcher model with the GLM index describes a decline in the biomass of the stock. However, the stock remains above the MSY level. Fishing mortality increases to the MSY level in 1995, and then remains just below this level. There is less

of a trend in the biomass or the fishing mortality when the geostatistical index is used, and the stock would be assumed stable and not undergoing or approaching overfishing. Comparing the fits of the Schaefer models to the Fletcher models, it is interesting to note that the credibility intervals are significantly wider for the Fletcher model. With both model types, the geostatistical index gives slightly more optimistic results. The posterior distributions of the current biomass and the ratio of current biomass to K are quite different when either the GLM or geostatistical indices are used (Figure 5.15). The GLM distributions are skewed toward the lower biomass values and a higher ratio of B_{current}/K while the geostatistical distributions are relatively uniform.



U.S. Indices with Full Japanese Index

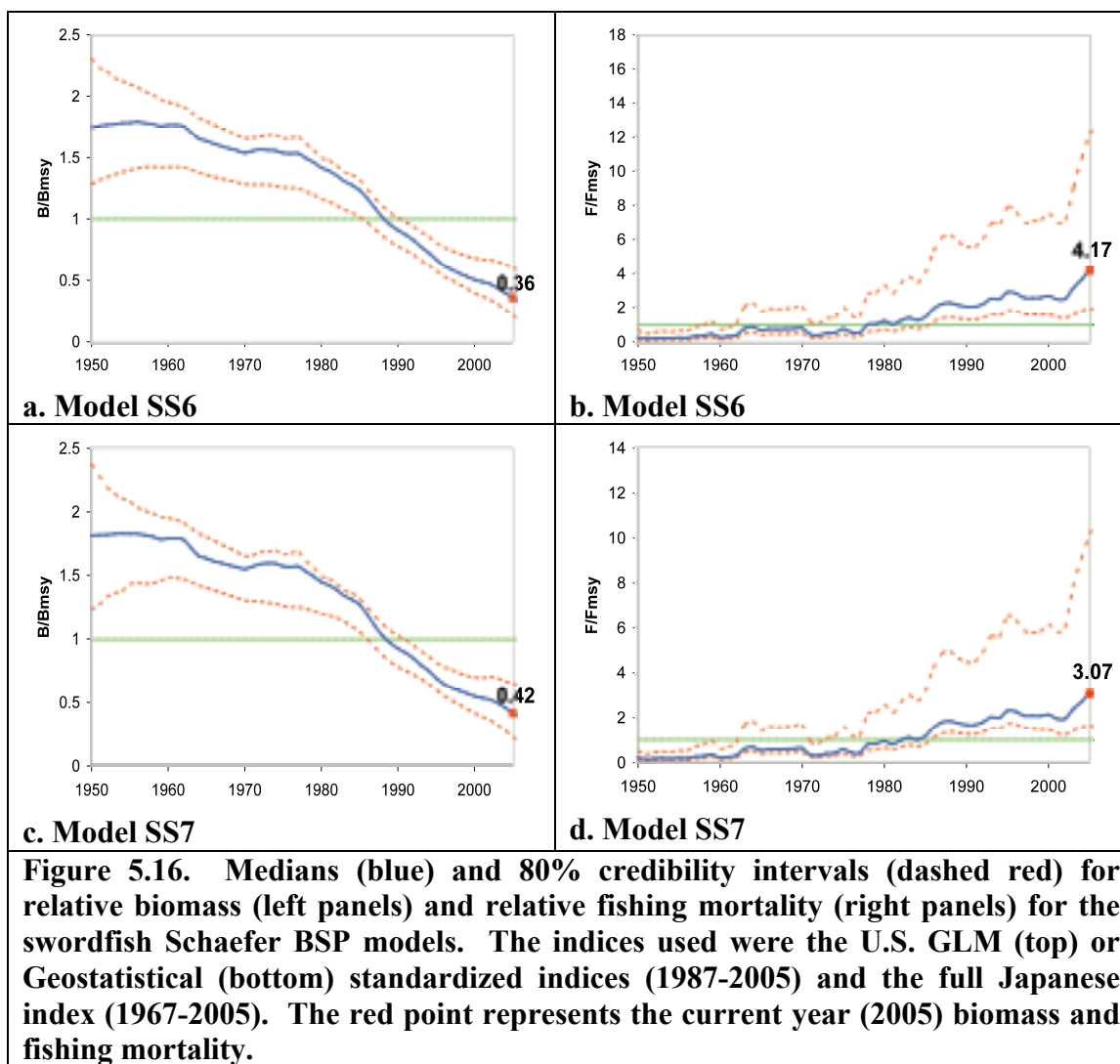
As expected, the longer Japanese index carries more weight in later years when the full index is incorporated in models with the U.S. indices (Table 5.10) and overshadows the differences in the U.S. indices.

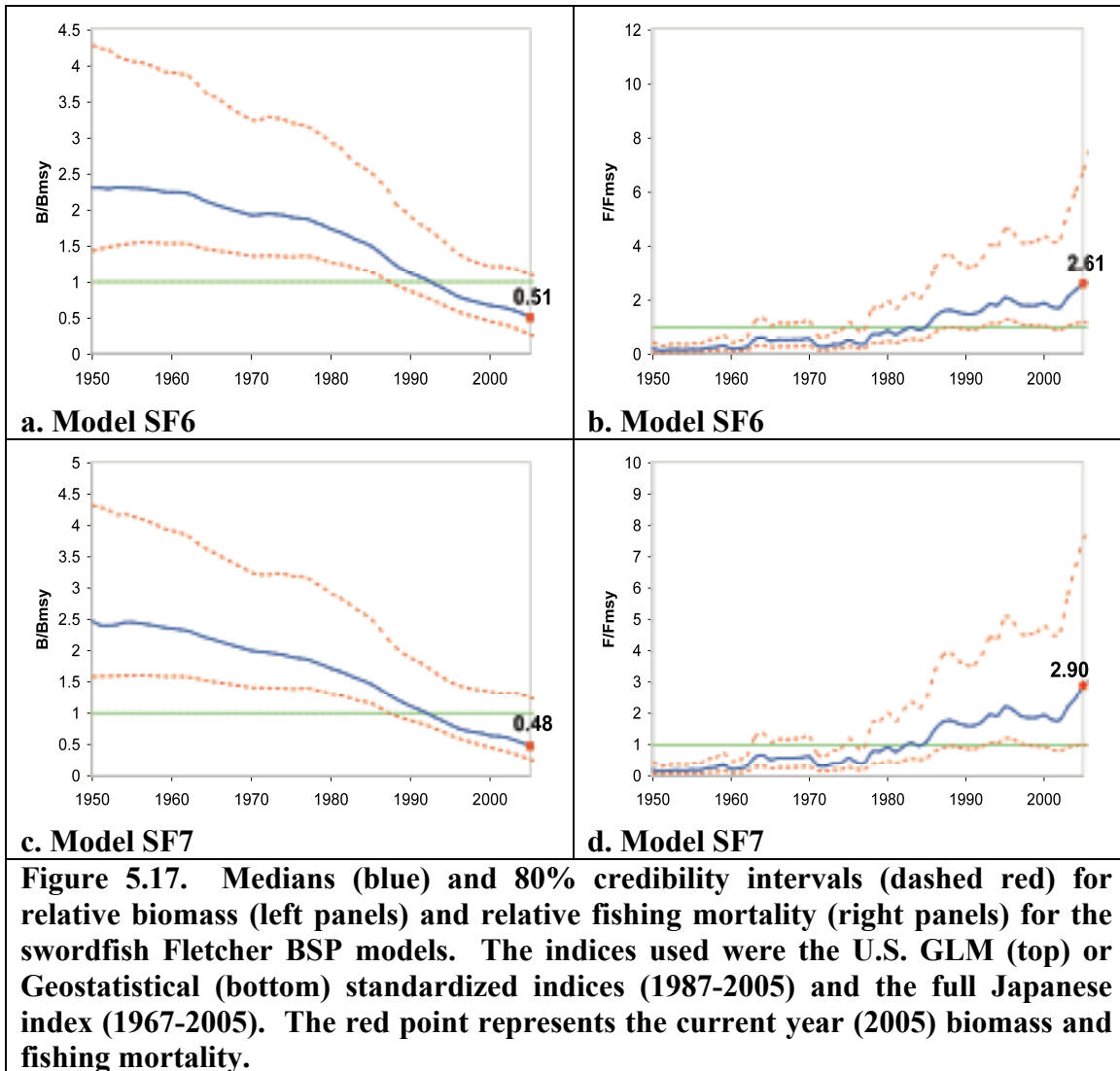
Schaefer Model					
Parameter	E(SS6)	CV(SS6)	E(SS7)	CV(SS7)	% Difference
E(K)	390588	0.44	333339	0.50	14.66
E(r)	0.12	0.88	0.16	0.80	39.25
E(MSY)	7781	0.47	9153	0.50	17.64
E(Bcur)	60414	0.78	59488	0.94	1.53
E(Bcur/K)	0.16	0.61	0.18	0.65	13.03
E(Binit1)	339039	0.46	296485	0.52	12.55
E(Bcur/Binit1)	0.19	0.65	0.21	0.71	13.15
E(Ccur/MSY)	1.95	0.65	1.55	0.55	20.66
E(Fcur/Fmsy)	10.24	1.26	6.97	1.06	31.95
E(Bcur/Bmsy)	0.32	0.61	0.36	0.65	13.03
E(Ccur/rep _y)	4.42	0.91	3.19	0.86	27.88
E(Bmsy)	195294	0.44	166669	0.50	14.66
E(rep _y)	4501	0.64	5536	0.55	23.00
Fletcher Model					
Parameter	E(SF6)	CV(SF6)	E(SF7)	CV(SF7)	% Difference
E(K)	415692	0.35	396551	0.39	4.60
E(r)	0.15	0.93	0.17	0.88	7.83
E(n)	1.17	0.63	1.24	0.65	5.73
E(MSY)	7960	0.56	8242	0.46	3.55
E(Bcur)	73807	0.79	67613	0.75	8.39
E(Bcur/K)	0.18	0.66	0.18	0.59	2.29
E(Binit)	363589	0.39	341378	0.44	6.11
E(Bcur/Binit)	0.21	0.70	0.21	0.61	2.10
E(Ccur/MSY)	1.82	0.65	1.78	0.71	2.07
E(Bmsy/K)	0.37	0.31	0.37	0.33	1.49
E(Fcur/Fmsy)	6.19	1.16	6.15	1.34	0.66
E(Bcur/Bmsy)	0.60	1.10	0.58	1.12	2.89
E(Ccur/rep _y)	3.18	0.83	3.11	0.91	2.09
E(Bmsy)	149917	0.45	143167	0.48	4.50
E(rep _y)	5661	0.60	5901	0.56	4.24

Table 5.10. Expected values (E) and coefficients of variation (CVs) of the posterior distribution of the parameters from the BSP model run with the full Japanese CPUE index (1967-2005) and either the U.S. GLM or geostatistical (GEO) index (1987-2005) (refer to Table 5.2 for model specifications). Parameters are as defined in Table 5.6.

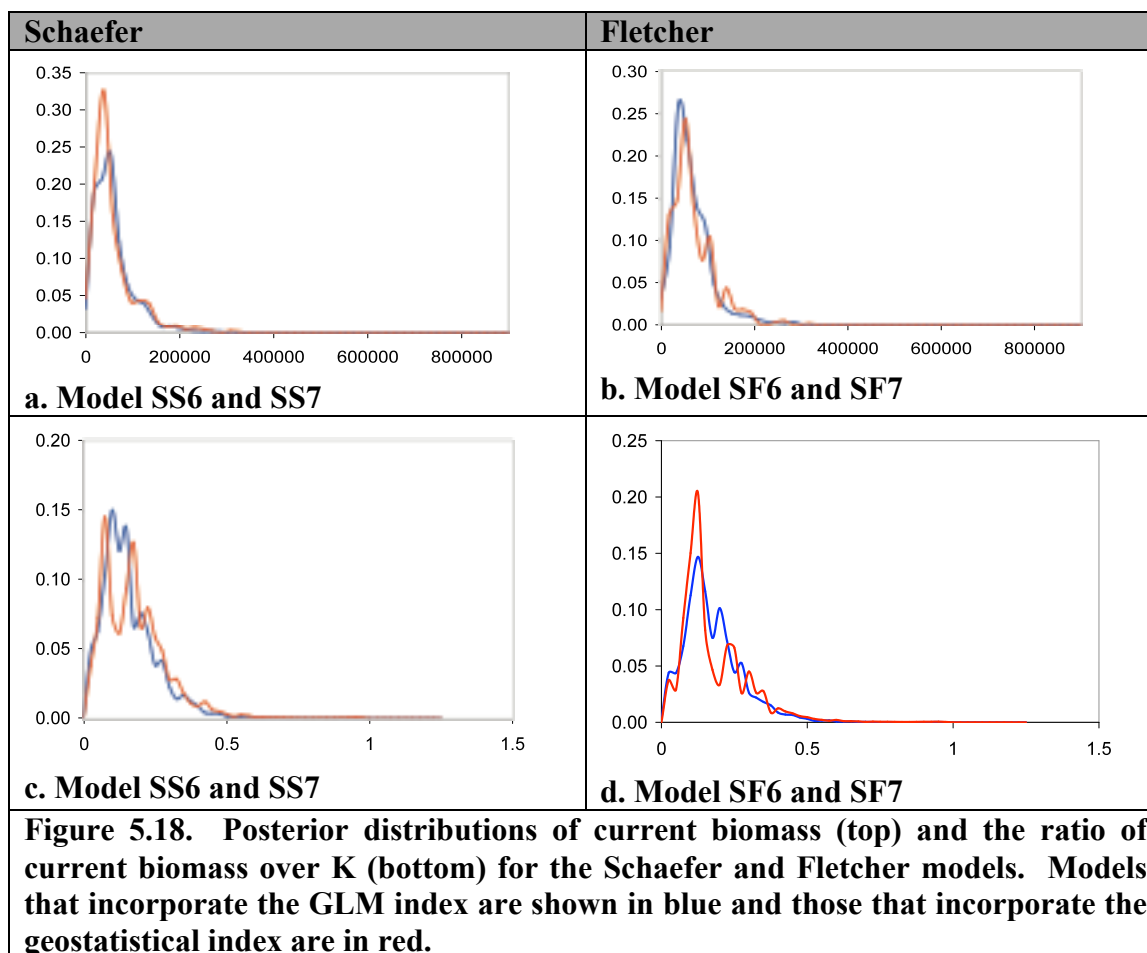
This index serves to pull down the biomass estimates and suggests that the stock is being fished well over the MSY level. These models estimate similar K and r values, however the percentage difference between these parameters when the U.S. index is varied is significantly greater for the Schaefer models. Both the Schaefer and the Fletcher models estimate that the current biomass is only at about 60% of the MSY level, and that the historical decline in biomass has been about 80% from the biomass at the start of the fishery. This trend in depletion is complemented by the fishing pressure ratio ($F_{current}/f_{msy}$) which for all models is greater than 6 times the MSY level.

When the full Japanese index is used, the biomass and fishing mortality trends look very similar to the model outputs for these parameters when the Japanese index is used alone (Figure 5.16 and Figure 5.17).



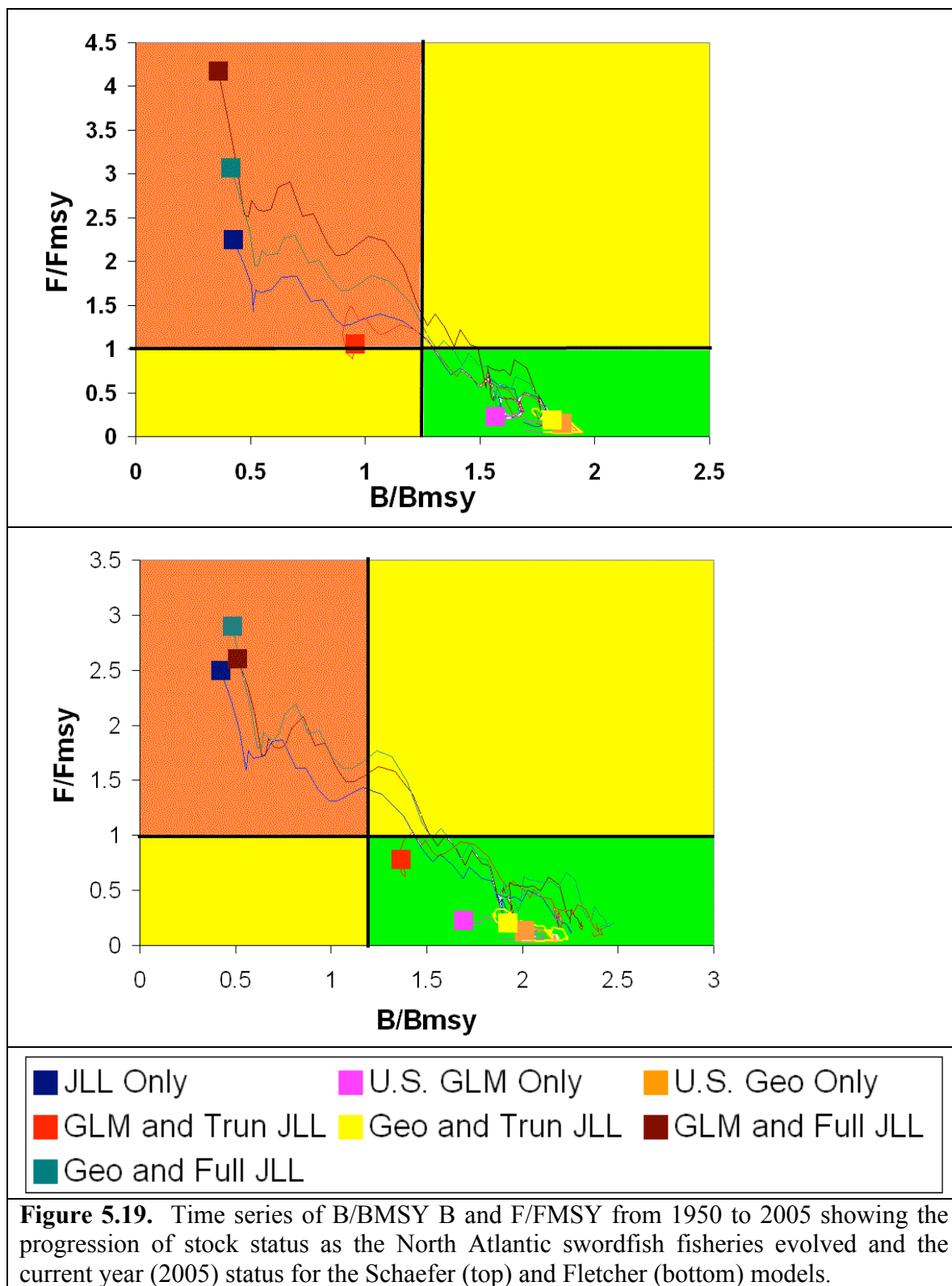


The difference is that the initial biomass in the two index model is higher and there is a greater decline to the current condition. Additionally, there is a significant tightening of the credibility intervals for the biomass trend of the Schaefer model. The posterior distributions are also very similar, emphasizing the pull that the Japanese index has on the overall model results (Figure 5.18).

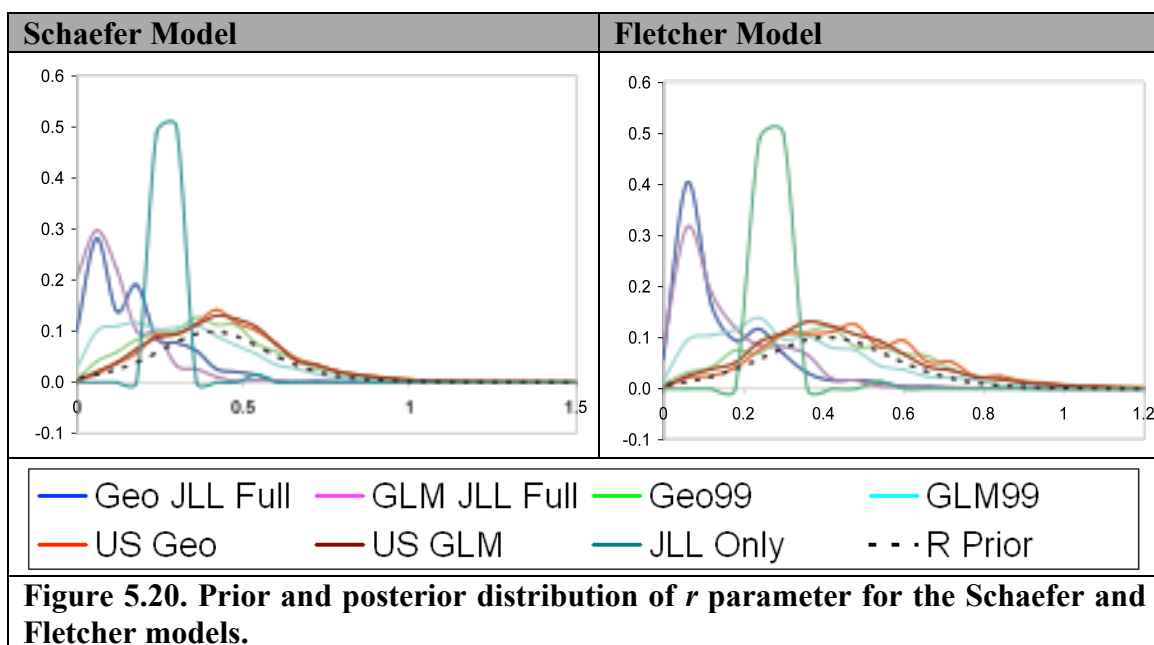


Synopsis of the Biological Reference Points and r Values (Swordfish Models)

The model results differ according to the indices incorporated as evidenced by the phase plots (Figure 5.19). The models that only use the U.S. GLM or geostatistical indices and the U.S. geostatistical and the truncated JLL index indicate that the stock appears to be in a healthy condition both historically and at present. The Schaefer model predicts that at the present time and over the past decade, the stock is experiencing overfishing. This is not the case with the Fletcher model, which shows that the stock is in a healthy condition although there may be a tendency towards decline. Both the Schaefer and the Fletcher models using the U.S. index with the truncated JLL index, and the U.S. GLM or geostatistical index and the full JLL depict the stock as experiencing overfishing.



A final comparison of the posterior distributions of r from all of the models highlights the influence of incorporating the Japanese index (Figure 5.20). The r posteriors from the models that incorporated the full Japanese index and either of the U.S. indices are skewed to lower values of r within a short range like the distribution from the model that used only the Japanese index. Truncating the Japanese index allows the current stock level to be dictated by the US indices and thus allows for the differences in the trends of the GLM and geostatistical indices to lead to differences in the perception of current stock status.



5.4 Interpretation of Model Results

A sound stock assessment requires data on the catch, abundance over time, biology, and other information such as age structure when available. This information is used to estimate where the historical levels of the stock have been, the current status of the stock in relation to benchmarks such as MSY, and the potential for sustainable harvests into the future. Managers rely on this information to set thresholds or limits to

the amount of harvest that can be made in order to optimize the biological and economic potential of the stock (Walters and Hilborn, 1978). The National Academy of Science (1998) reviewed the current methods available for stock assessment and found that one of the most important pieces of the stock assessment puzzle is a robust index of the relative abundance of a stock. These indices can come from a formal design-based research survey or from analyses of the catch rates of the fishery. Research surveys are typically less biased than catch rate data because sampling is close to random but often also less precise because sample sizes are usually small in relation to fishery dependent catch rate data. In pelagic species, these types of surveys are not often available as they are expensive to implement. Fishery-dependent relative abundance indices have their own set of issues. Because the fishery is targeting a stock or set of stocks, fishing is typically occurring in areas where consistently high catches are found, which can bias the index in serious ways. One example is when technology and knowledge lead to an increase in catchability by the fleet over time. This increase, if not adjusted for, would cause one to be overly optimistic about abundance trends. Another example that is relevant to this analysis is that clustered observations will be subject to spatial autocorrelation that may violate the assumption made for a relative abundance index: random, uncorrelated samples. With respect to these issues, catch and effort data from the commercial fisheries are still the most widely used form of abundance information used to estimate annual indices of stock abundance in the absence of fishery-independent survey data, especially in the case of pelagic species. These indices are incorporated into stock assessment models to predict trends in biomass and fishing mortality as well as life history parameters of the stock. Models such as the GLM use statistical techniques and allow for

the partitioning of sources of variability ranging from annual and seasonal trends in abundance to gear and targeting strategies to ensure that the CPUE index is representative of the actual abundance of the species.

Despite the improvements made in standardization techniques, there are still problems with these methods. Biases in the indices can stem from problems obtaining a balance of observations in each of the factors of the model, deciding which factors to include in the model based on the amount of variability they account for, and ensuring that the assumptions of stationarity and uncorrelated samples are met. This last problem has been identified as a significant problem for CPUE standardization of fishery-dependent catch rates (Walters, 2003; Campbell, 2004) and is addressed by this analysis. If there are violations of these assumptions this makes it difficult to assess whether the catch rates are actually reflecting the stock abundance directly when there are changes in the spatial allocation of the fishing effort combined with movement of the stock.

While the Bayesian surplus production models presented in this chapter are representative of the types of models that are used to assess the status of various fisheries in formal stock assessments, the goal of this chapter was not to perform a stock assessment for dolphinfish or swordfish, but to determine the amount of variation that may occur in the model results when different indices are incorporated. More importantly, this analysis provides the ability to make some qualitative observations on how these differences might influence a fishery scientist's perception of the status of the stock and a fishery manager's decision to set benchmarks or guidelines for how the stock should be harvested.

It was hypothesized that there would be very little difference between the BSP models for dolphinfish when the geostatistical and GLM indices were incorporated. The indices were almost identical. One can presume that because of the short range of autocorrelation of the catch rates, there was less of a benefit to account for the spatial variability as the majority of the samples would be outside of the range of autocorrelation and therefore uncorrelated. Overall, the results of these models are interesting as a comparison to the model that Prager (2000) developed in ASPIC for dolphinfish (Table 5.11).

Parameter	ASPIC model	BSP model (GLM Index)	BSP model (Geostatistical)
MSY	12,241 mt (8506-21,110)	28,772 mt (1.05)	27,176 mt (1.09)
F_{current}/F_{MSY}	1997 value: 0.51 (0.34-0.85)	1997 value: 0.29 2005 value: 0.87 (1.78)	1997 value: 0.32 2005 value: 1.10 (1.91)
r	0.98 / year	0.82 / year (0.52)	0.80 / year (0.53)
K	49,963 mt	146,233 mt (0.79)	140,744 mt (0.81)

Table 5.11. Comparison of MSY, F_{current}/F_{MSY}, r, and K from an ASPIC surplus production model (Prager, 2000) with the upper and lower bounds of the nonparametric 80% confidence estimates in parentheses and two Bayesian surplus production models that incorporate different indices of abundance (GLM vs. geostatistical). The CVs of the values from the BSP models are given in parentheses. The current year in the ASPIC model was 1997, so the corresponding estimate for 1997 is provided along with the current (2005) value for the BSP model.

The estimate of *K* from both BSP models is about 3 times the value of *K* estimated by the ASPIC model. The *r* values from the BSP models are lower than the value of 0.98 estimated by the ASPIC model, but still feasible for a species that is fast-growing and short-lived like dolphinfish. Because the *r* value in the BSP model was strongly driven by the prior distribution, it was not expected that it would be similar to the ASPIC *r* value. The main difference between the models is that the fishing pressure estimated by

the ASPIC model is much lower (roughly half of the MSY level) than either of the BSP models. Additionally, the BSP model that includes the geostatistical index estimates the fishing pressure to be above the MSY level. The differences between the spatial geostatistical index and the nonspatial GLM index for swordfish are manifested in the differences between the productivity parameters from the BSP model. While the differences are less obvious when the U.S. indices are used alone, they are interesting nonetheless. The differences in later years of the U.S. indices paint different pictures of the current situation of the stock. When the Japanese index is used to drive the productivity of the early years, the differences between the stock statuses is significantly different and would probably lead to very different management strategies. This is especially true with respect to F/F_{MSY} , which is a very important management parameter. The results of this analysis suggest that this parameter is rather sensitive to the index used and highlights the fact that one could arrive at very different conclusions about stock status by incorporating different information. This analysis does not attempt to address whether one index is providing the correct picture of the stock abundance. Using the Japanese index in this way also contributes to contrast between the abundance index and the landings data. It is well known that biomass dynamic models require large contrast in stock size (a biomass trajectory that includes at least one episode of depletion and rebuilding) to accurately estimate productivity parameters. A comparison of U.S. swordfish indices and the Japanese index, shows that whereas US indices change by a factor of about two over the period of data, the Japanese index changed by a factor of five (see Figure 5.1). While the Japanese index does provide additional information about the earlier years of the fishery, there are several caveats to these data that should be

addressed. During the early years of the fishery, the Japanese index increased during the period that the catches were also increasing. The increasing biomass trend from 1950 to 1985 is not consistent with the increasing catches during that time. Therefore, the model is forced to assume that this discrepancy is due to measurement error. As such, the Japanese series is not as informative and likely adds uncertainty to the model output. When the full Japanese index is used with the U.S. indices, there are some differences between the predictions, but the low abundances of the Japanese heavily influence the output, driving down the estimates of current biomass regardless of whether the U.S. geostatistical or GLM index is used. This is also illustrated by the distribution of the posterior distributions of the r parameter for each of the models (see Figure 5.19). Therefore, differences between the U.S. geostatistical and GLM indices are seen most clearly when they are incorporated with a truncated Japanese index. This combination allows the U.S. indices to largely determine the current situation in the fishery. According to the GLM index, there is a much lower abundance in the current year than the geostatistical index predicts. This translates to a reduction of the current biomass predictions and an increase in the current fishing mortality estimates.

One of the main questions that must be asked is why there are differences between the GLM and geostatistical indices that are so pronounced in certain years. The assumption for the difference is that the geostatistical index is accounting for spatial variability while the GLM ignores this factor by equally weighting all observations. In other words, if there is a cluster of observations in an area, the GLM counts these as individual replicates. When there is spatial autocorrelation in the system, the geostatistical model will down weight the clustered observations relative to an

observation from an area with fewer values. This provides a means to address the issue of how to deal with areas where there are zeros. Certainly the mean of the values may not be the optimal value to fill in these areas, however with the GLM, there is no other option. Additionally, if there are clustered observations and a relatively long range of autocorrelation then this suggests that more of the observations will be subject to spatial bias if one does not account for the spatial pattern.

5.5 Chapter Conclusions

The analysis presented in this chapter represents one method of accounting for spatial variability in CPUE index standardization. The downside to this type of spatial analysis is that it is more labor intensive than a typical GLM standardization. However, as there is a shift towards ecosystem based management and models that incorporate space, there is a need for indices that are spatially explicit. The MULTIFAN-CL model for fisheries stock assessment is a length-based, age, and spatially-structured model. The requirements are an index of abundance that is both spatial and seasonal in nature. This model is used frequently in the Pacific to assess pelagic species such as bigeye and bluefin tuna. Another hurdle with a geostatistical model is determining the correct window of space and time. In this analysis, the choice was made to partition the spatial modelling into time components of a year-season and to restrict the analysis to the Gulf of Mexico. The temporal division has the upside that one could account for annual and seasonal variability in a spatial manner. Because the GLM standardizes for annual and seasonal variability in the index, these factors should be accounted for in the spatial index. The issue is that because the CPUE index input to the BSP or other surplus production model is annual, at some level, it is necessary to aggregate over the

predictions in an area to compute the geostatistical annual index. This leads to questions on how to best average the seasonal predictions. A further investigation that should be made is to compare the geostatistical index obtained when variograms for an entire year are calculated and used to make predictions of abundance annually over the region.

GENERAL CONCLUSIONS

There are several main conclusions from this analysis:

- (1) Dolphinfish is a species that is important both ecologically and commercially. Despite this importance, there has been little improvement to the current stock assessment status of this species and there is an increased need to find new techniques to enhance the information on this data-limited species
- (2) Dolphinfish are correlated with prominent oceanographic features in the Atlantic. These include SST and proximity to frontal regions.
- (3) Satellite derived oceanographic data can be used to enhance the standardization of indices of abundance of dolphinfish when catch rate data includes spatial locational information. Including this information in an abundance index leads to increased confidence of the trends observed.
- (4) The degree of spatial autocorrelation can have an impact on the indices of abundance, especially in years where there are clustered observations of catch. As such, the spatial autocorrelation in a system should be addressed when attempting to derive robust indices of abundance.
- (5) Accounting for spatial variability may prevent bias in the CPUE index if there is a longer range of autocorrelation and clustered catches in an area.

- (6) If the spatial variability in the system is sufficiently high that accounting for the variability affects the overall trend in the CPUE index, this can translate into differences in the outcomes of a stock assessment model.
- (7) Different outcomes in the assessment can lead fisheries managers to different perceptions about the appropriate strategies required to achieve management goals. Therefore, it is worthwhile to investigate the spatial autocorrelation in a system to determine if it significantly affects the abundance index.

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Appendix A: Variogram Parameters

Spring					Summer				
Year	Num Obs.	Nug	Sill	Range	Year	Num Obs.	Nug	Sill	Range
1987	87	0.00	0.746	X	1987	433	0.30	0.749	69
1988	164	0.00	0.582	27	1988	424	0.15	0.684	41
1989	208	0.15	0.756	48	1989	480	0.30	1.392	89
1990	272	0.20	0.740	113	1990	636	0.67	1.752	48
1991	355	0.30	0.856	60	1991	742	0.60	1.542	28
1992	305	0.35	0.904	106	1992	670	0.65	1.671	114
1993	203	0.05	0.482	86	1993	566	0.52	1.308	48
1994	195	0.25	0.668	42	1994	523	0.67	1.569	45
1995	316	0.20	0.853	77	1995	768	0.45	1.530	69
1996	284	0.20	0.811	107	1996	955	0.61	1.734	64
1997	394	0.48	1.498	44	1997	1047	0.50	1.380	50
1998	135	0.05	0.289	55	1998	736	0.47	1.130	44
1999	370	0.40	1.193	81	1999	835	0.45	1.054	57
2000	211	0.22	0.549	29	2000	807	0.30	0.807	53
2001	317	0.12	0.407	49	2001	935	0.30	0.836	34
2002	364	0.20	0.519	65	2002	1072	0.30	0.785	39
2003	334	0.18	0.572	81	2003	927	0.31	0.807	23
2004	499	0.25	0.735	43	2004	1111	0.40	1.052	62
2005	181	X	X	X	2005	550	0.20	0.504	18
Average	273	0.20	0.731	65	Average	748	0.43	1.173	52

Fall					Winter				
Year	Num Obs.	Nug	Sill	Range	Year	Num Obs.	Nug	Sill	Range
1987	184	0.30	0.825	45	1987	107	0.00	0.229	24
1988	178	0.10	0.482	93	1988	180	0.00	0.358	15
1989	397	0.28	0.925	78	1989	217	0.00	0.297	27
1990	368	0.30	1.022	53	1990	228	0.15	0.490	54
1991	457	0.30	1.025	49	1991	217	0.19	0.585	47
1992	265	0.35	1.004	39	1992	348	0.30	0.800	51
1993	287	0.33	0.768	40	1993	149	0.03	0.345	64
1994	223	0.15	0.564	57	1994	121	0.10	0.481	52
1995	207	0.15	0.648	33	1995	223	0.30	0.732	51
1996	287	0.15	0.486	78	1996	150	0	0.200	33
1997	247	0.10	0.343	44	1997	250	0.07	0.236	15
1998	175	0.07	0.386	70	1998	97	X	X	X
1999	203	0.10	0.432	66	1999	148	0.06	0.215	28
2000	238	0.07	0.250	76	2000	107	X	X	X
2001	389	0.12	0.469	28	2001	110	0	0.110	120
2002	240	0.05	0.259	54	2002	376	0.14	0.461	37
2003	278	X	X	X	2003	82	X	X	X
2004	204	X	X	X	2004	88	X	X	X
2005	75	0.03	0.174	148	2005	71	X	X	X
Average	258	0.17	0.592	62	Average	172	0.10	0.396	44

Table A1. Variogram parameters for log of positive dolphinfish catch for each year-season and average for each season.

Spring					Summer				
Year	Num Obs.	Nug	Sill	Range	Year	Num Obs.	Nug	Sill	Range
1987	1416	0.000	0.000	90	1987	1569	0.018	0.048	56
1988	1329	0.000	0.001	84	1988	1093	0.015	0.068	111
1989	1309	0.001	0.007	72	1989	1007	0.008	0.084	162
1990	987	0.015	0.059	154	1990	961	0.000	0.025	58
1991	945	0.010	0.054	85	1991	1094	X	X	X
1992	1217	0.007	0.020	52	1992	986	0.010	0.036	114
1993	919	X	X	X	1993	976	0.020	0.073	133
1994	883	0.006	0.024	49	1994	939	0.020	0.078	32
1995	866	0.015	0.066	83	1995	1106	0.004	0.017	64
1996	1188	0.009	0.030	84	1996	1414	0.017	0.043	89
1997	935	0.010	0.061	70	1997	1551	0.003	0.021	62
1998	890	0.001	0.007	27	1998	1311	0.035	0.096	88
1999	1231	0.014	0.053	45	1999	1301	0.021	0.057	136
2000	1116	0.006	0.017	30	2000	1336	0.029	0.084	98
2001	1130	0.020	0.051	43	2001	1436	0.010	0.053	63
2002	1022	0.030	0.079	72	2002	1556	0.020	0.054	68
2003	1359	0.010	0.031	82	2003	1537	0.010	0.047	105
2004	1466	0.025	0.071	140	2004	1564	0.016	0.040	29
2005	1272	0.002	0.006	61	2005	1022	0.045	0.108	36
Average	1131	0.01006	0.035	74	Average	1250	0.017	0.057	84
Fall					Winter				
Year	Num Obs.	Nug	Sill	Range	Year	Num Obs.	Nug	Sill	Range
1987	1194	0.001	0.006	127	1987	1020	0.0001	0.001	81
1988	1013	0.005	0.013	74	1988	1599	0.0012	0.004	65
1989	973	0.010	0.072	66	1989	1902	0.0015	0.006	69
1990	846	0.025	0.094	47	1990	1593	0.0100	0.036	45
1991	872	0.020	0.073	82	1991	859	0.0230	0.065	98
1992	758	0.020	0.079	103	1992	1066	X	X	X
1993	873	0.013	0.045	103	1993	765	0.0030	0.011	115
1994	702	0.010	0.051	29	1994	717	0.0050	0.031	109
1995	841	0.010	0.036	87	1995	1006	0.0030	0.009	22
1996	1066	0.008	0.038	40	1996	967	0.0120	0.031	46
1997	894	0.006	0.037	101	1997	1221	X	X	X
1998	760	0.009	0.028	18	1998	817	0.0028	0.007	31
1999	1080	0.008	0.017	23	1999	1025	0.0015	0.005	13
2000	1255	0.003	0.012	51	2000	967	X	X	X
2001	1066	0.035	0.089	61	2001	861	0.0300	0.095	88
2002	1164	0.008	0.024	63	2002	850	X	X	X
2003	1171	0.012	0.034	70	2003	1039	X	X	X
2004	1153	0.005	0.015	42	2004	967	0.0006	0.002	27
2005	468	0.001	0.009	122	2005	975	0.0000	0.001	115
Average	955	0.011	0.041	69	Average	1064	0.0067	0.022	66

Table A2. Variogram parameters for indicator (proportion positive) dolphinfish catch for each year-season and average for each season.

Spring					Summer				
Year	Num Obs.	Nugget	Sill	Range	Year	Num Obs.	Nugget	Sill	Range
1987	621	0.48	1.786	229	1987	525	0.20	1.082	92
1988	898	0.46	1.349	82	1988	487	0.08	2.452	355
1989	935	0.45	1.427	79	1989	529	0.19	1.458	96
1990	521	0.40	1.388	72	1990	411	0.25	1.591	102
1991	623	0.30	1.053	142	1991	451	0.25	0.934	59
1992	620	0.30	1.393	135	1992	346	0.30	0.876	78
1993	557	0.20	0.769	127	1993	383	0.43	1.449	53
1994	409	0.00	1.847	203	1994	294	0.00	1.587	96
1995	552	0.00	0.709	72	1995	542	0.30	1.193	74
1996	753	0.00	0.717	114	1996	570	0.20	0.996	116
1997	552	0.00	0.616	61	1997	646	0.20	0.947	132
1998	427	0.10	0.675	65	1998	565	0.32	0.889	52
1999	743	0.30	0.912	19	1999	499	0.30	0.891	61
2000	672	0.44	1.247	129	2000	568	0.30	0.841	33
2001	724	0.55	1.459	188	2001	598	0.30	0.867	47
2002	602	0.27	0.965	115	2002	724	0.23	0.786	67
2003	724	0.38	1.050	119	2003	528	0.30	0.923	42
2004	724	X	X	X	2004	436	0.30	0.791	64
2005	787	0.30	0.751	63	2005	472	0.30	0.824	50
Average	655	0.27	1.117	112	Average	504	0.25	1.125	88

Fall					Winter				
Year	Num Obs.	Nugget	Sill	Range	Year	Num Obs.	Nugget	Sill	Range
1987	602	0.50	1.484	98	1987	658	0.00	0.826	89
1988	670	0.30	1.291	87	1988	1213	0.00	1.024	50
1989	568	0.20	1.274	87	1989	1610	0.40	0.997	126
1990	458	0.30	1.459	113	1990	1169	X	X	X
1991	478	0.40	1.218	89	1991	677	0.30	1.598	239
1992	394	0.30	0.974	84	1992	755	0.30	0.969	95
1993	517	0.40	1.982	76	1993	567	0.20	0.811	139
1994	378	0.20	1.230	158	1994	484	0.20	1.139	159
1995	550	0.40	0.960	114	1995	790	0.00	1.229	188
1996	632	0.30	0.988	173	1996	712	0.30	0.954	107
1997	378	0.20	0.776	71	1997	888	0.20	0.724	48
1998	434	0.20	0.747	60	1998	590	0.10	0.761	65
1999	560	0.40	1.020	77	1999	727	0.30	0.890	45
2000	750	0.40	1.075	69	2000	665	0.00	0.896	147
2001	526	X	X	X	2001	691	0.40	0.874	41
2002	658	0.30	0.739	64	2002	531	0.30	0.813	34
2003	501	0.20	0.775	89	2003	786	0.20	1.001	233
2004	687	0.30	0.854	83	2004	632	0.30	0.837	81
2005	264	0.27	0.813	70	2005	703	0.30	0.815	61
Average	527	0.31	1.092	92	Average	781	0.21	0.975	108

Table A3. Variogram parameters for log of positive swordfish catch for each year-season and average for each season.

Spring					Summer				
Year	Num Obs.	Nugget	Sill	Range	Year	Num Obs.	Nugget	Sill	Range
1987	1416	0.01	0.070	143	1987	1569	0.005	0.038	101
1988	1329	0.02	0.065	55	1988	1093	0.005	0.067	293
1989	1309	0.00	0.034	106	1989	1007	0.005	0.060	127
1990	987	0.00	0.061	94	1990	961	0.000	0.057	60
1991	945	0.01	0.052	71	1991	1094	0.010	0.070	66
1992	1217	0.03	0.097	70	1992	986	0.030	0.079	38
1993	919	0.00	0.057	145	1993	976	0.019	0.057	82
1994	883	0.00	0.048	93	1994	939	0.000	0.024	32
1995	866	0.00	0.065	176	1995	1106	0.000	0.053	90
1996	1188	0.00	0.043	95	1996	1414	X	X	X
1997	935	0.01	0.072	127	1997	1551	0.020	0.066	85
1998	890	0.01	0.069	108	1998	1311	0.027	0.083	68
1999	1231	0.02	0.072	78	1999	1301	0.020	0.083	72
2000	1116	0.02	0.082	83	2000	1336	0.030	0.093	70
2001	1130	0.03	0.079	53	2001	1436	0.010	0.063	48
2002	1022	0.01	0.048	91	2002	1556	0.035	0.086	100
2003	1359	0.02	0.091	89	2003	1537	0.010	0.045	59
2004	1466	0.03	0.099	81	2004	1564	0.010	0.073	174
2005	1272	0.02	0.064	76	2005	1022	0.005	0.038	142
Average	1131	0.01	0.067	97	Average	1250	0.013	0.063	95
Fall					Winter				
Year	Num Obs.	Nugget	Sill	Range	Year	Num Obs.	Nugget	Sill	Range
1987	1194	0.03	0.100	132	1987	1020	0.035	0.092	67
1988	1013	0.01	0.059	151	1988	1599	0.010	0.029	133
1989	973	0.00	0.064	76	1989	1902	0.000	0.004	125
1990	846	0.01	0.080	80	1990	1593	0.000	0.026	84
1991	872	0.01	0.069	54	1991	859	0.000	0.015	88
1992	758	0.01	0.057	86	1992	1066	0.000	0.033	74
1993	873	0.01	0.073	90	1993	765	0.000	0.036	161
1994	702	0.01	0.074	50	1994	717	0.000	0.056	110
1995	841	0.00	0.044	100	1995	1006	0.000	0.028	119
1996	1066	0.00	0.052	113	1996	967	0.000	0.027	125
1997	894	0.00	0.051	73	1997	1221	0.000	0.034	116
1998	760	0.00	0.052	64	1998	817	0.010	0.048	79
1999	1080	0.03	0.096	64	1999	1025	0.005	0.034	104
2000	1255	0.01	0.061	67	2000	967	0.000	0.036	144
2001	1066	0.02	0.085	52	2001	861	0.000	0.013	67
2002	1164	0.00	0.047	94	2002	850	0.020	0.066	31
2003	1171	0.04	0.103	120	2003	1039	0.002	0.021	200
2004	1153	0.01	0.055	40	2004	967	0.010	0.048	114
2005	468	X	X	X	2005	975	X	X	X
Average	955	0.01	0.068	84	Average	1064	0.005	0.036	108

Table A4. Variogram parameters for indicator (proportion positive) swordfish catch for each year-season and average for each season.

Appendix B—Variograms

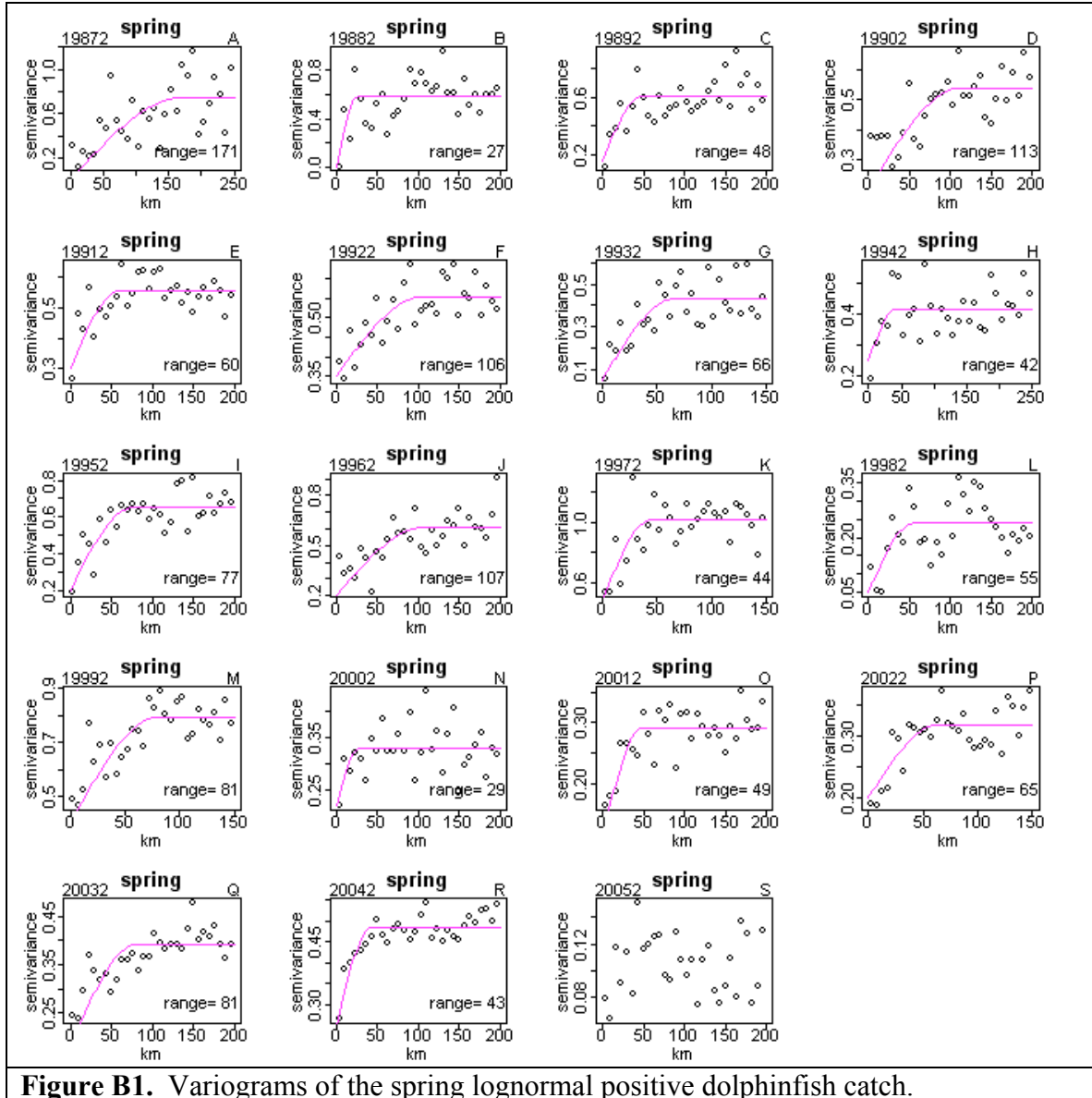


Figure B1. Variograms of the spring lognormal positive dolphinfish catch.

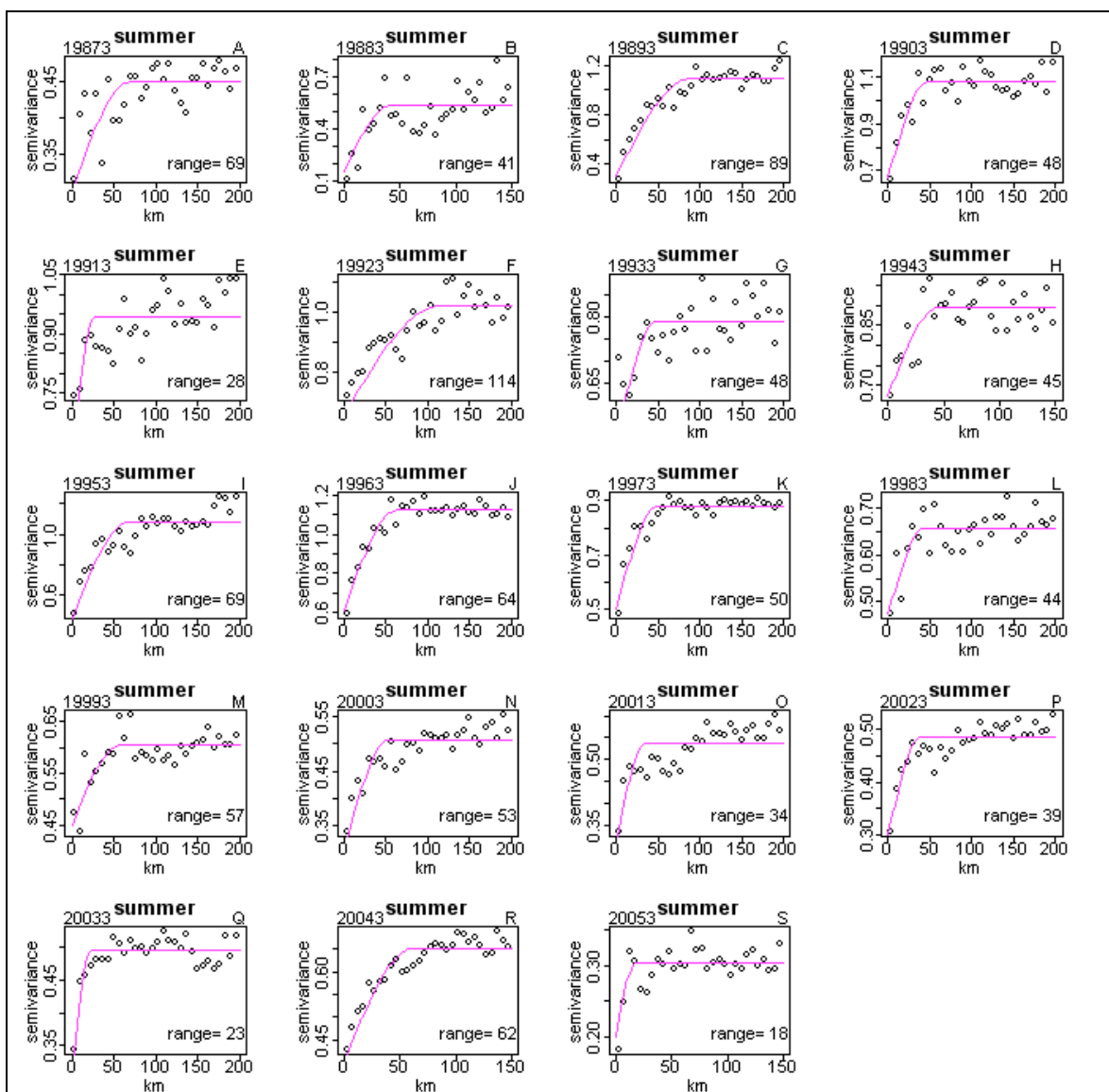
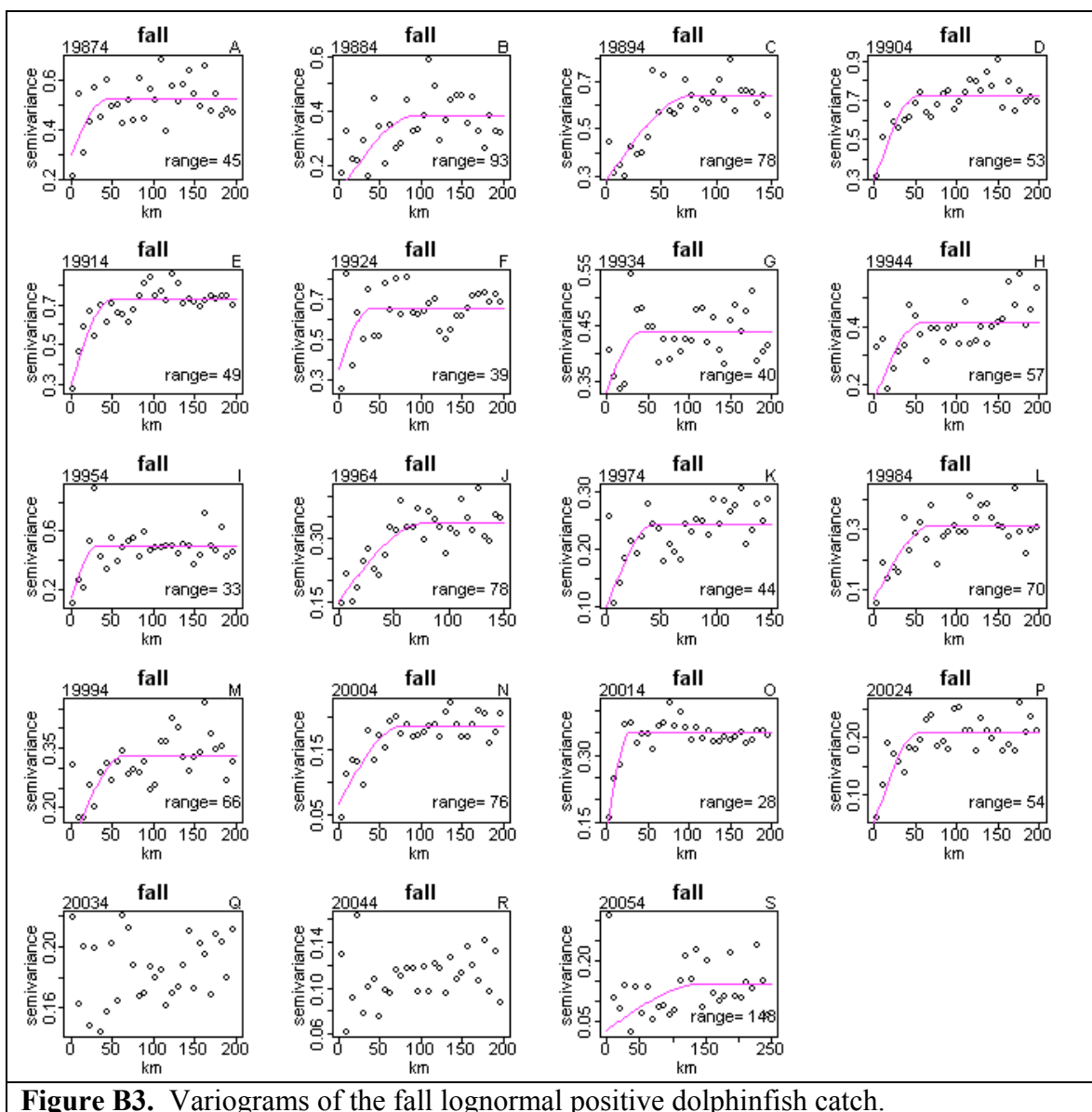


Figure B2. Variograms of the summer lognormal positive dolphinfish catch.



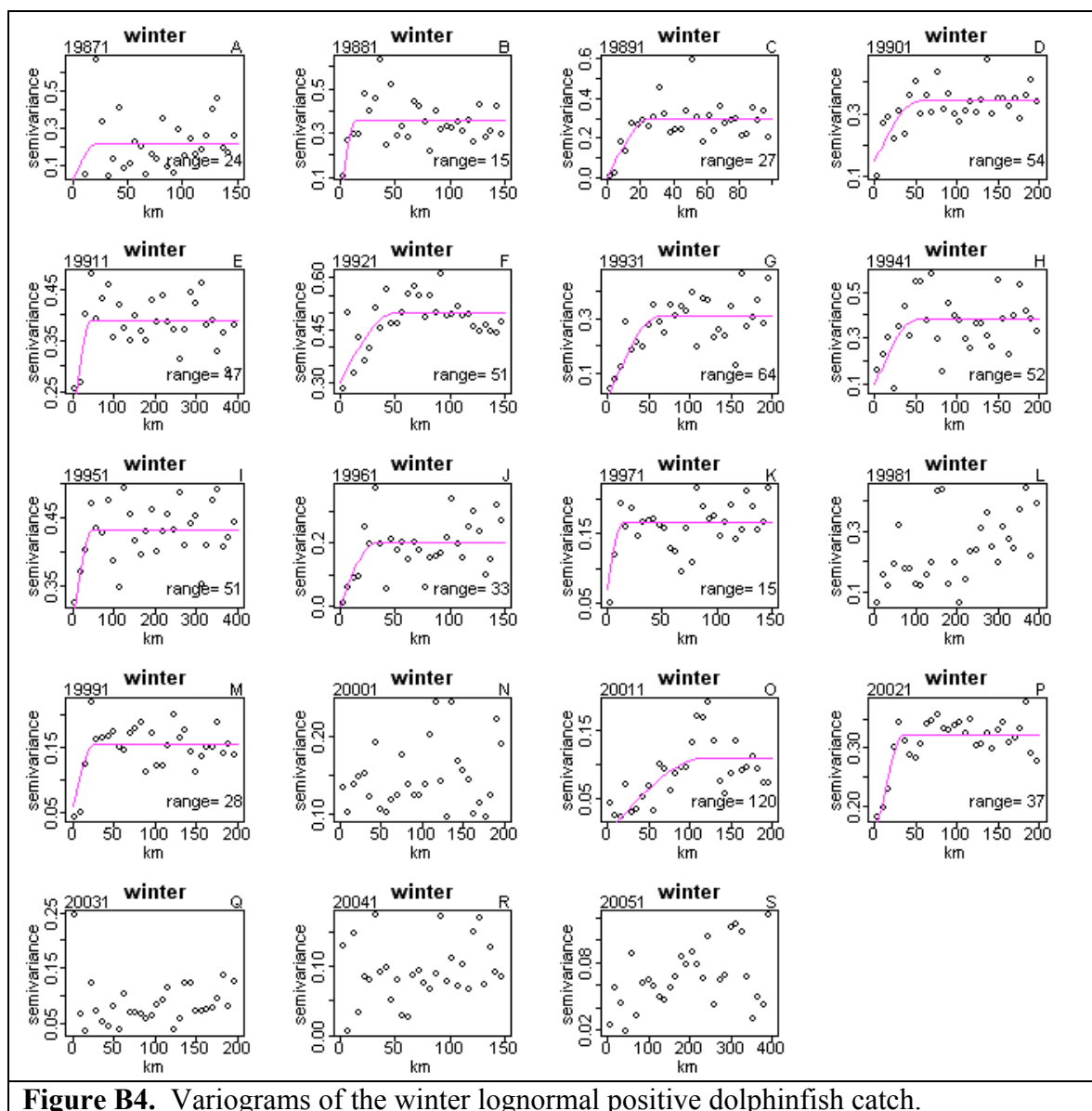


Figure B4. Variograms of the winter lognormal positive dolphinfish catch.

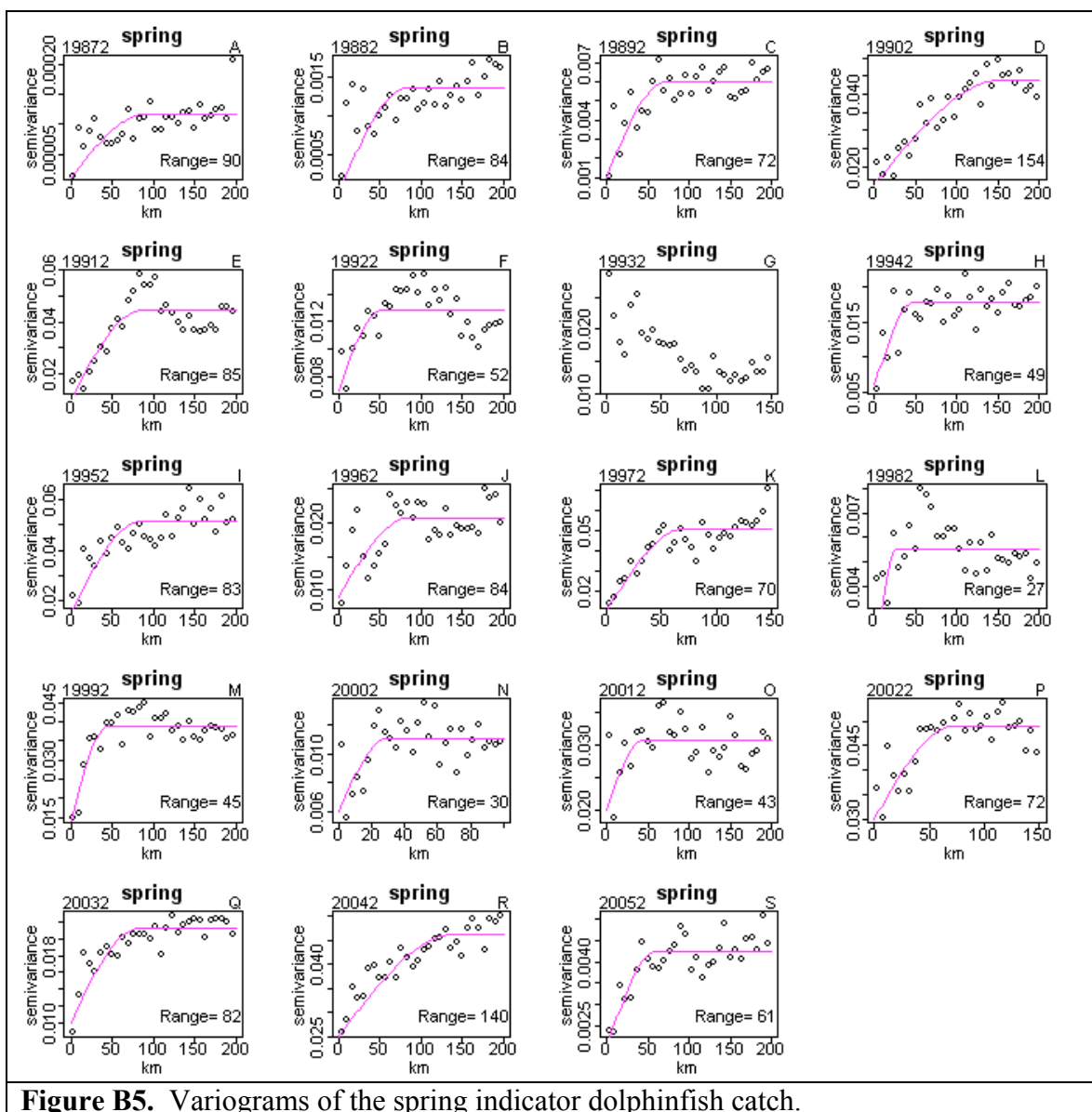
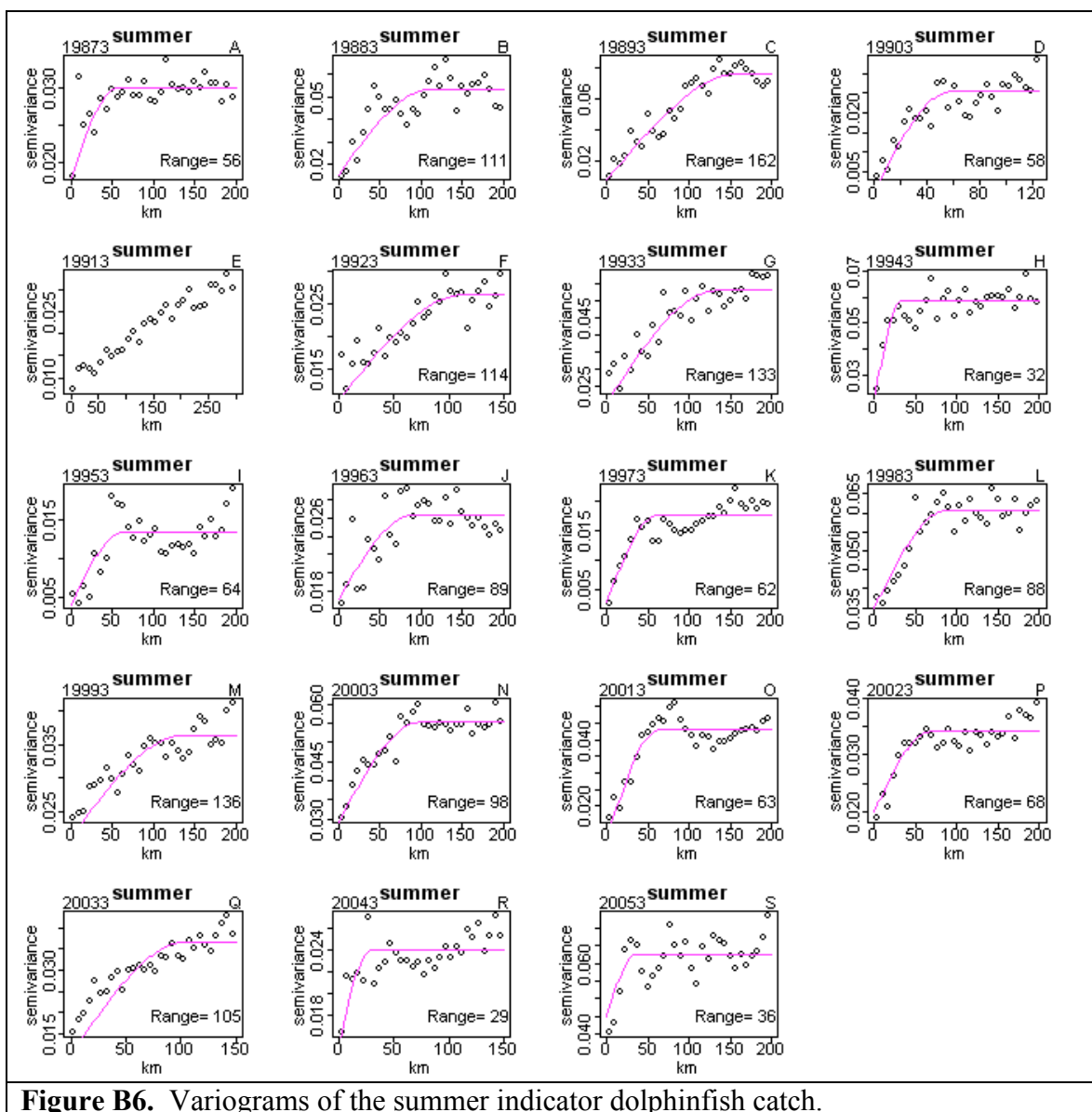
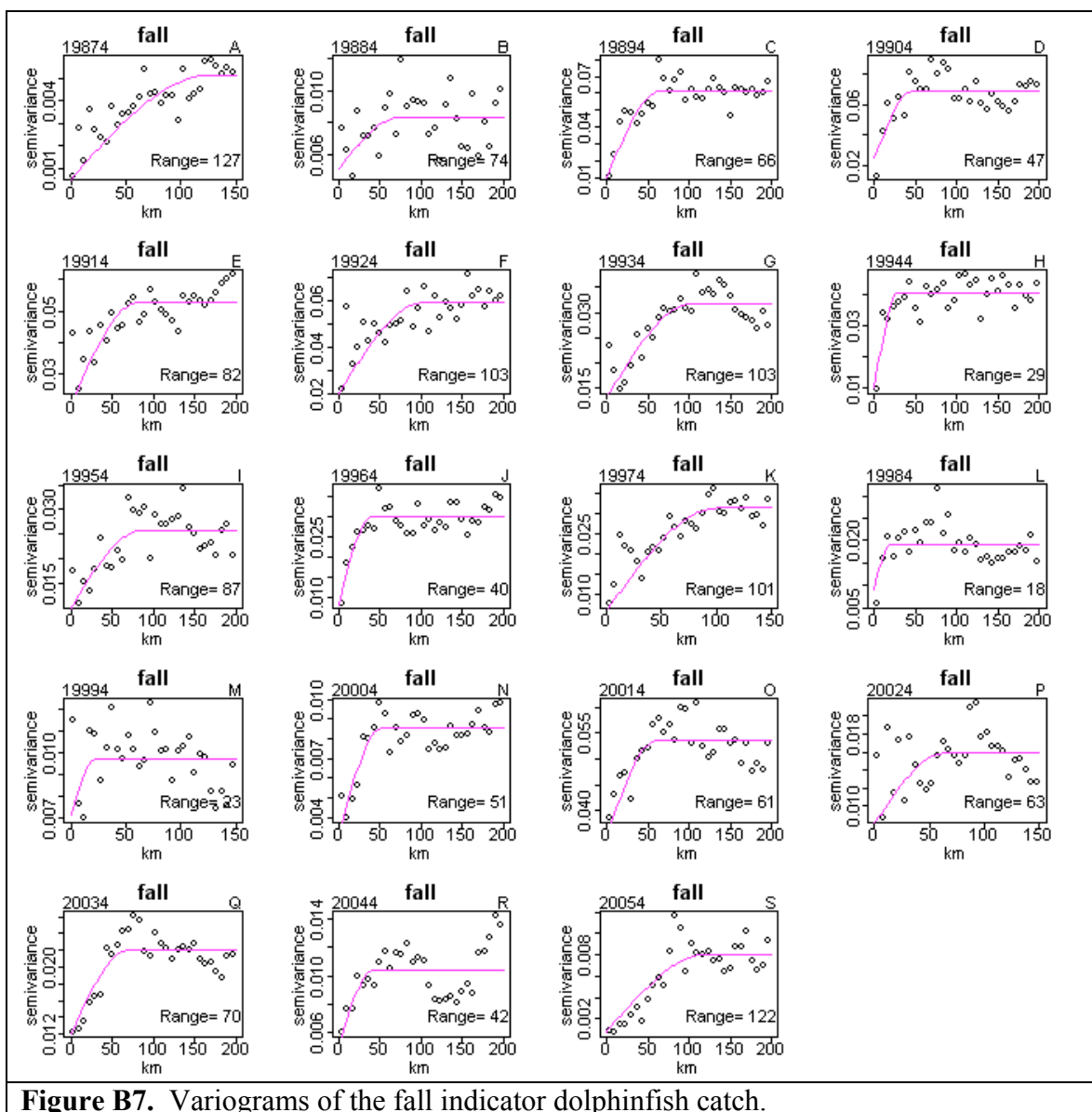
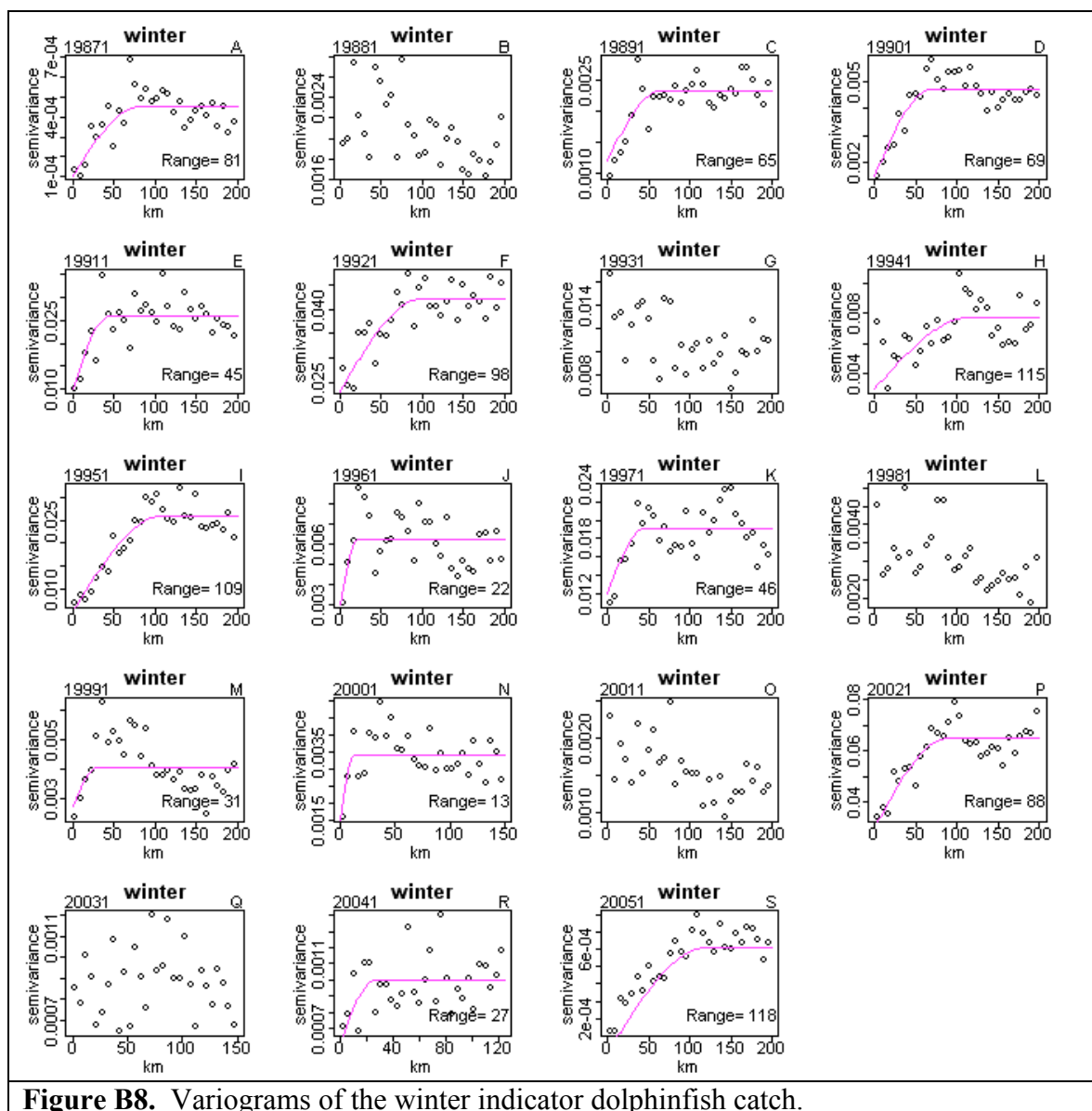
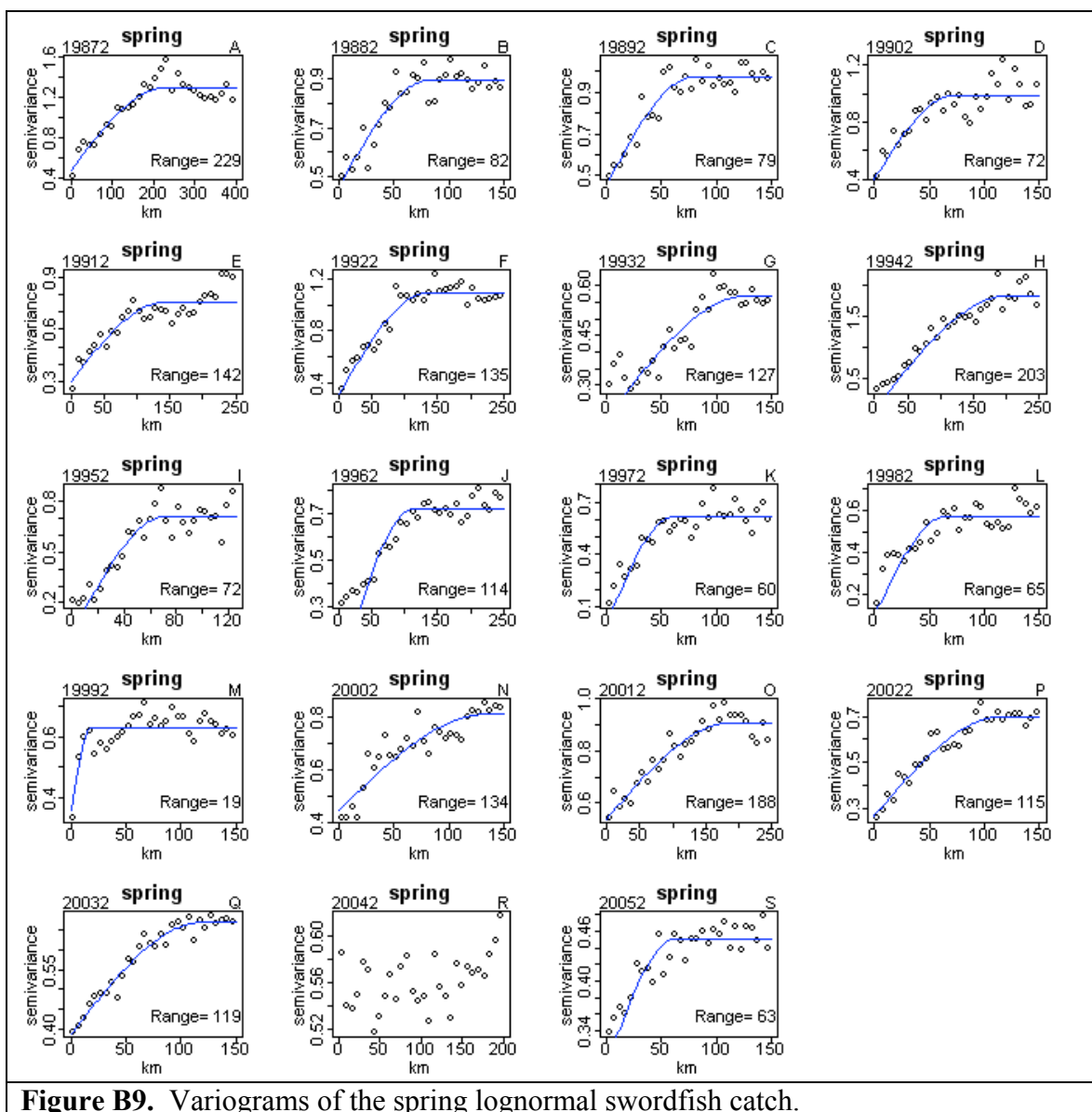


Figure B5. Variograms of the spring indicator dolphinfish catch.









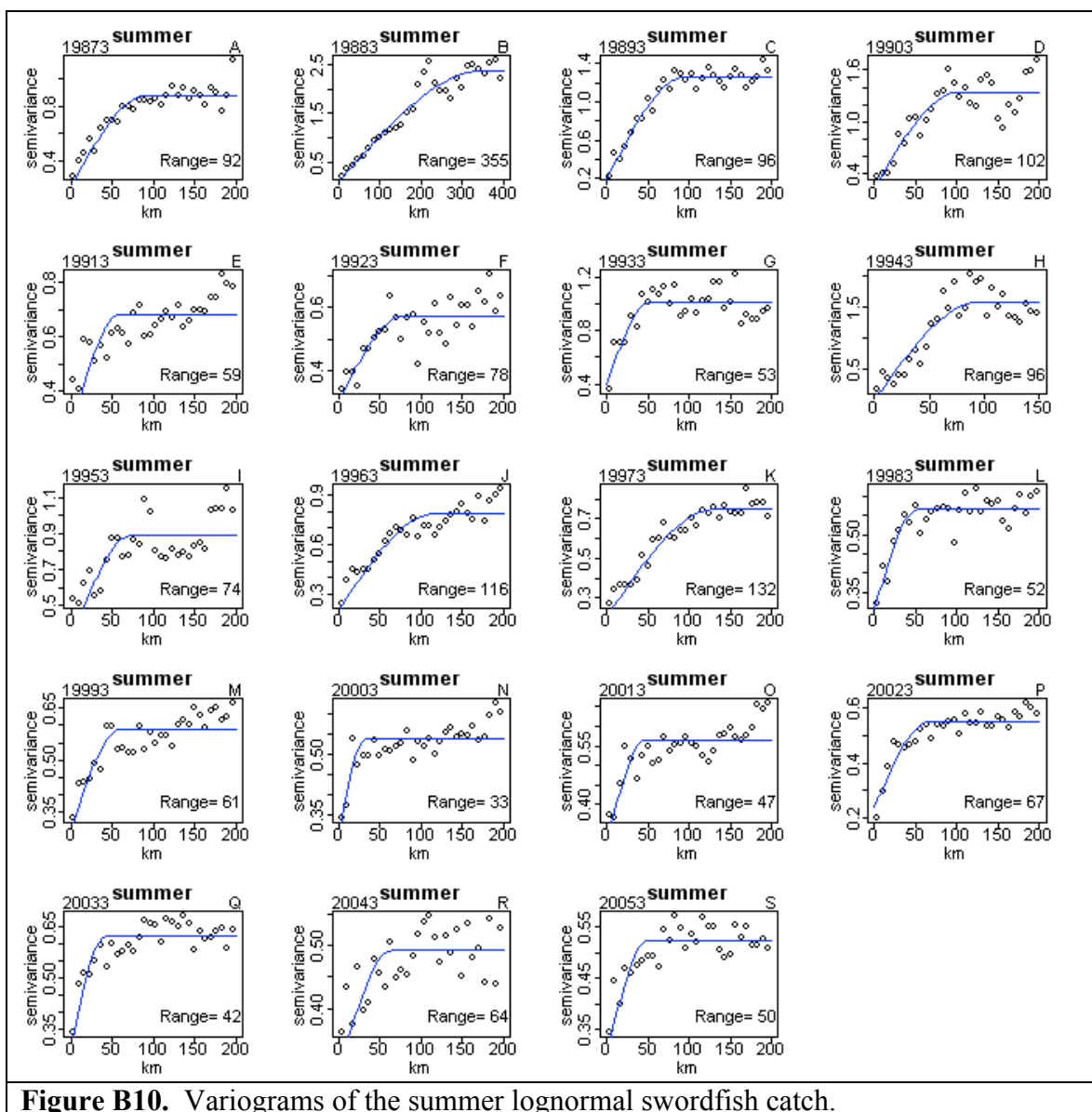
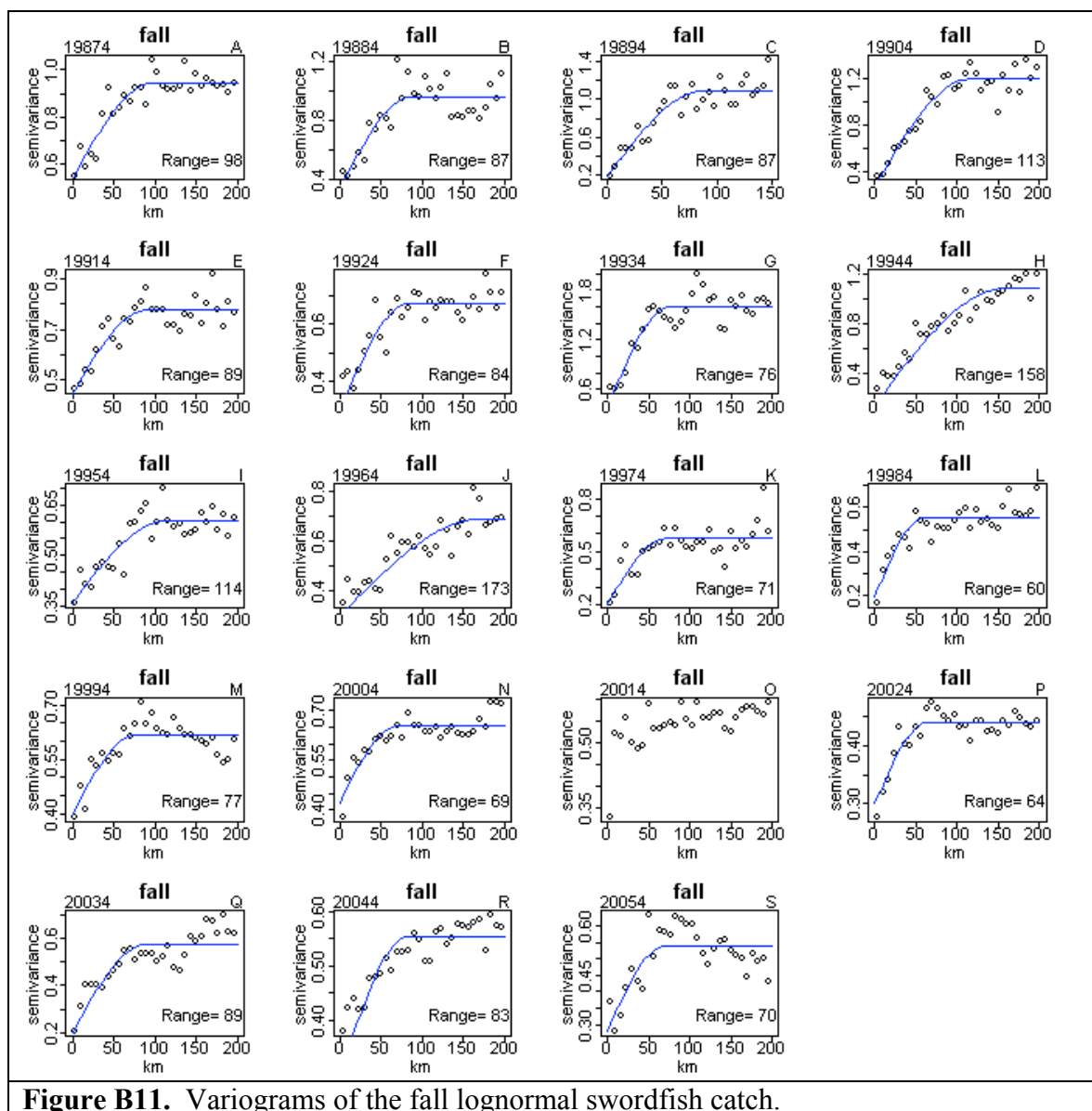
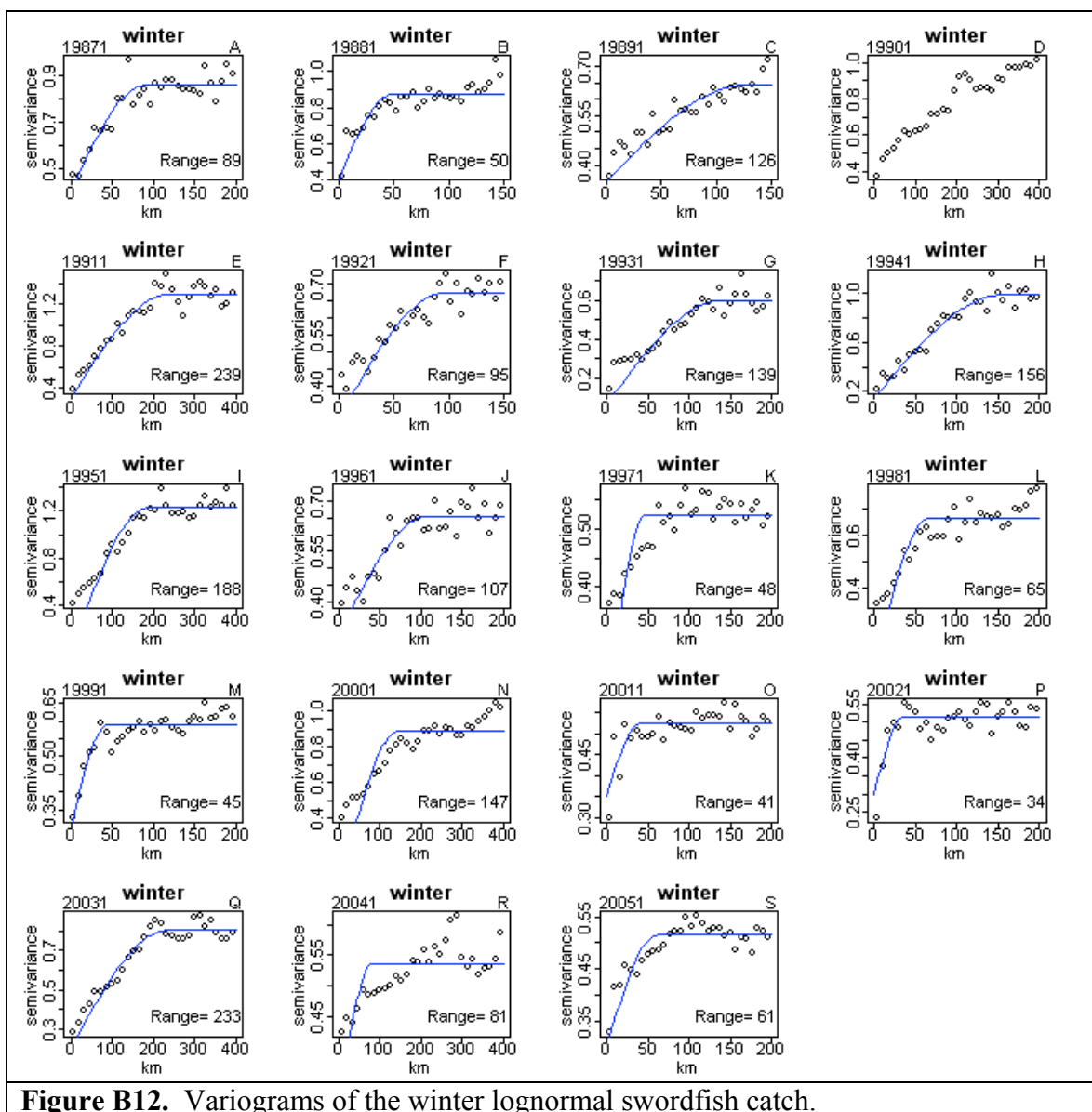
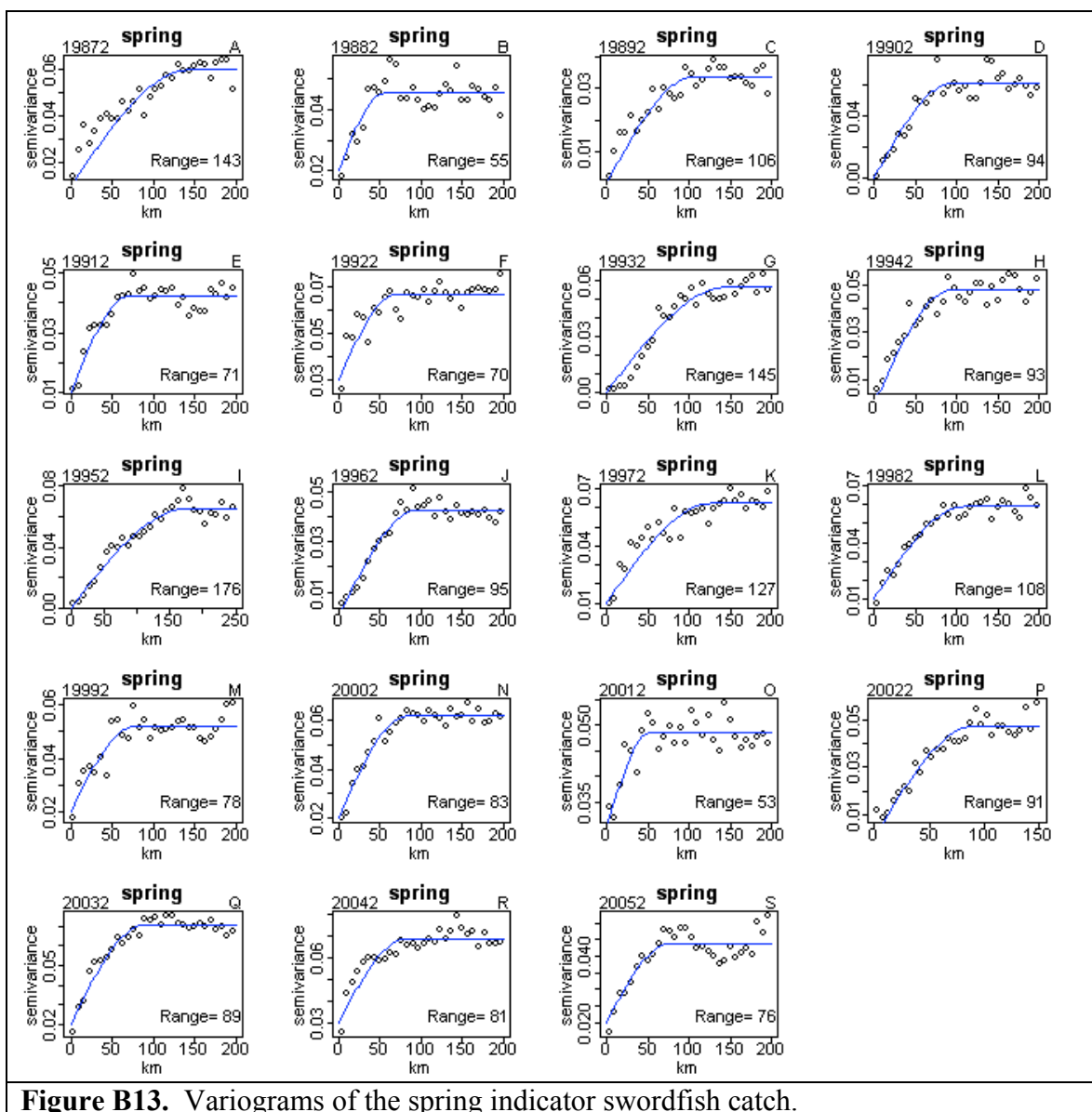


Figure B10. Variograms of the summer lognormal swordfish catch.







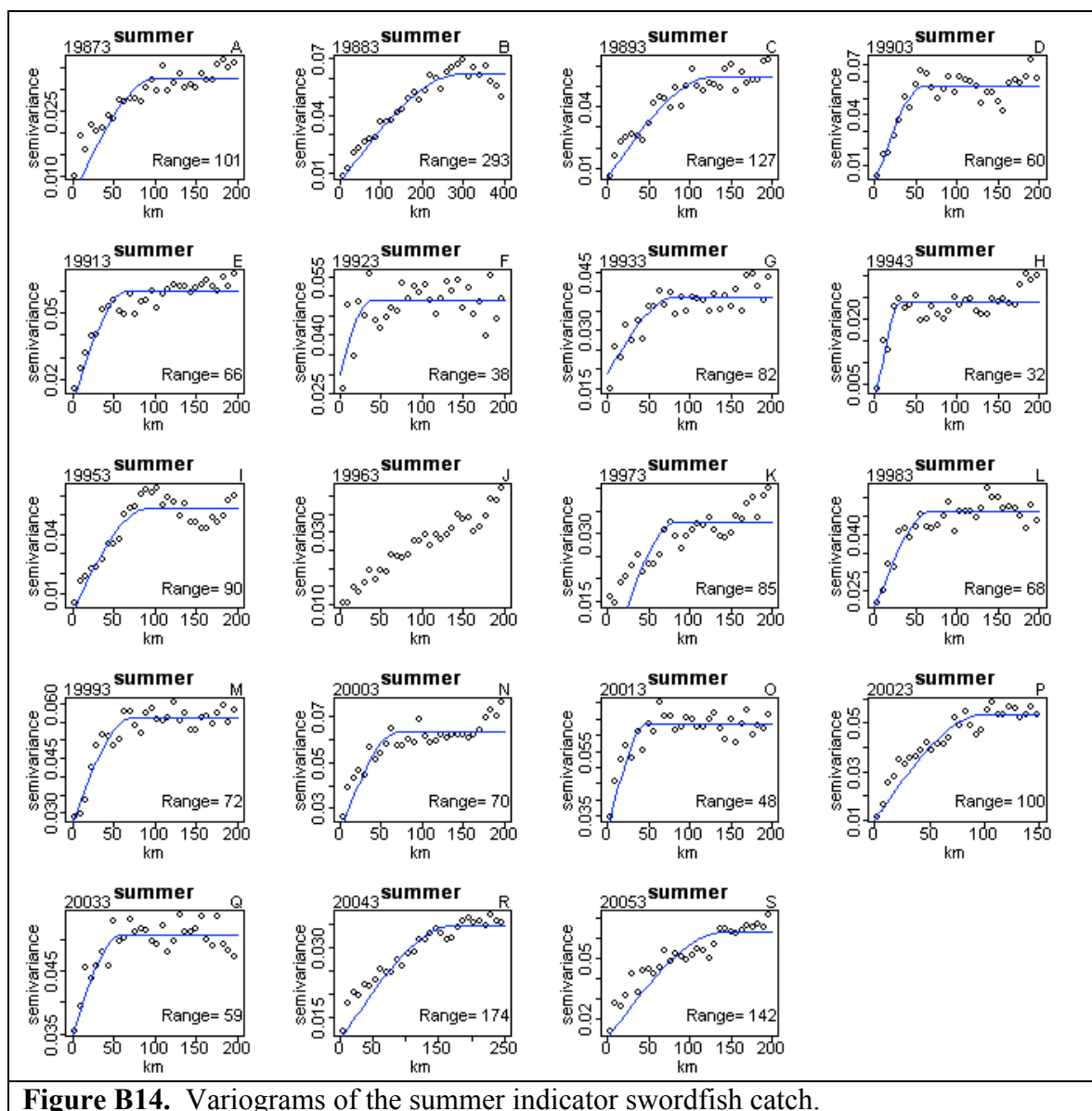
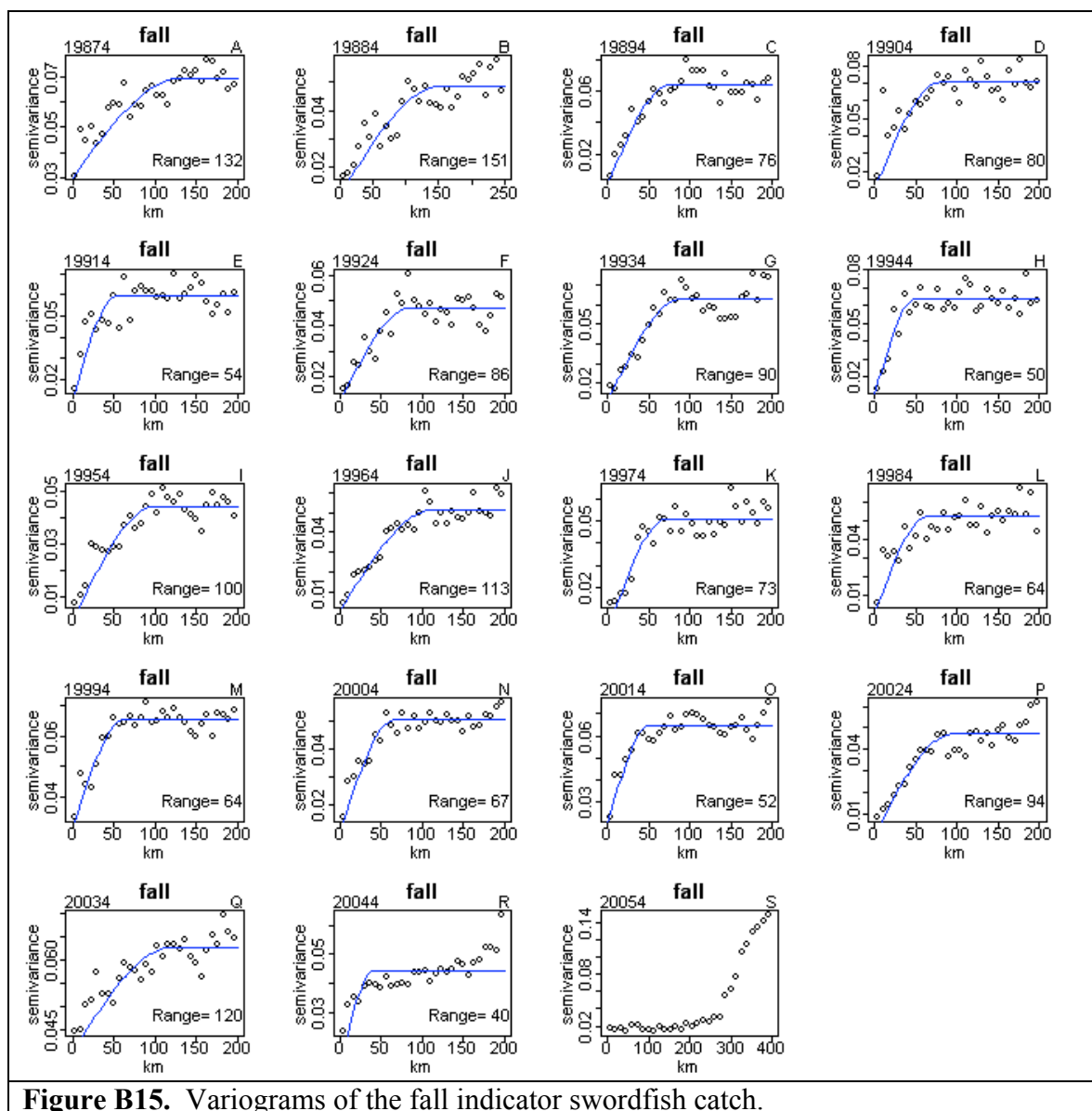


Figure B14. Variograms of the summer indicator swordfish catch.



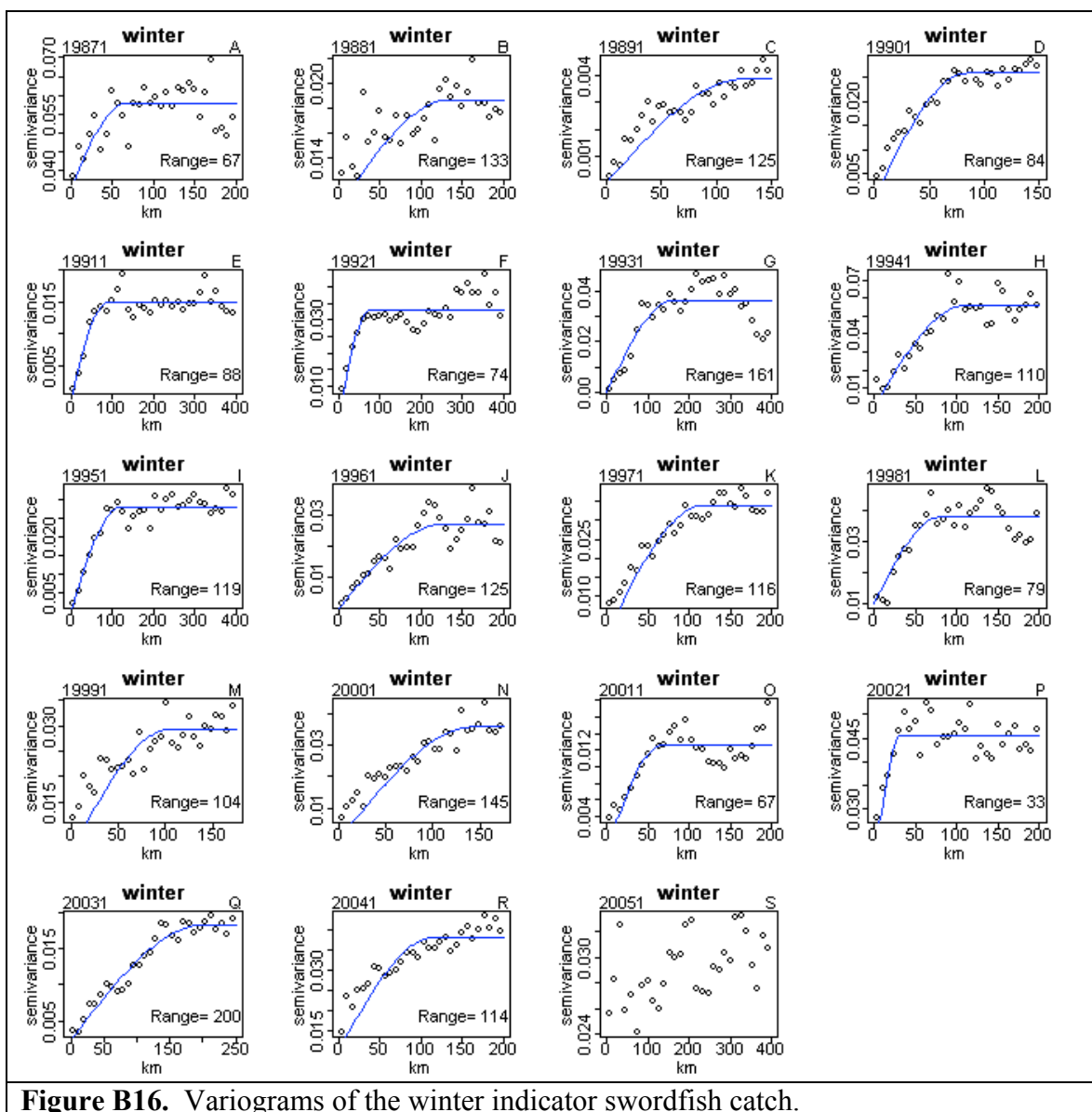
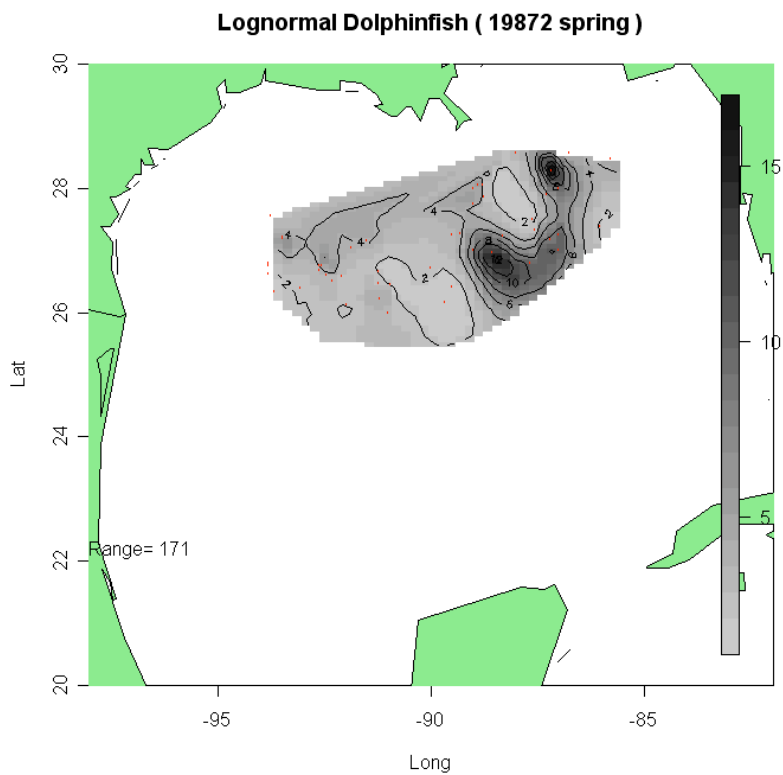


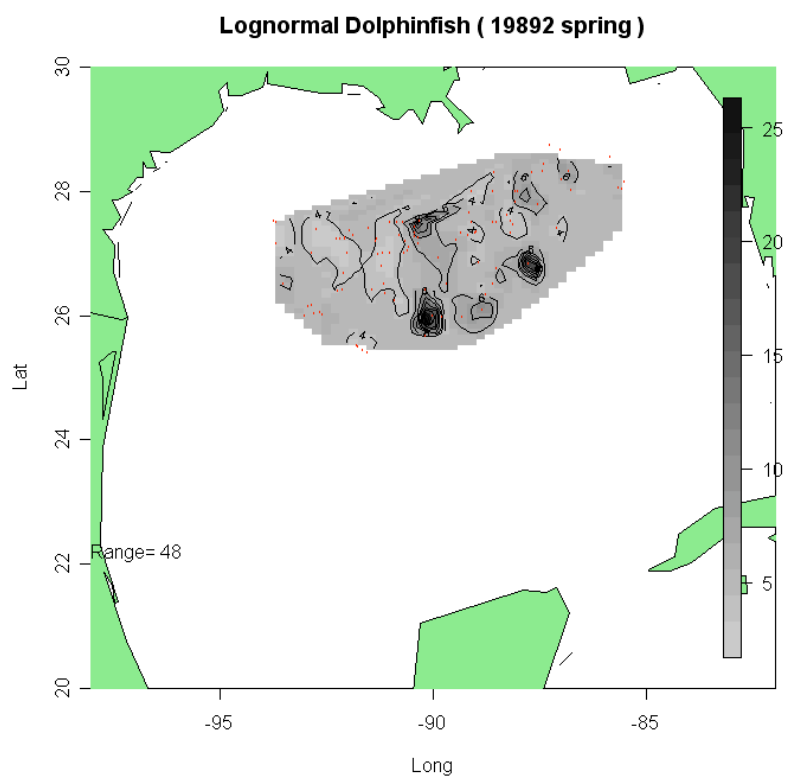
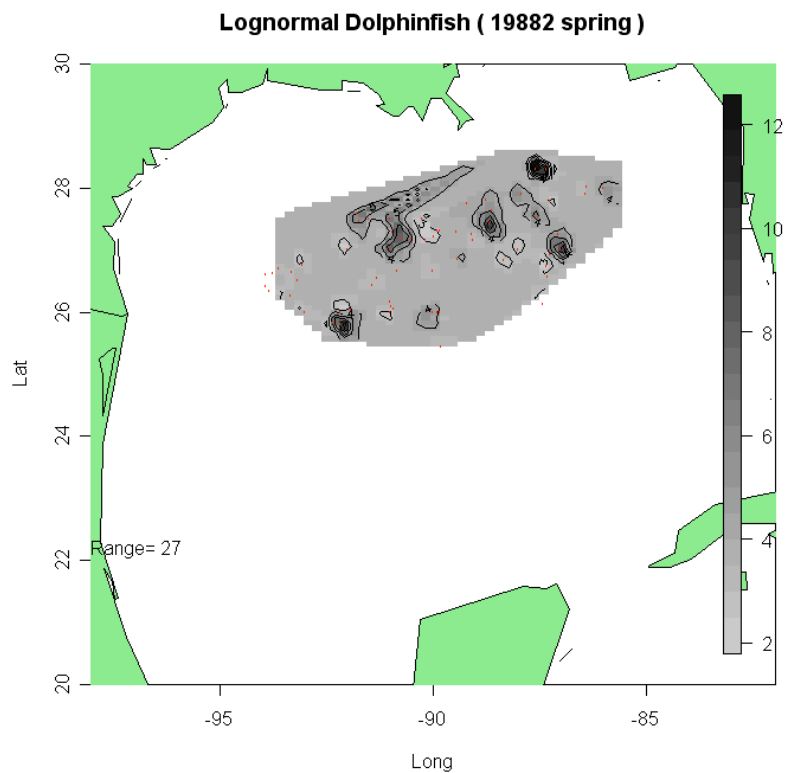
Figure B16. Variograms of the winter indicator swordfish catch.

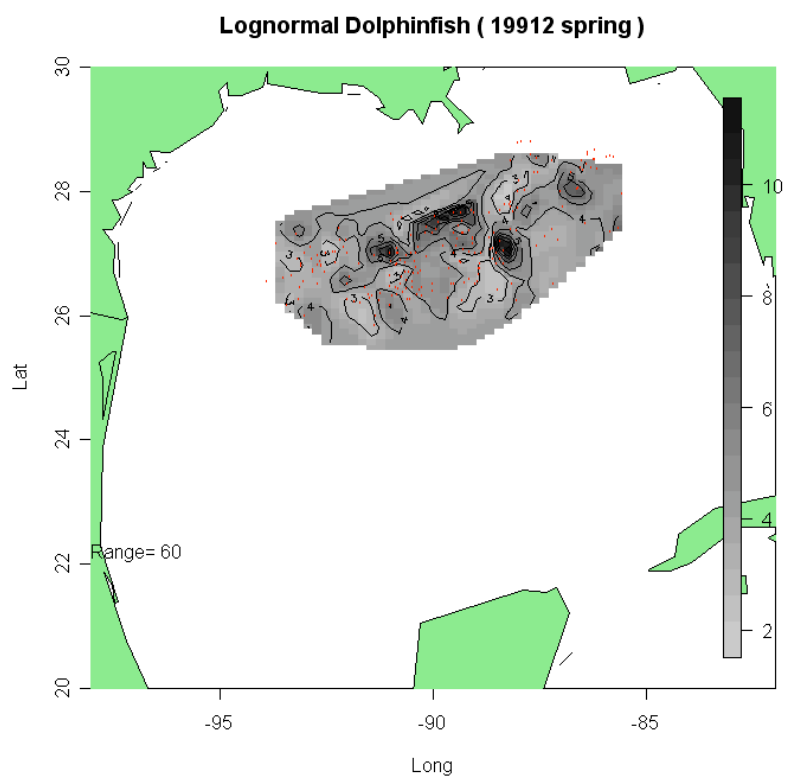
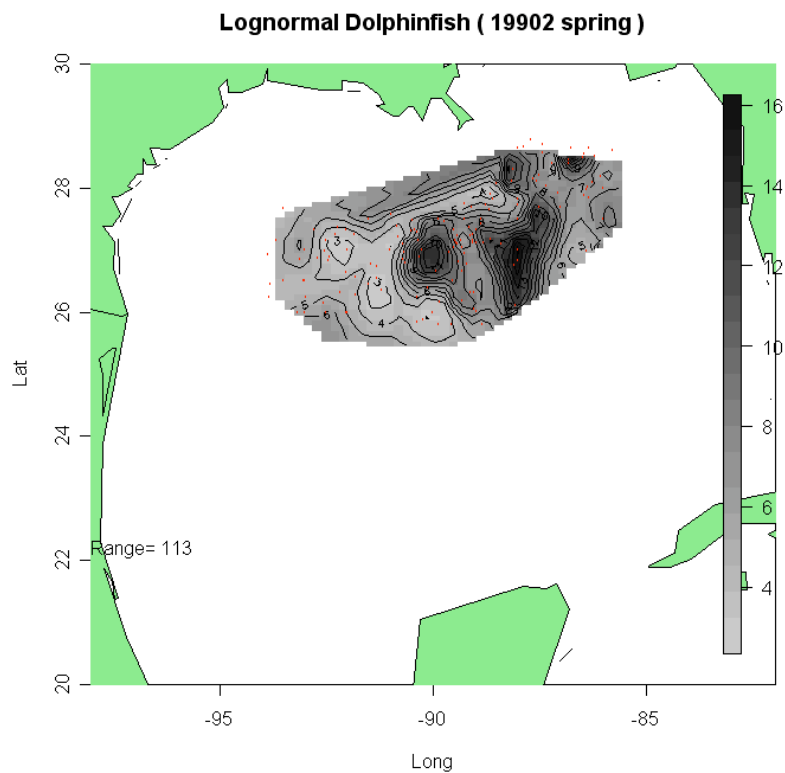
Appendix C—Dolphinfish Kriging Maps

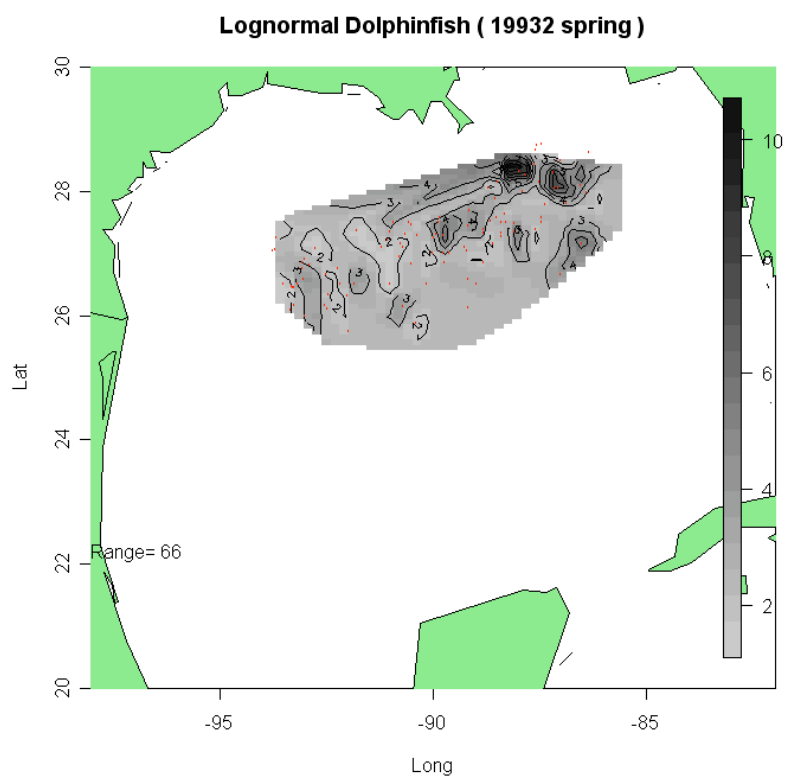
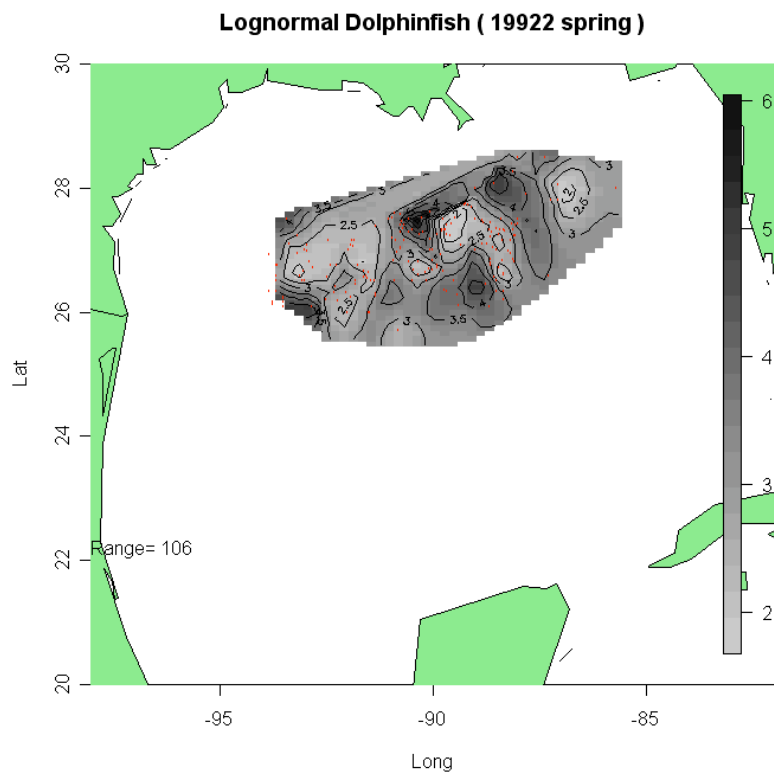
These kriging maps are based on the variogram models presented in Appendix B for each year season. The maps are grouped by seasons. Within each season, the maps based on the lognormal positive observations are displayed first, followed by the indicator (proportion positive) maps.

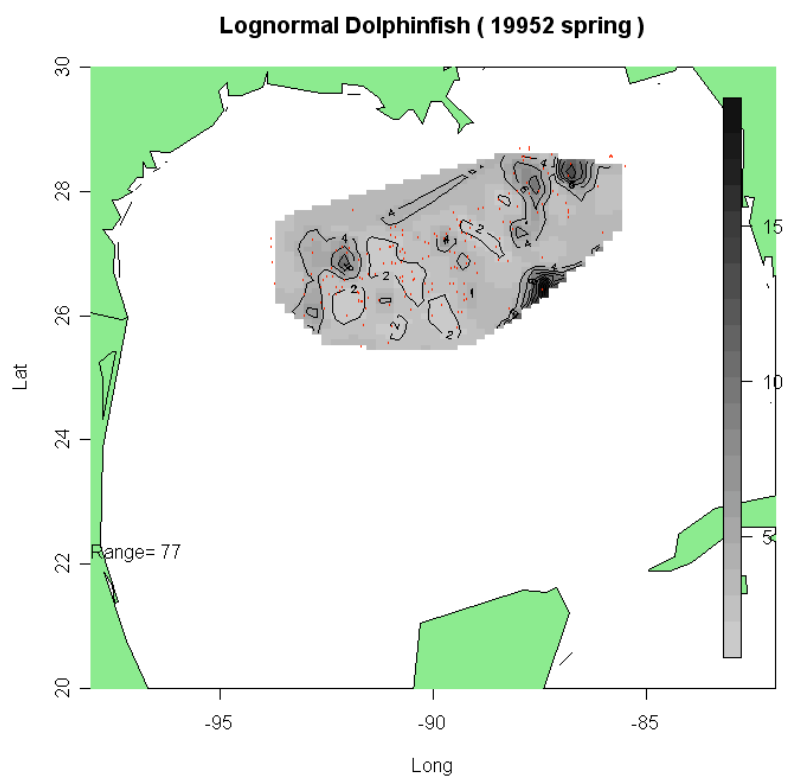
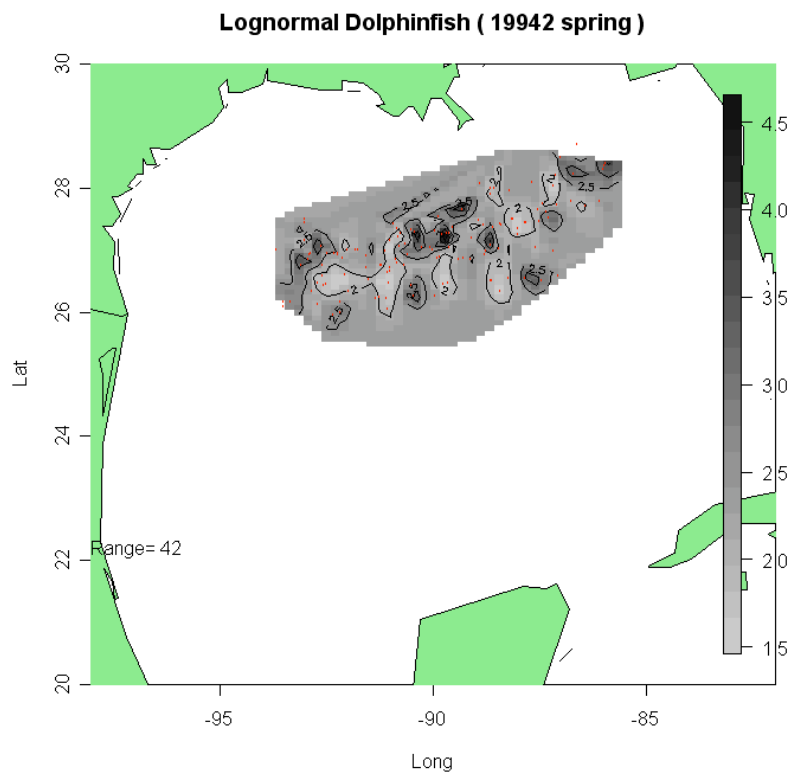
Spring Kriging Maps

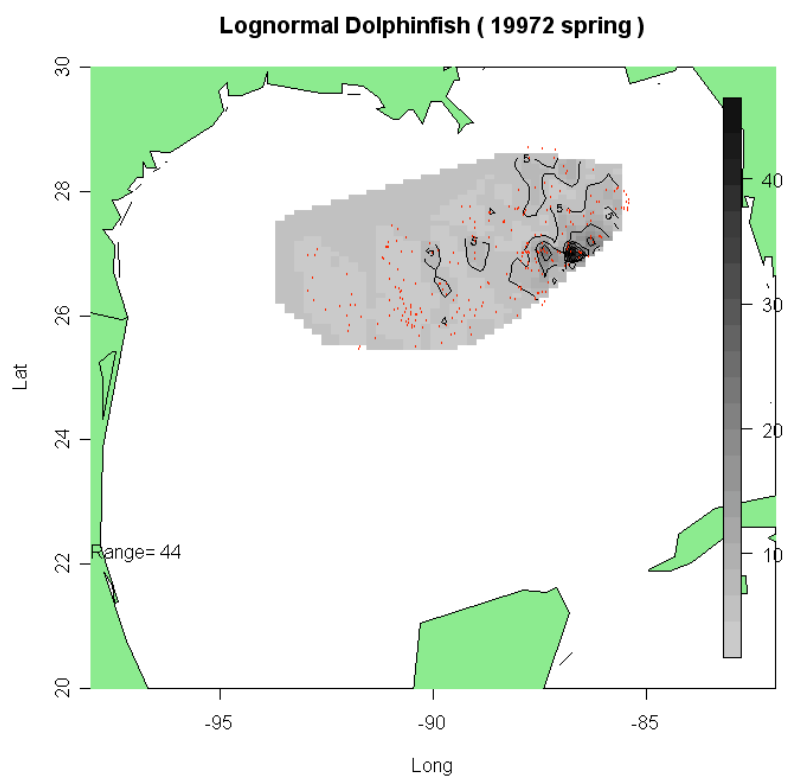
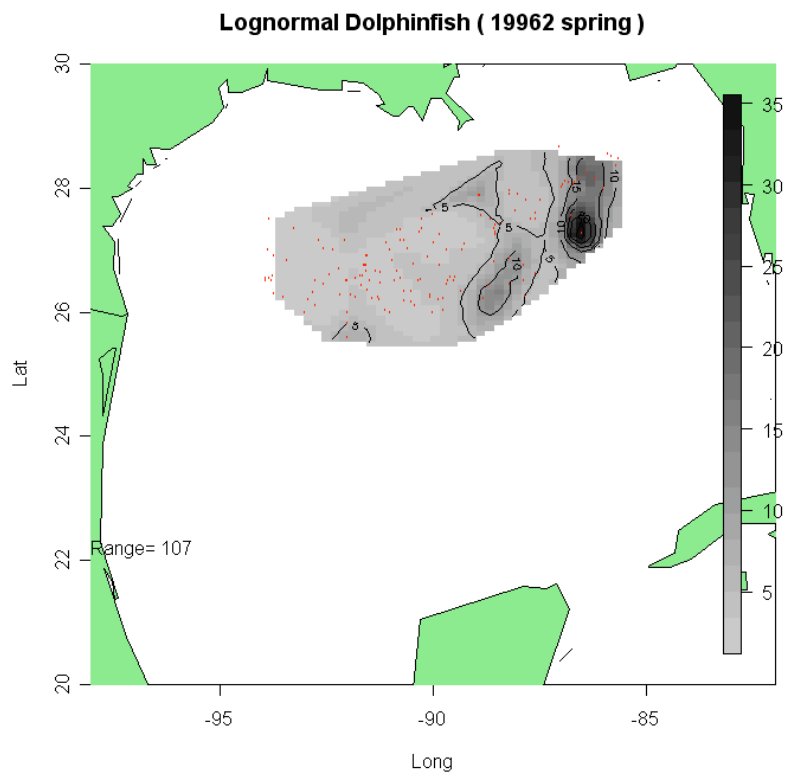


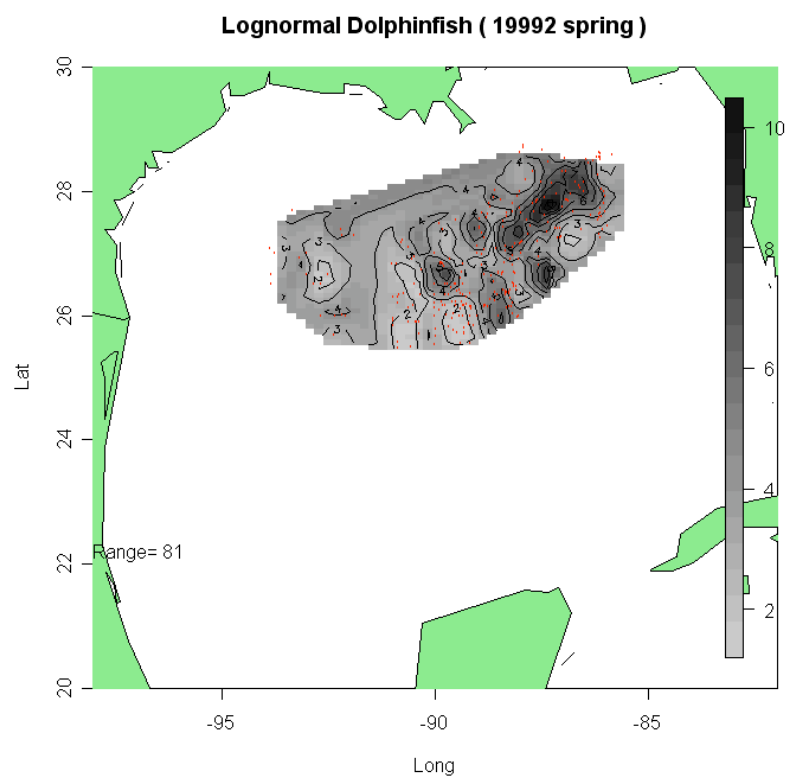
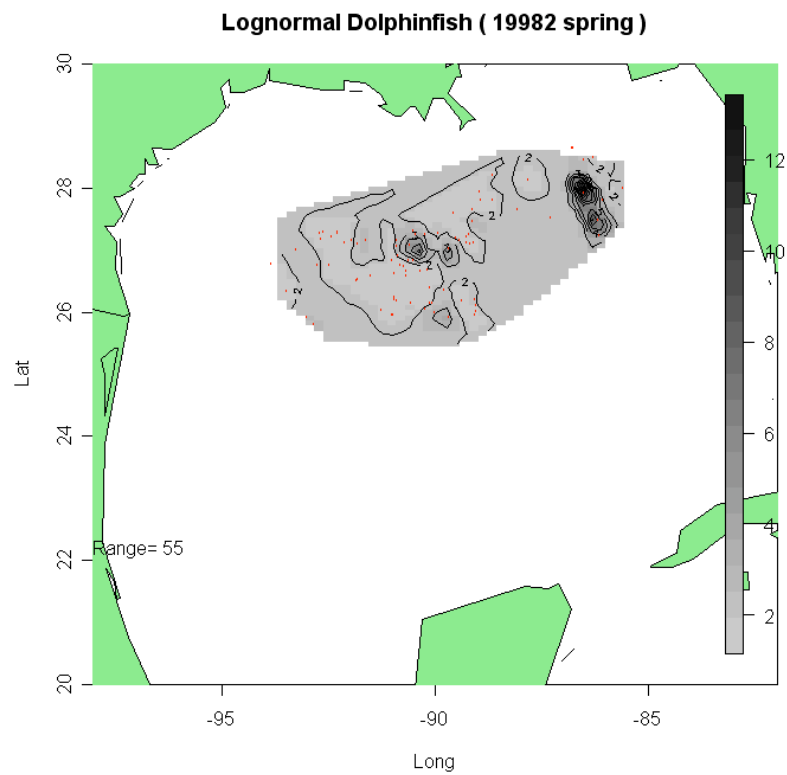


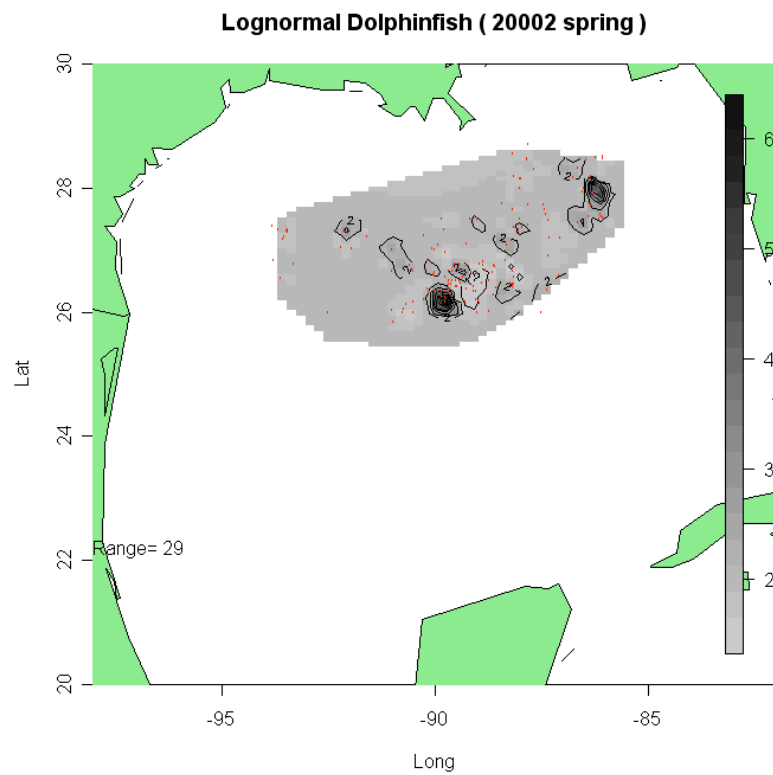


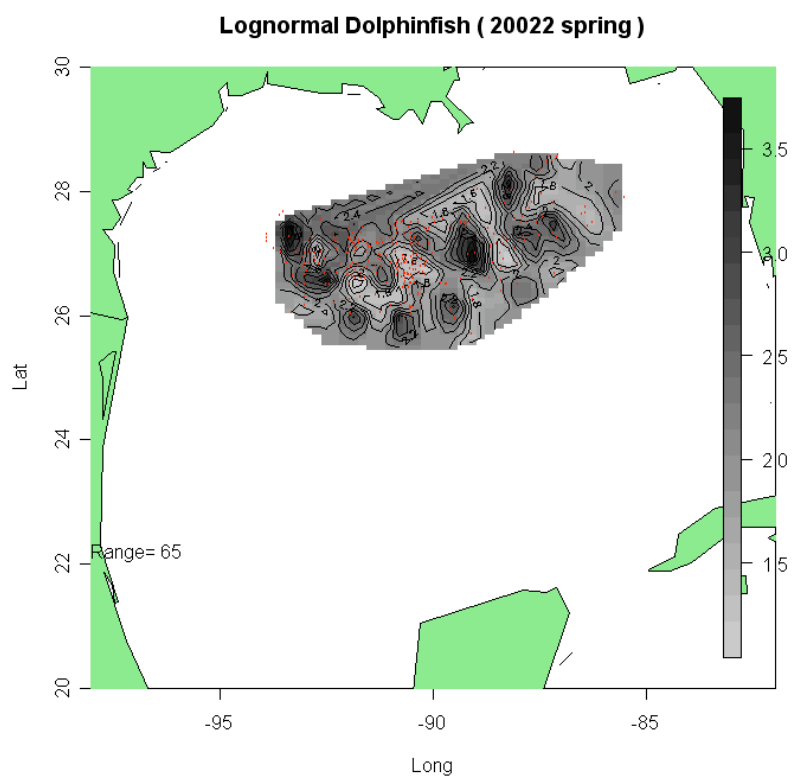
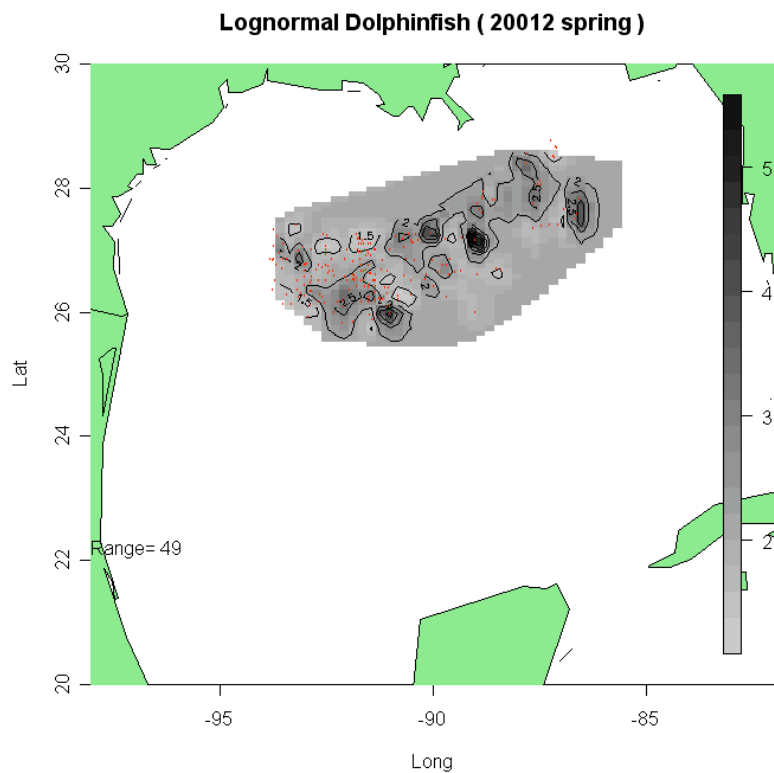


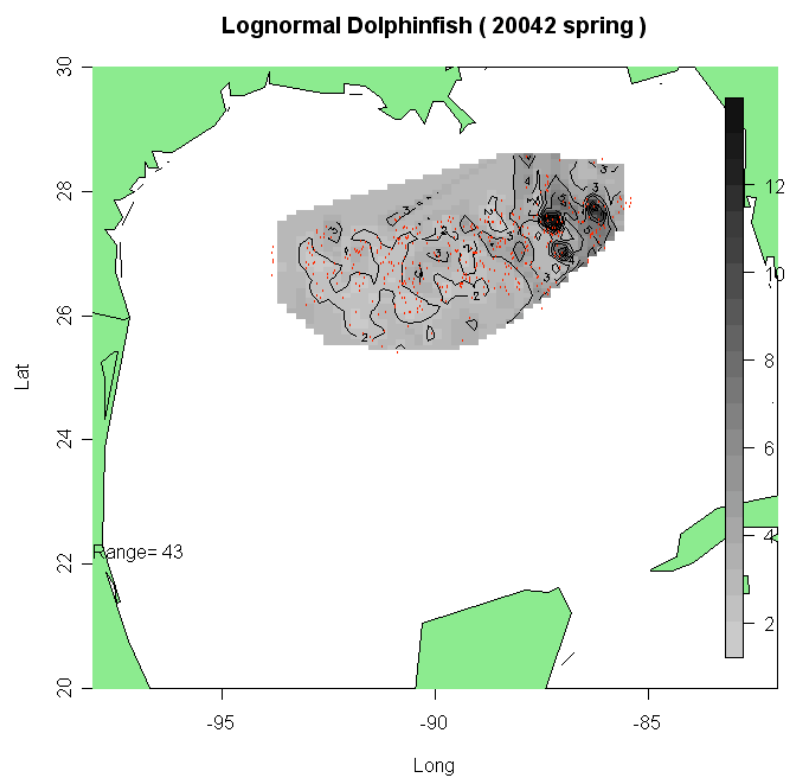
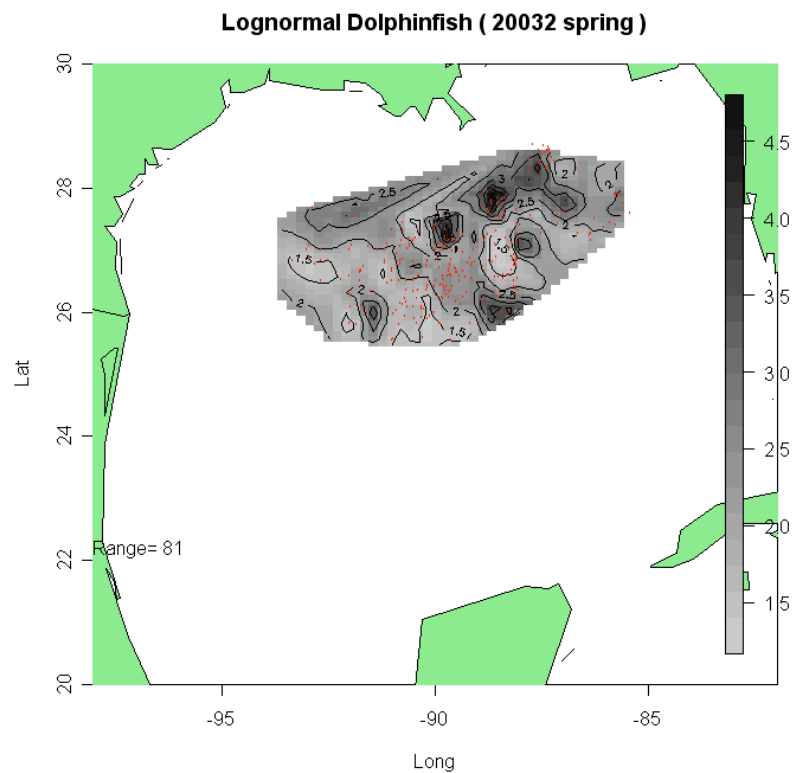


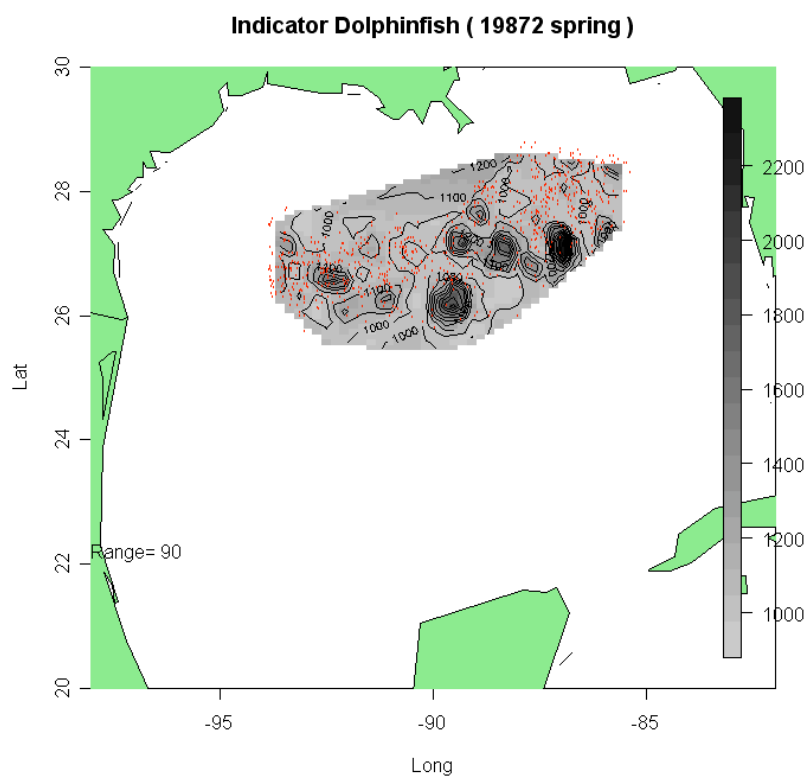
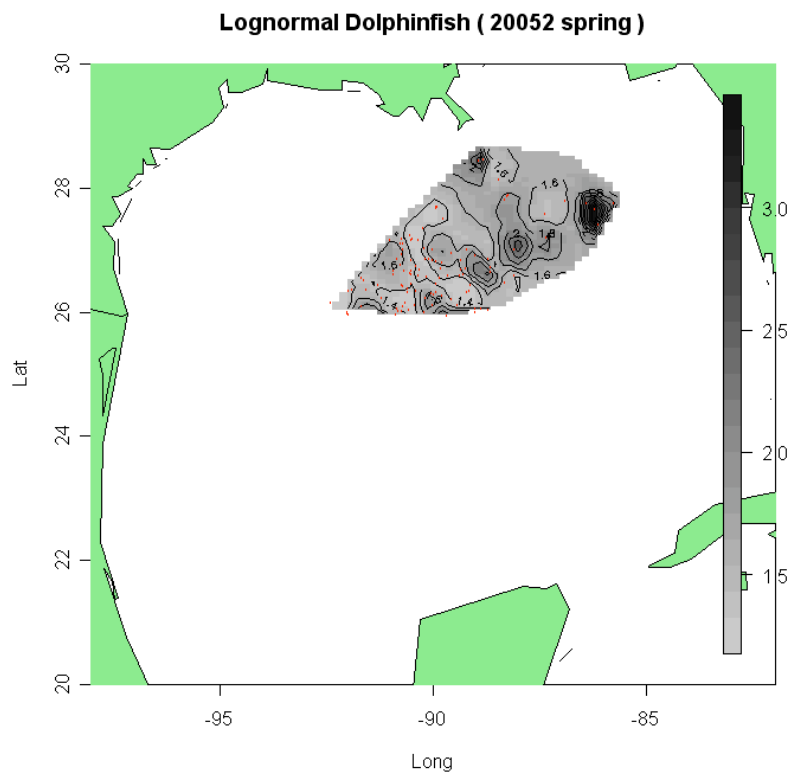


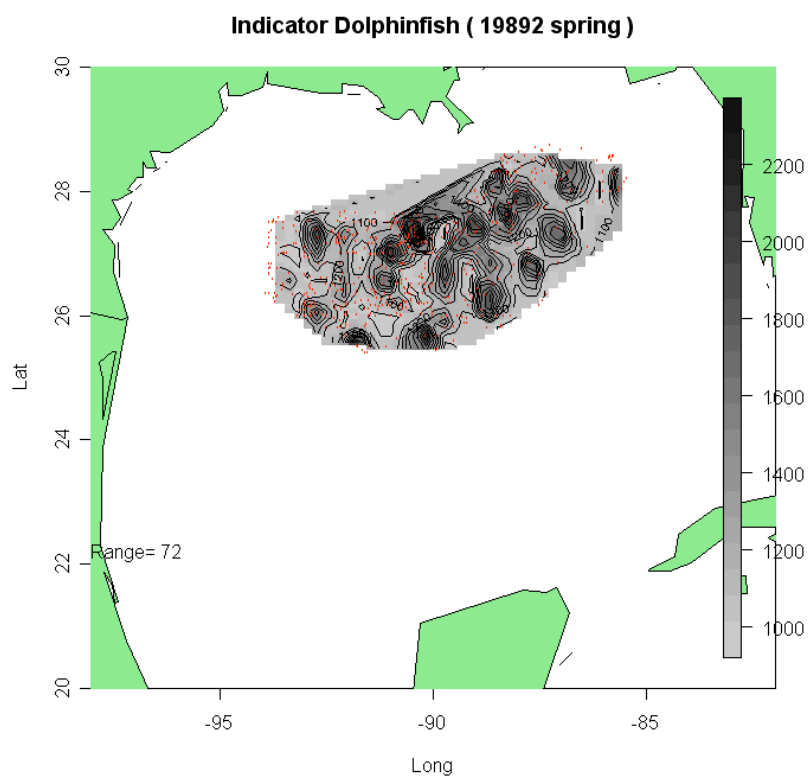
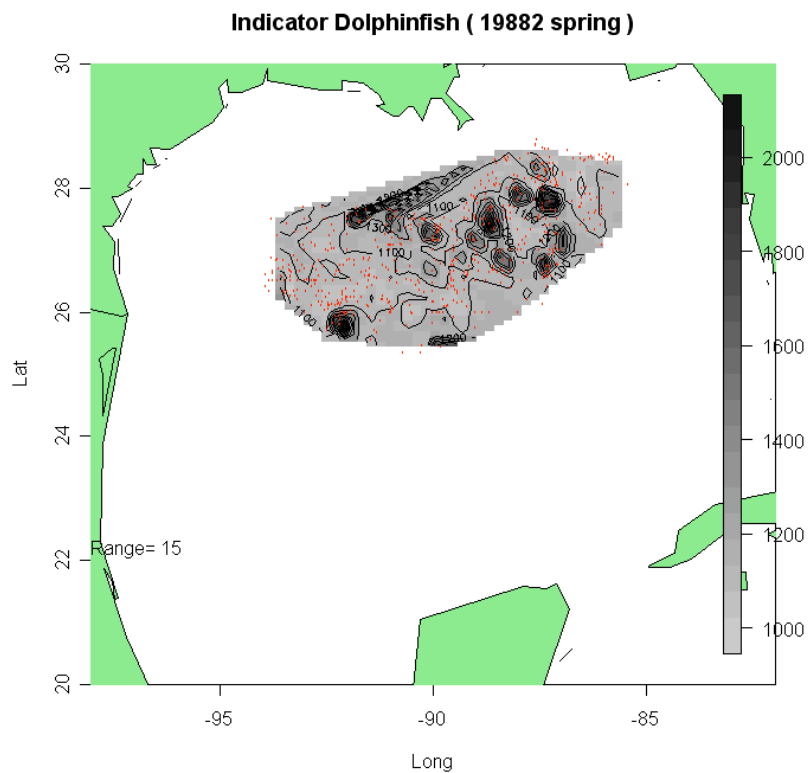


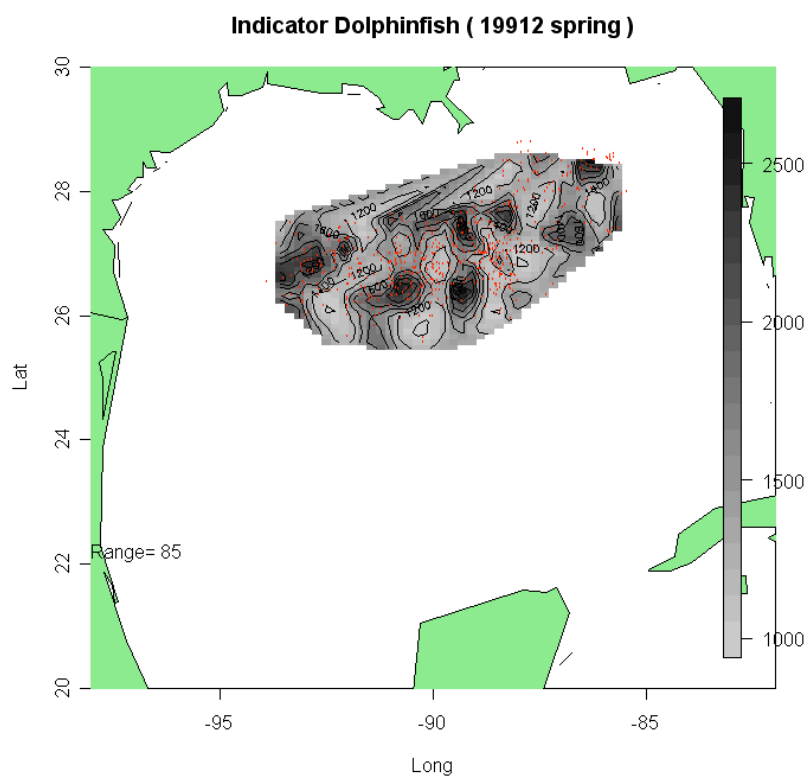
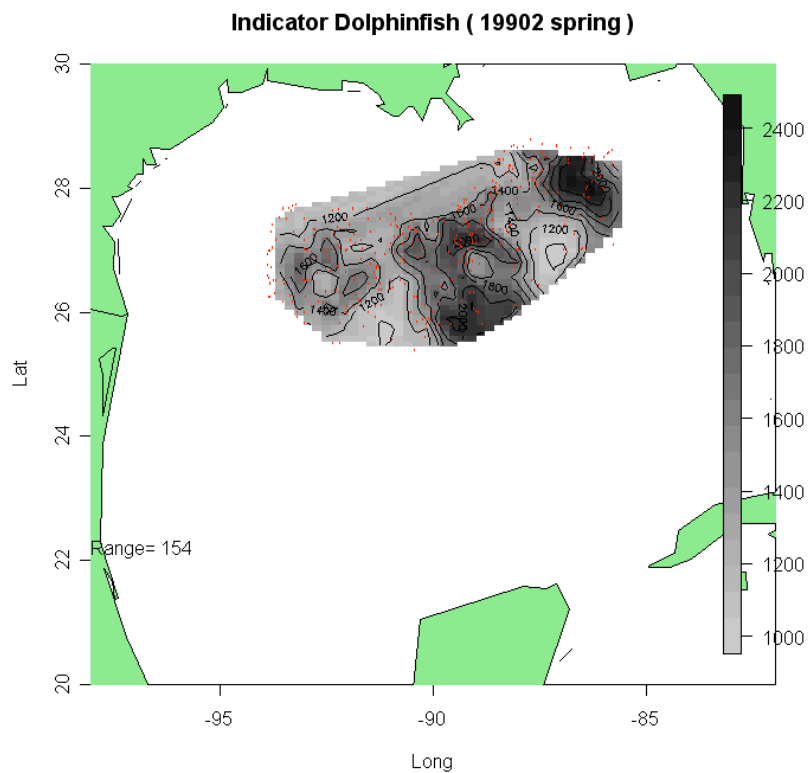


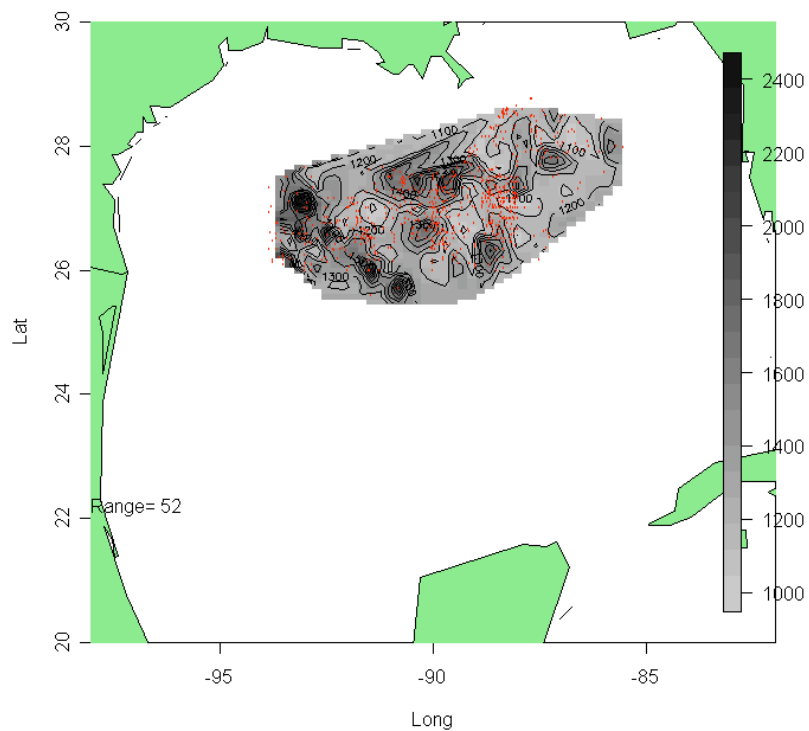
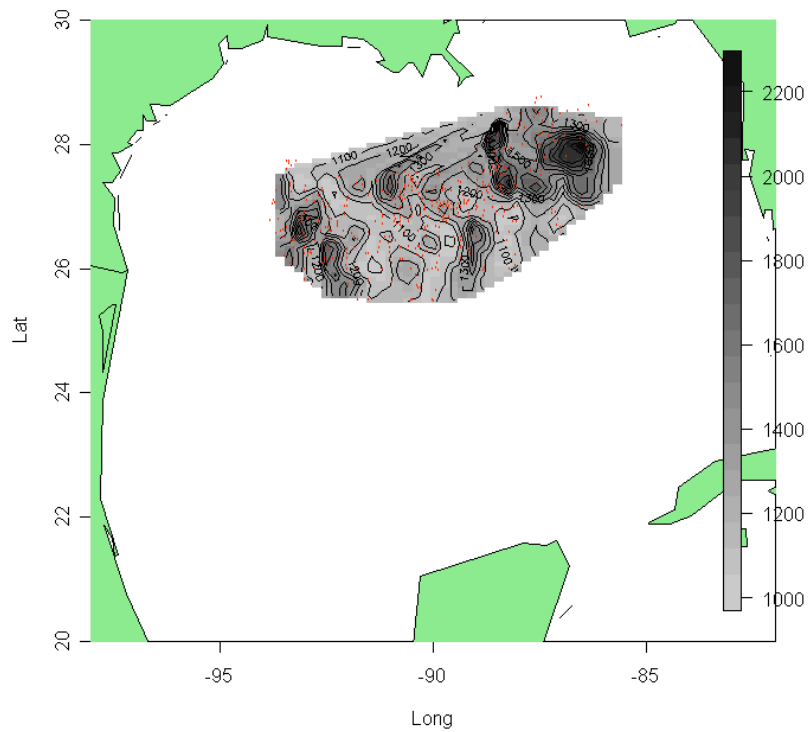


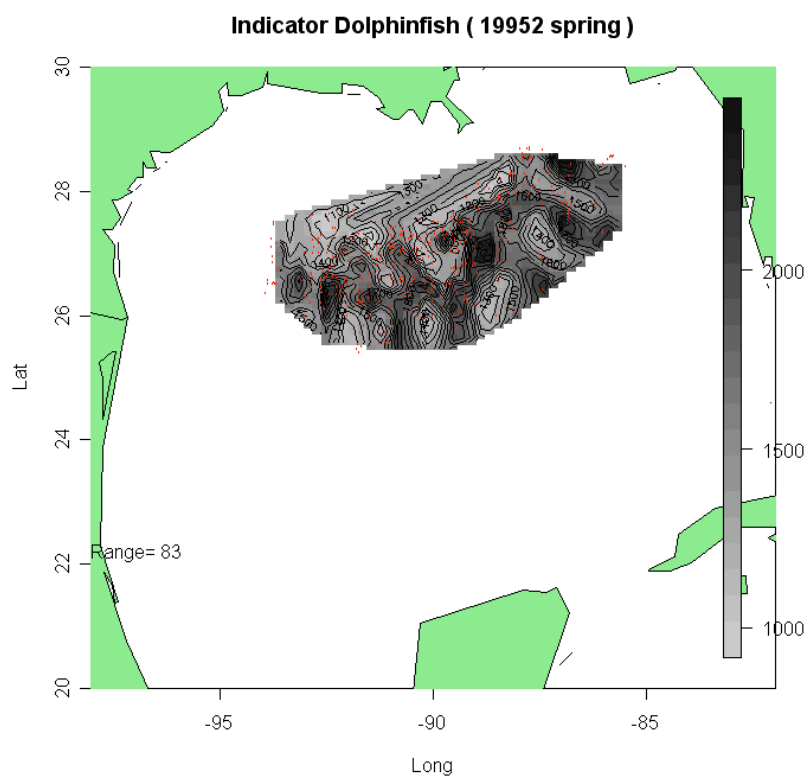
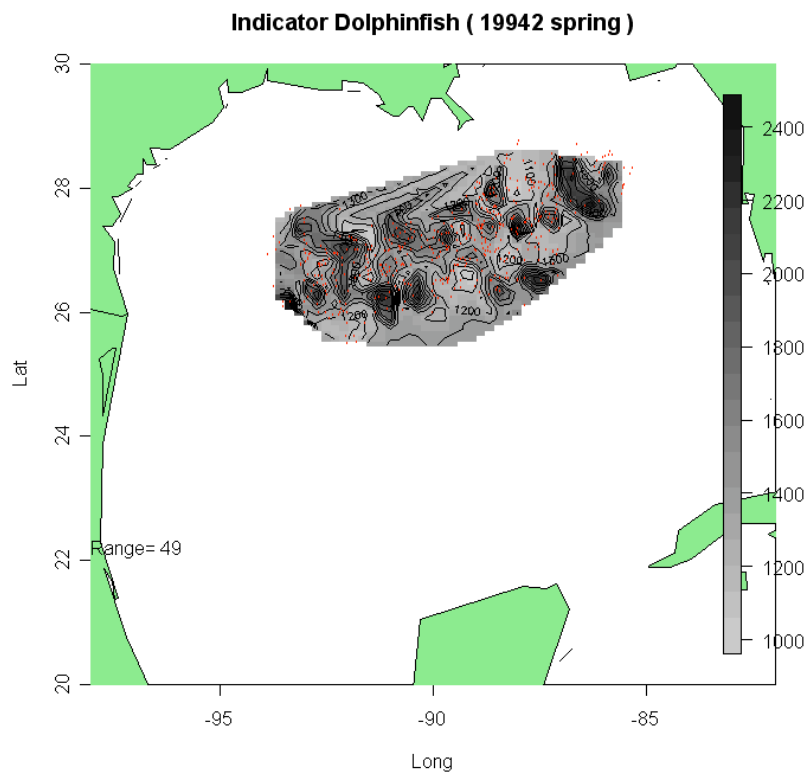


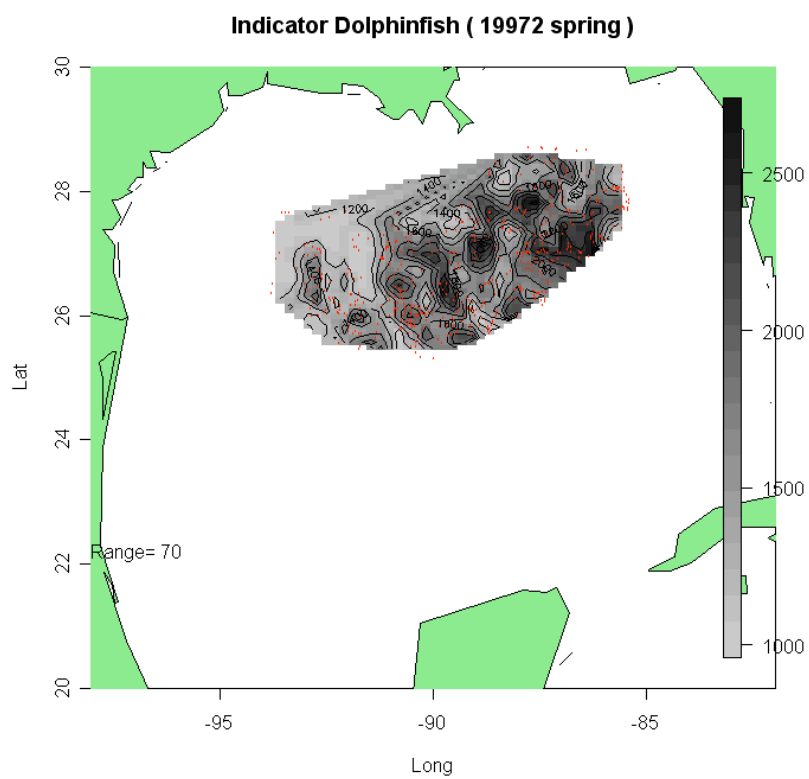
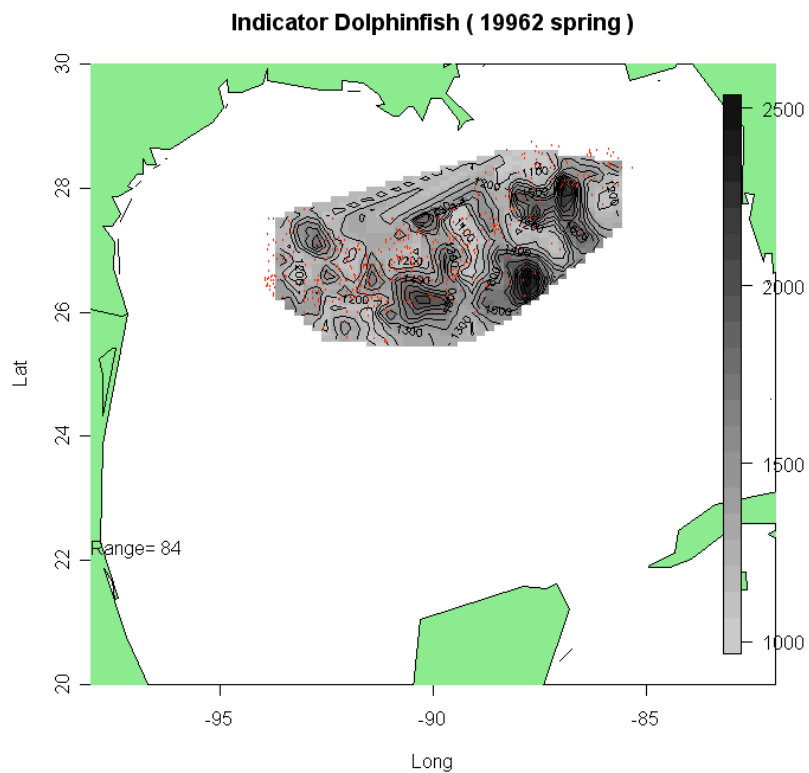


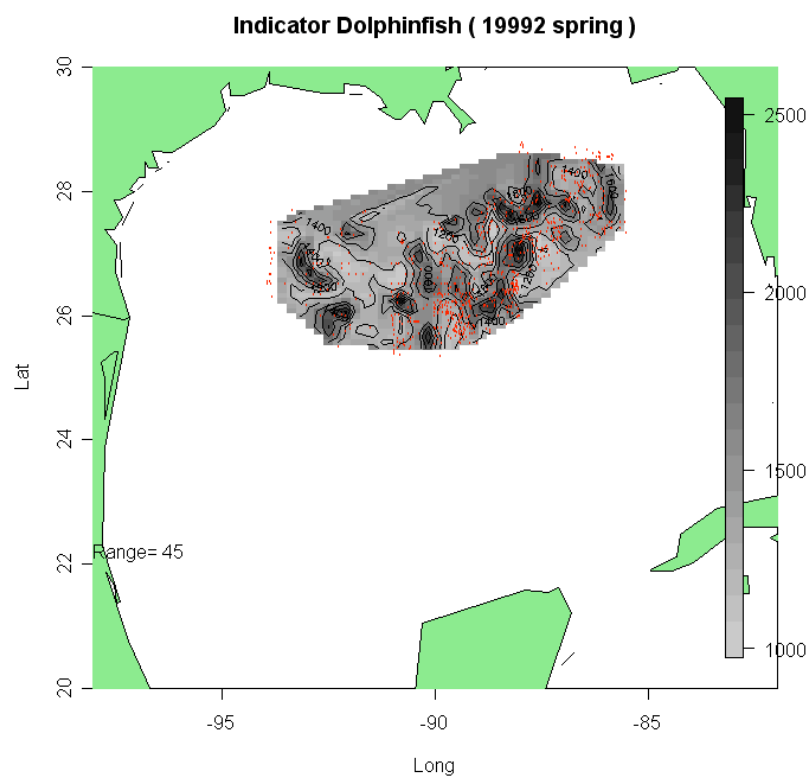
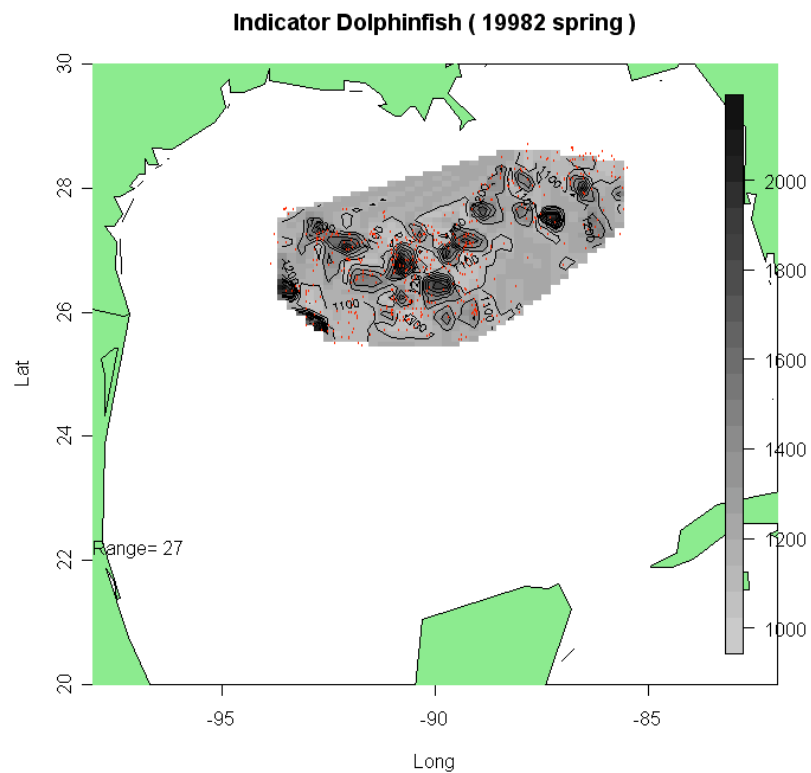


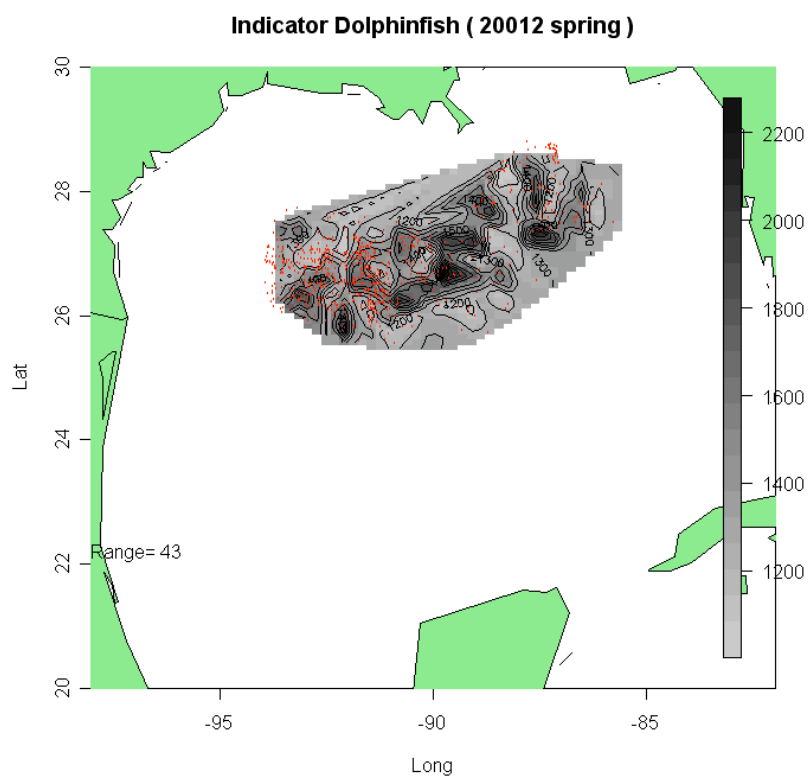
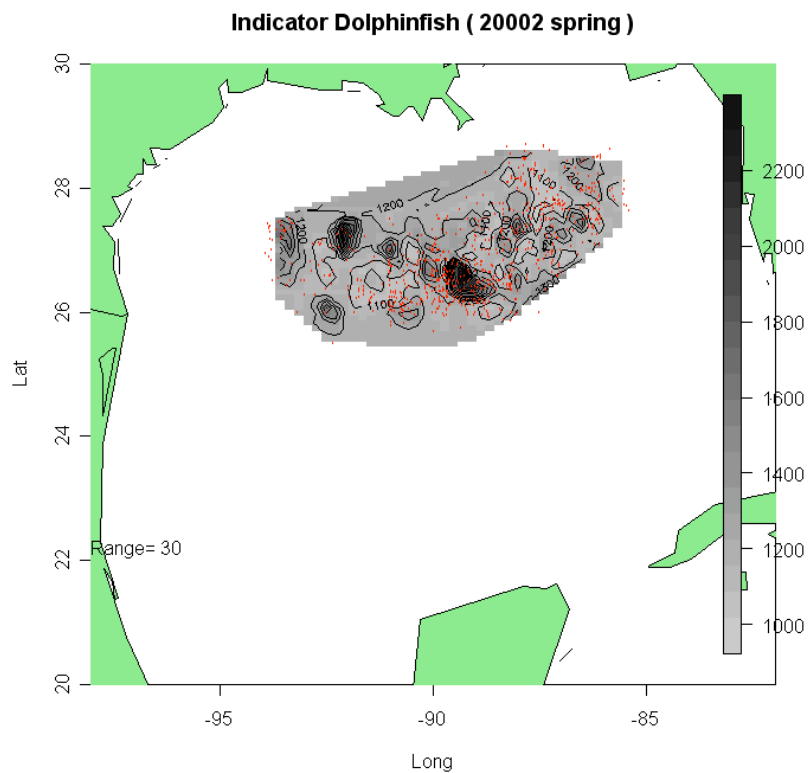


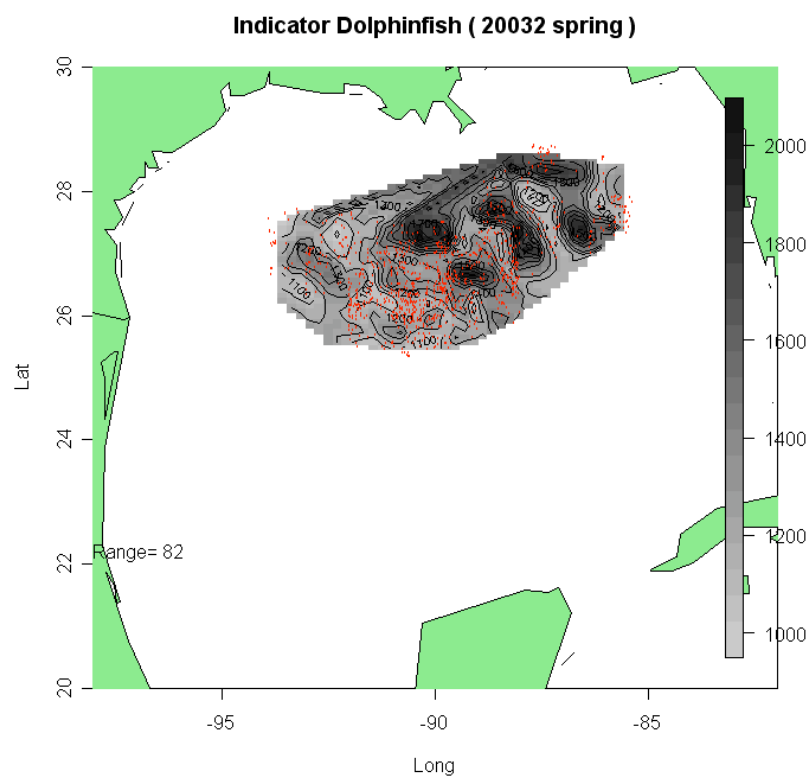
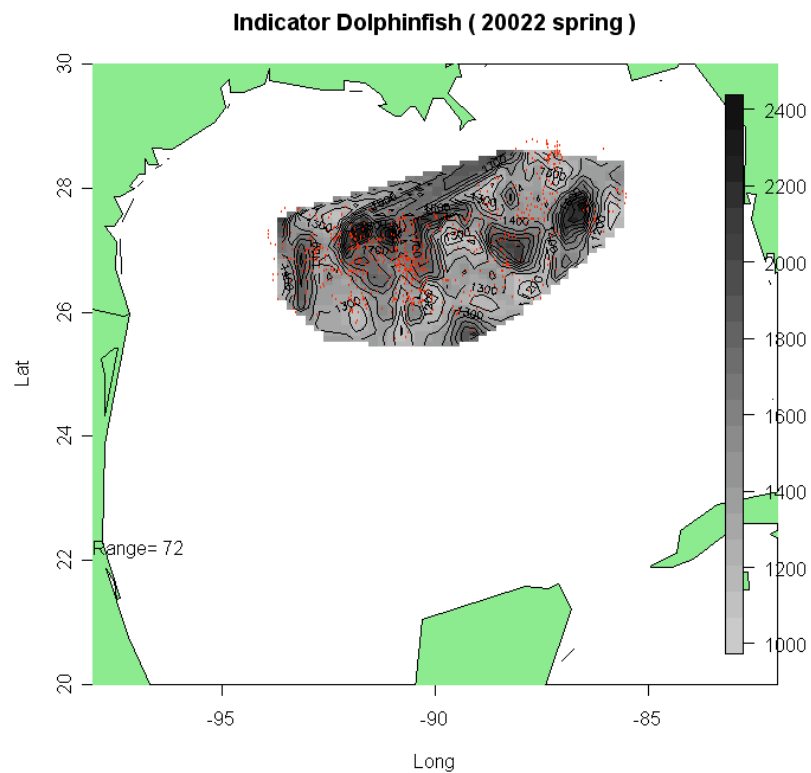
Indicator Dolphinfish (19922 spring)**Indicator Dolphinfish (19932 spring)**

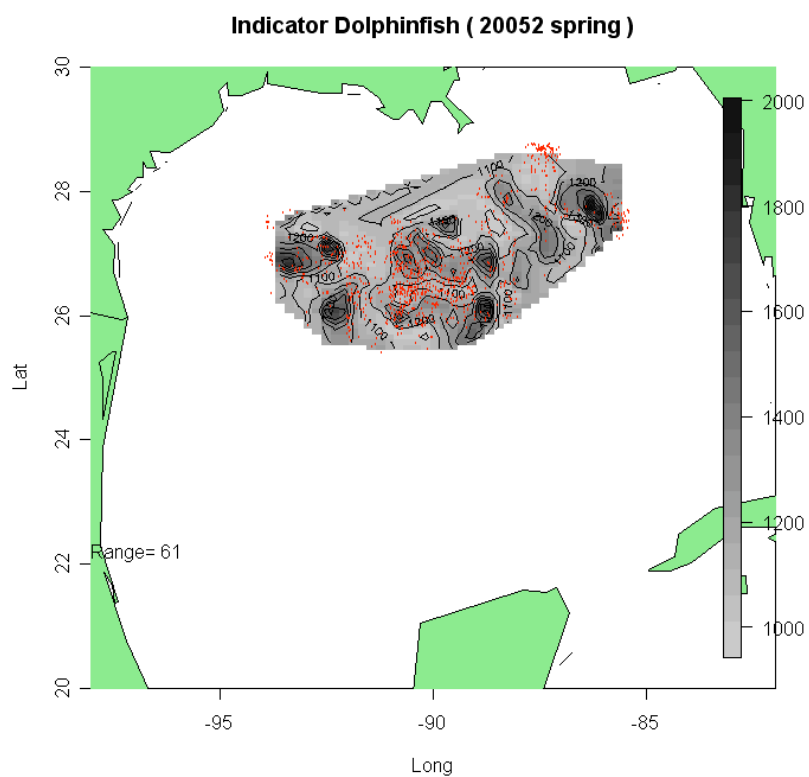
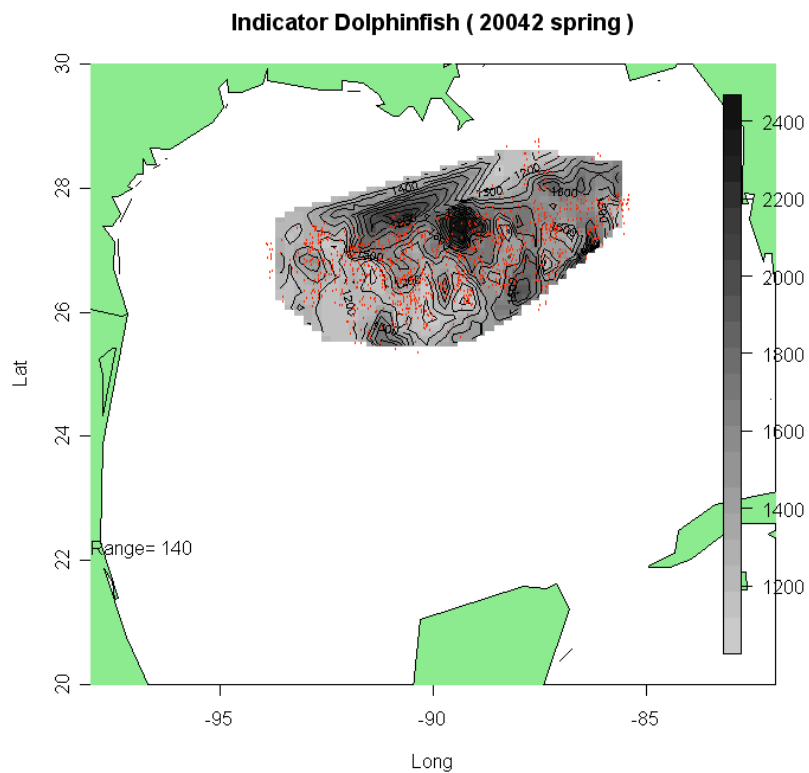


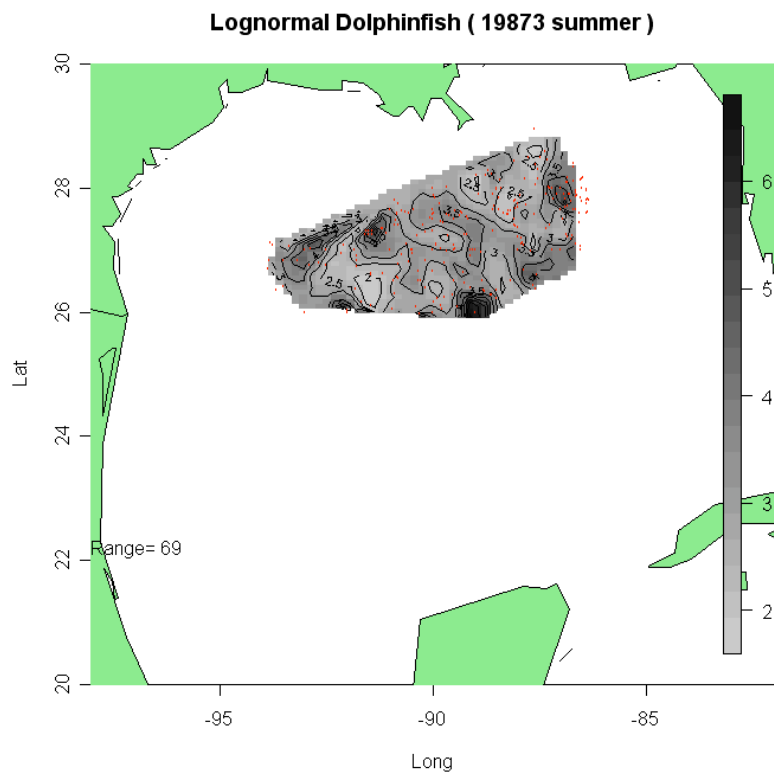




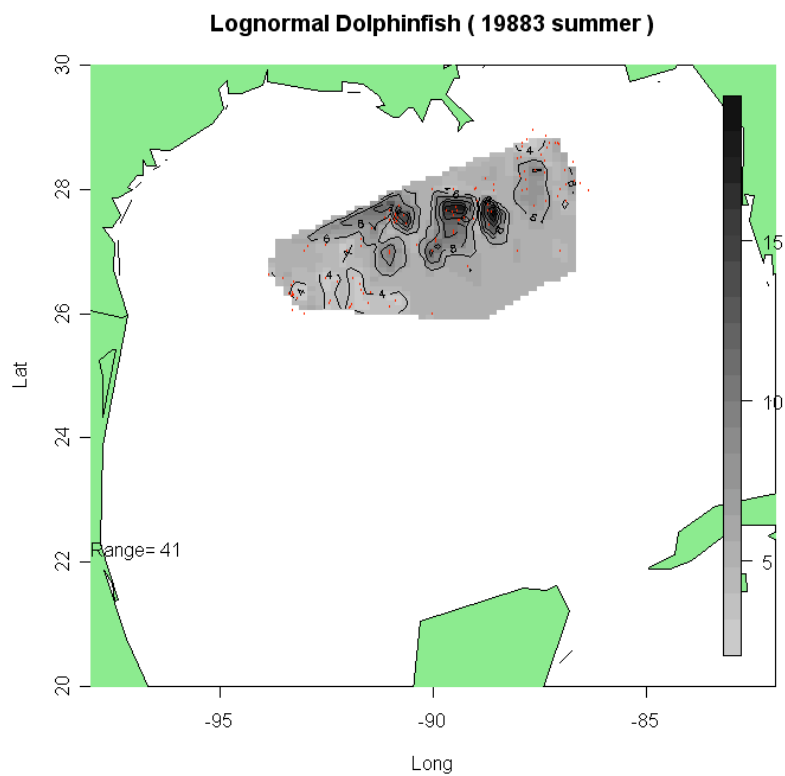


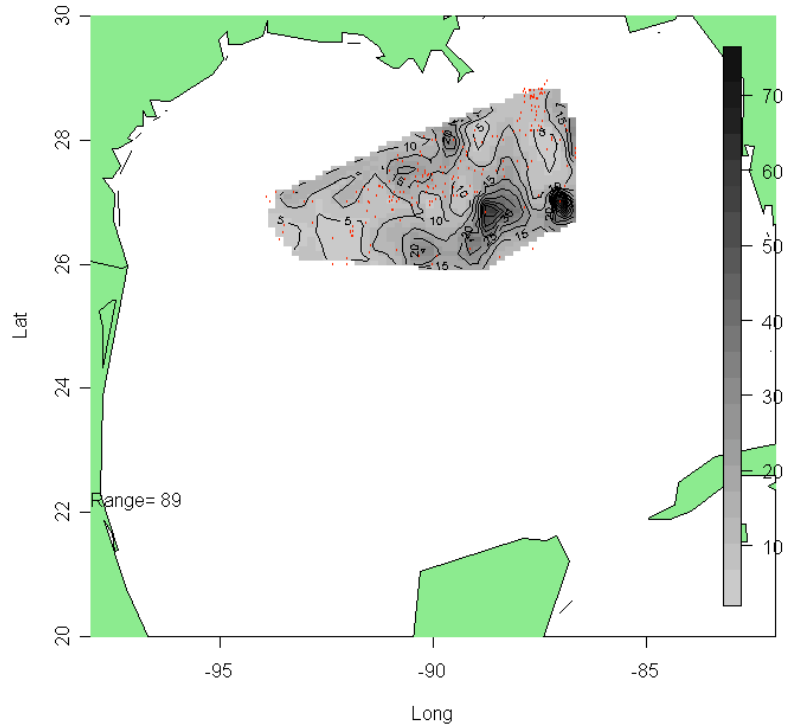
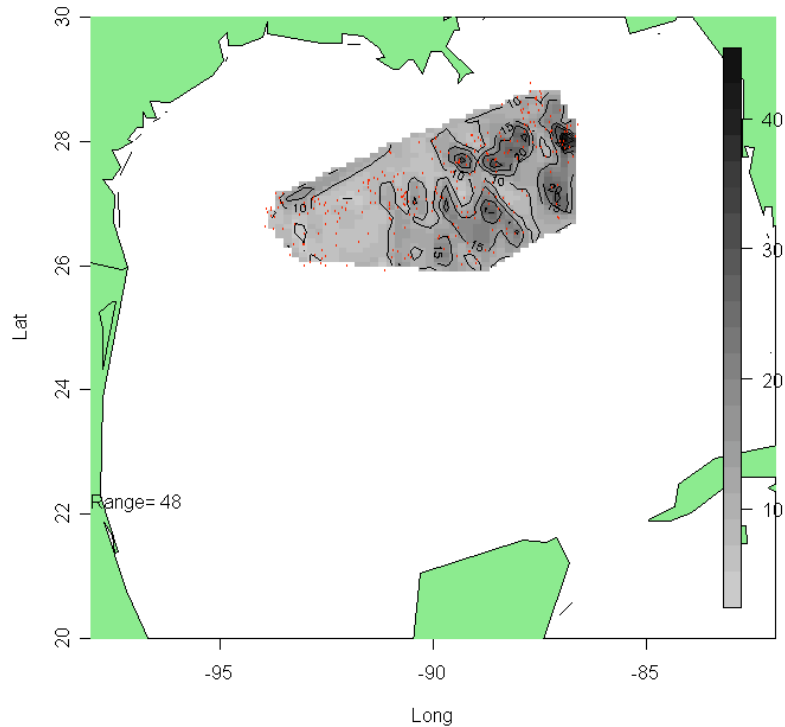


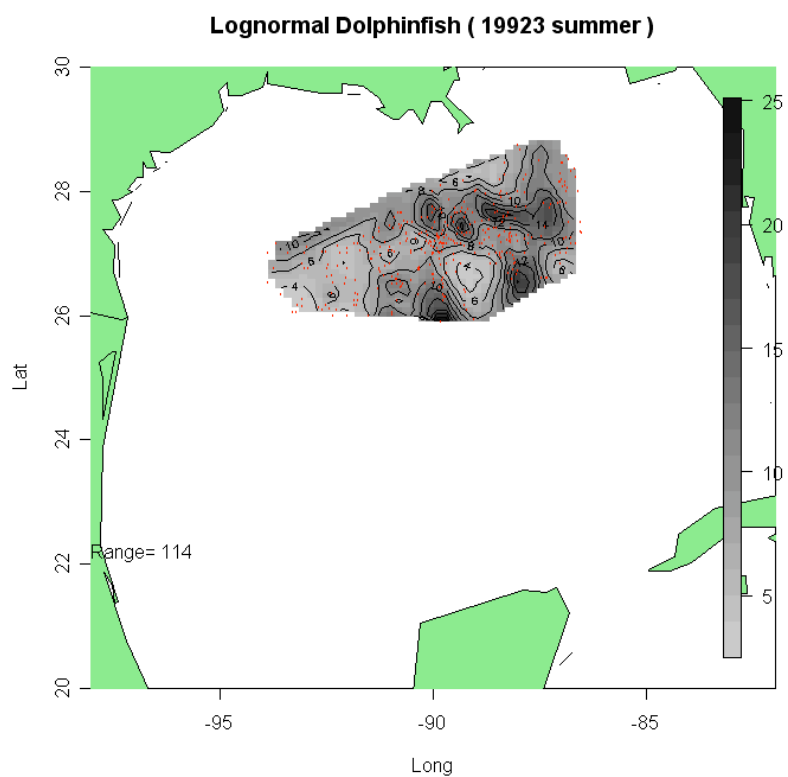
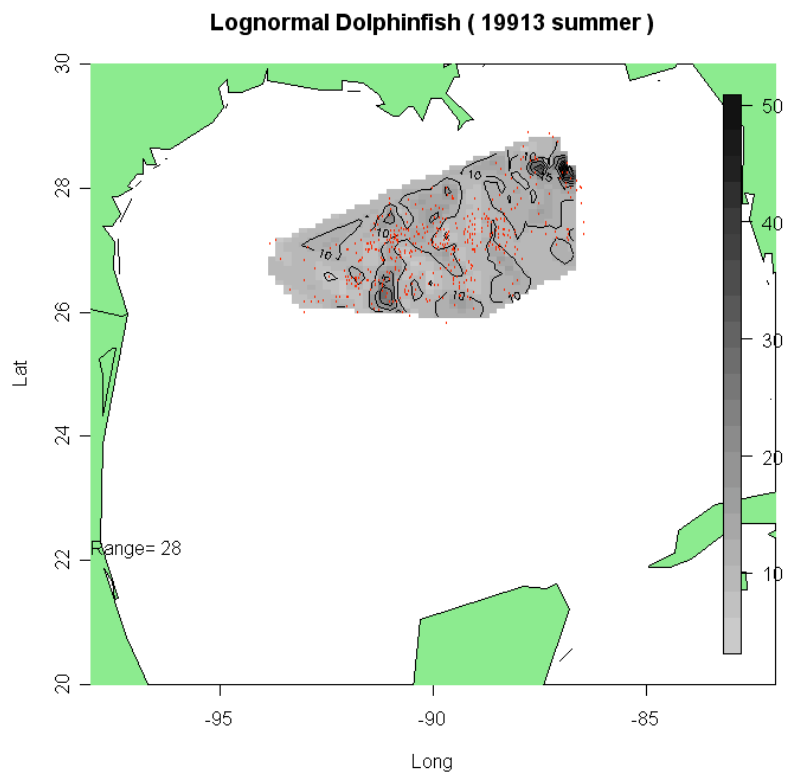


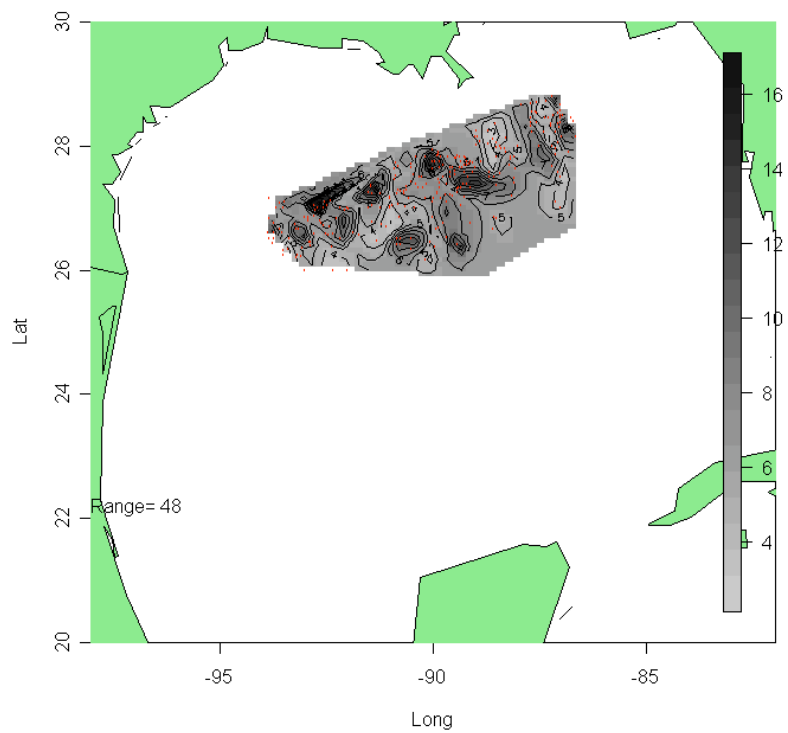
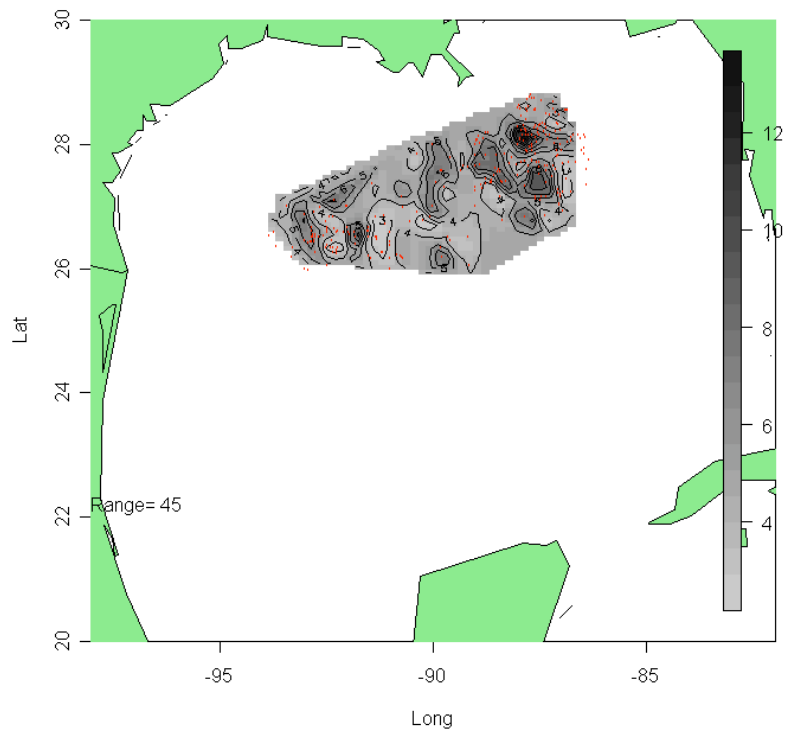


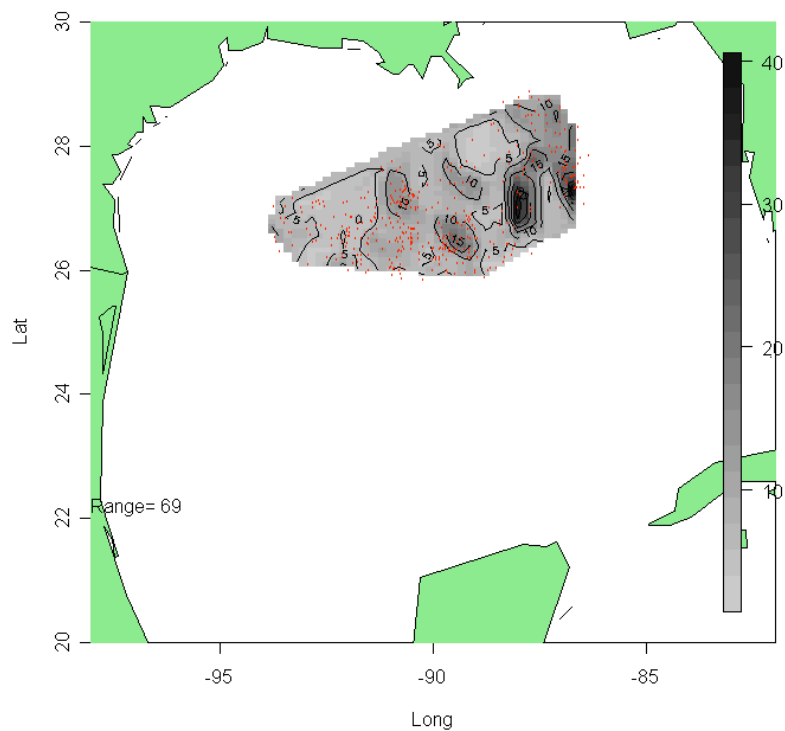
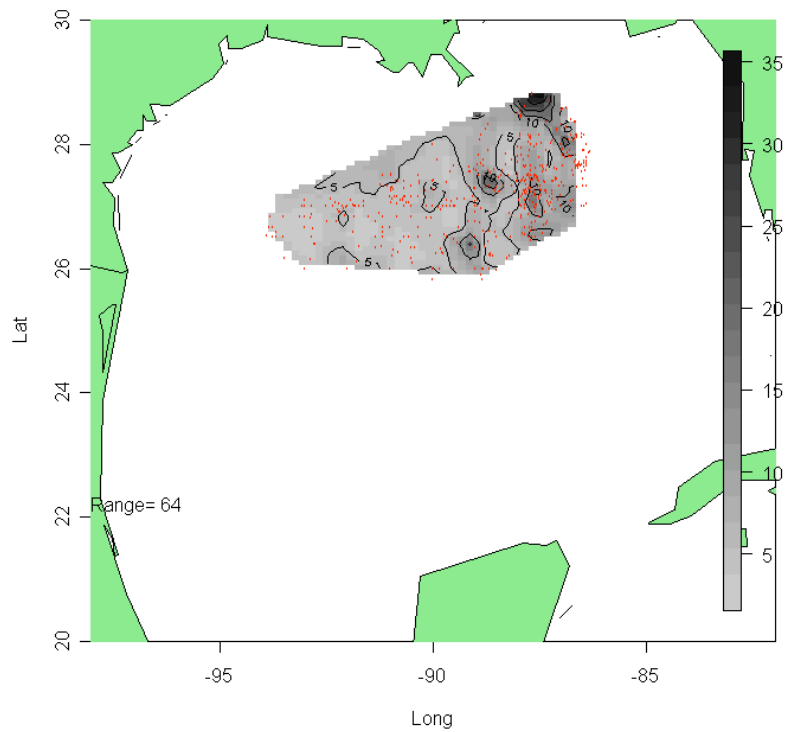
Summer Kriging Maps

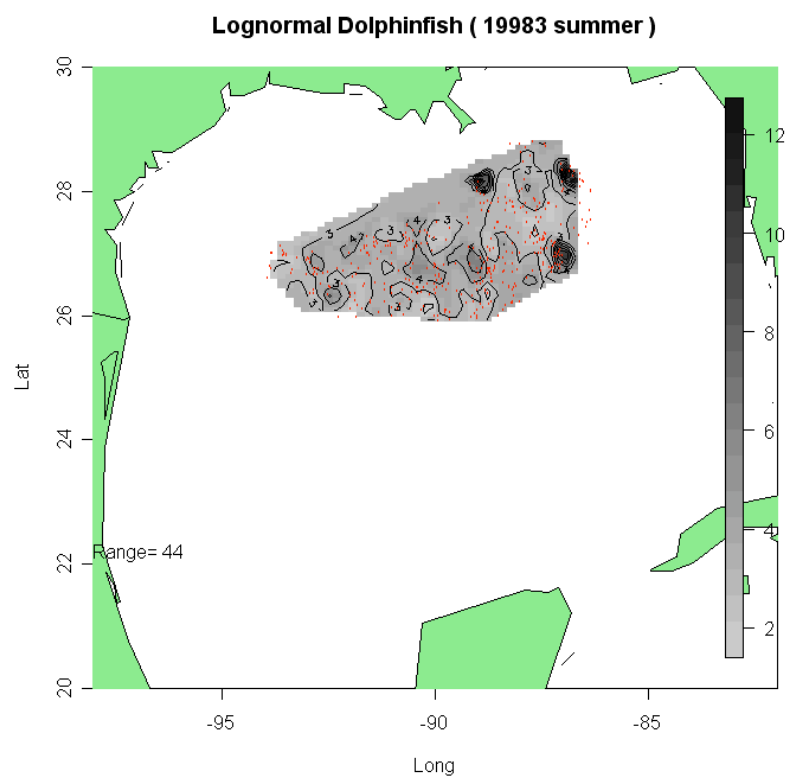
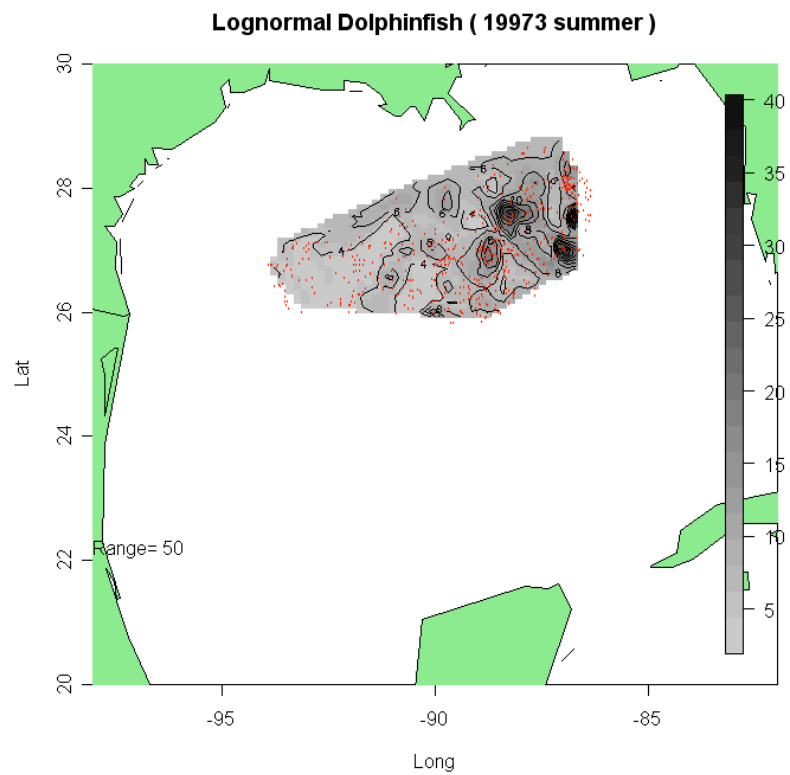


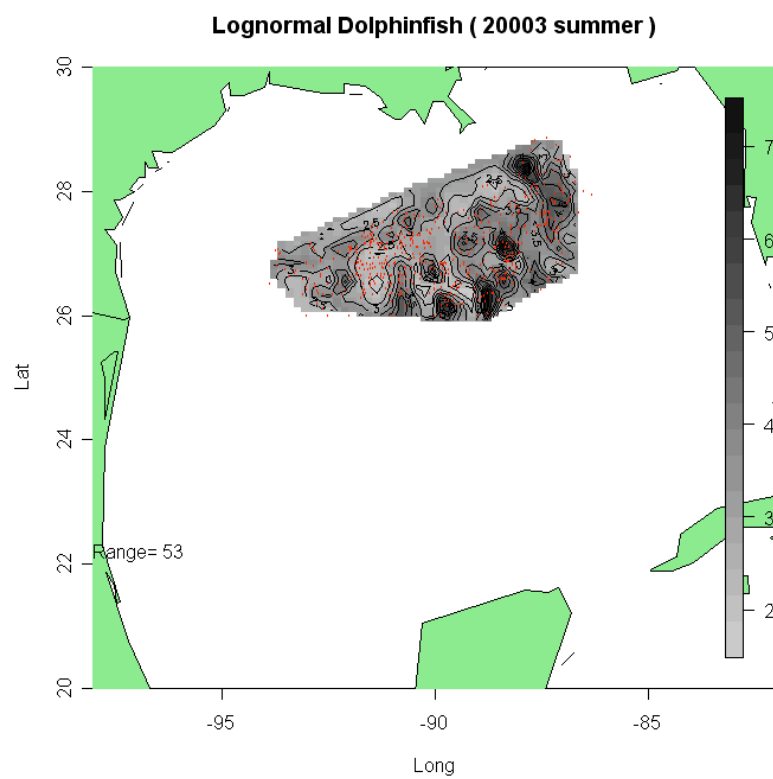
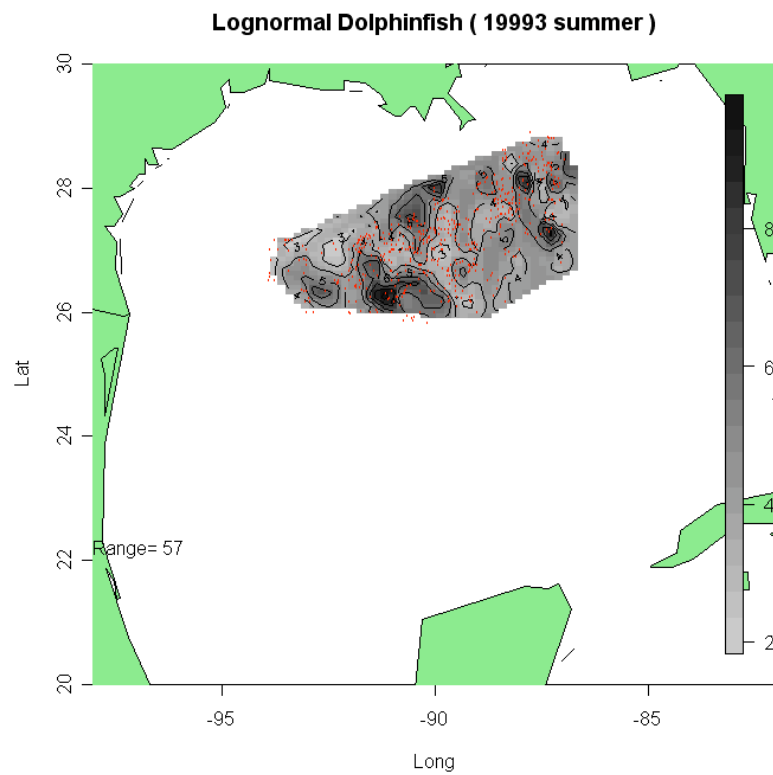
Lognormal Dolphinfish (19893 summer)**Lognormal Dolphinfish (19903 summer)**

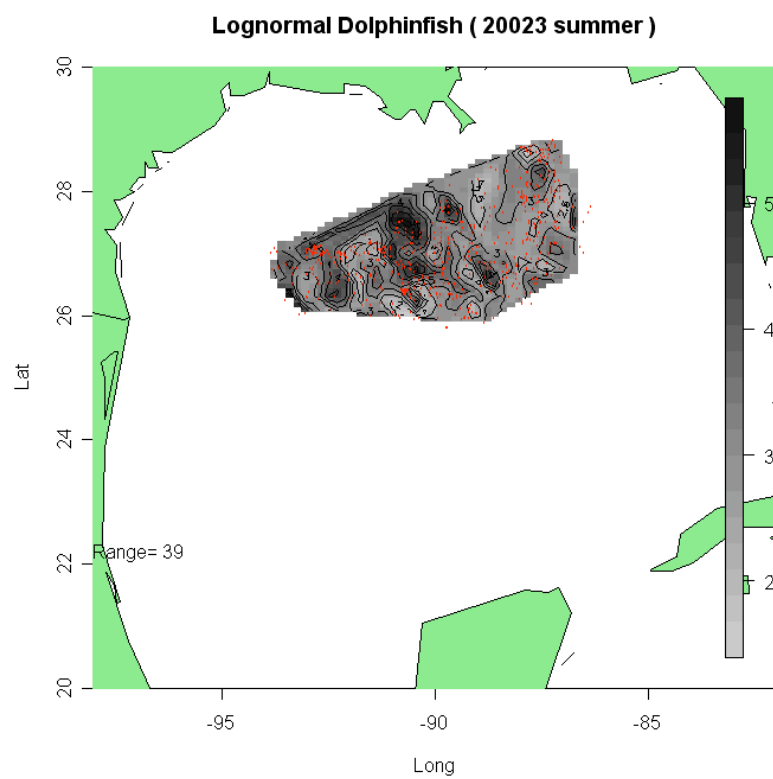
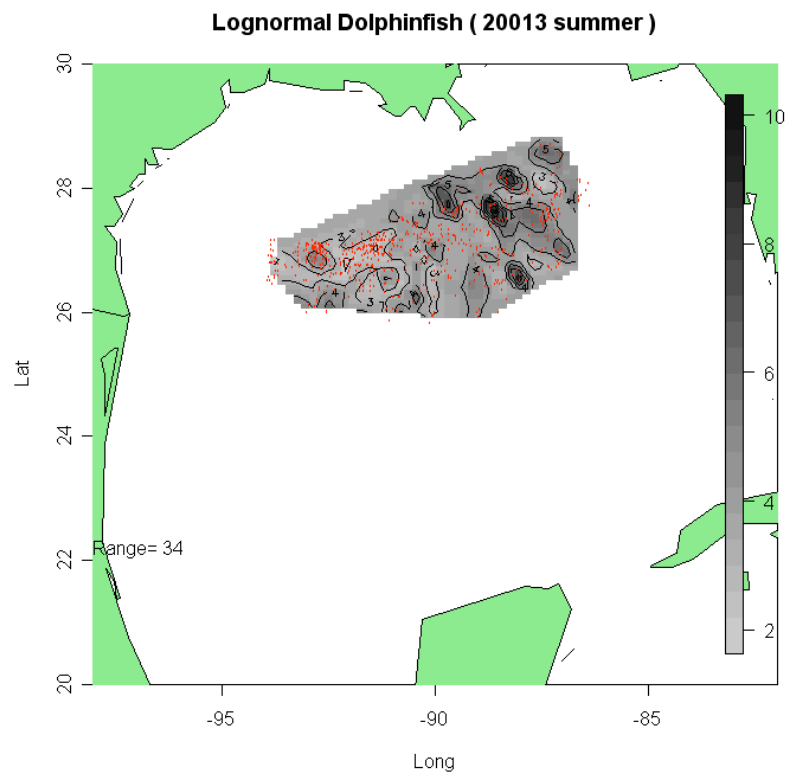


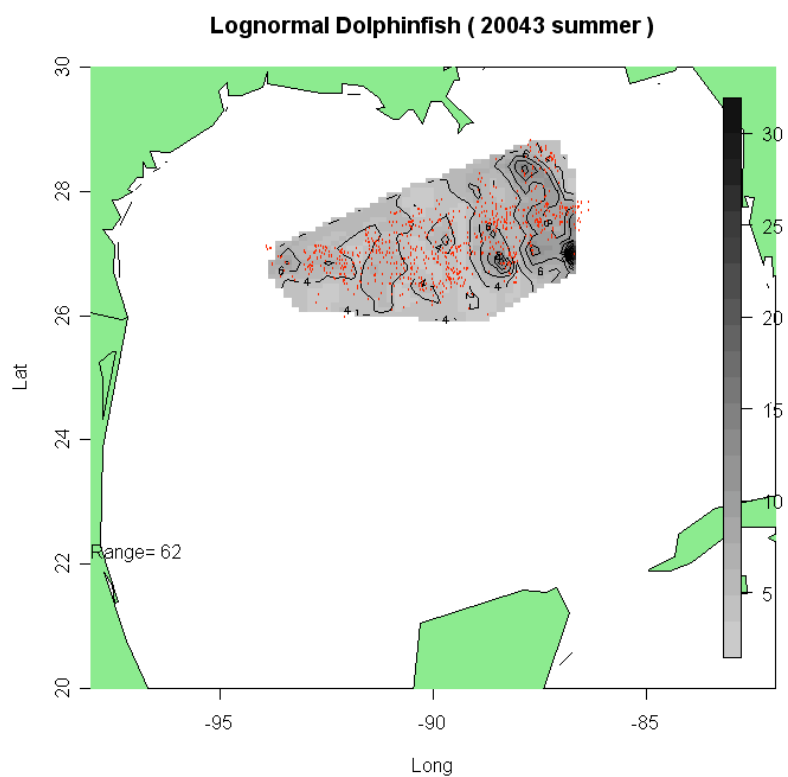
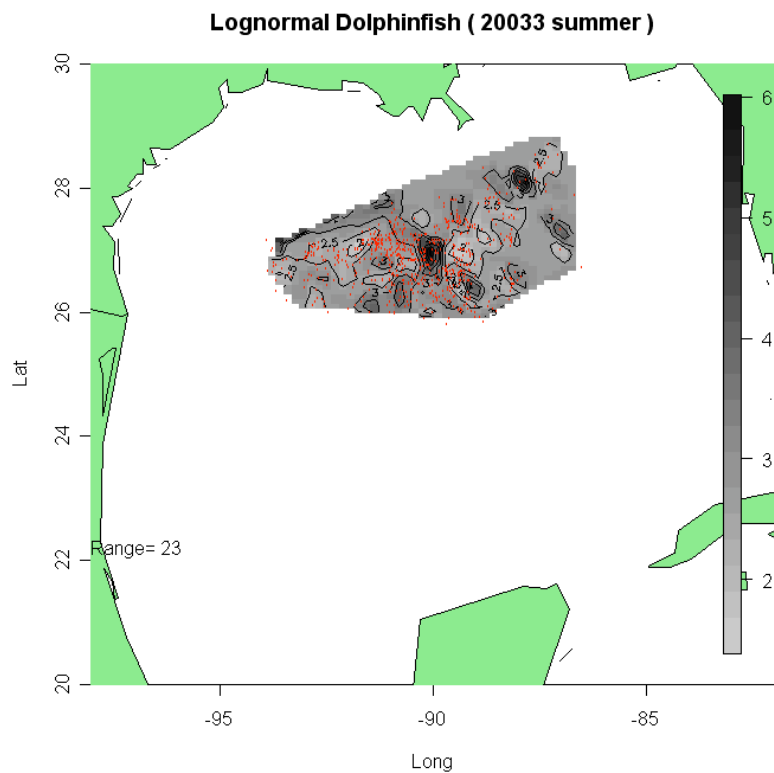
Lognormal Dolphinfish (1993 summer)**Lognormal Dolphinfish (19943 summer)**

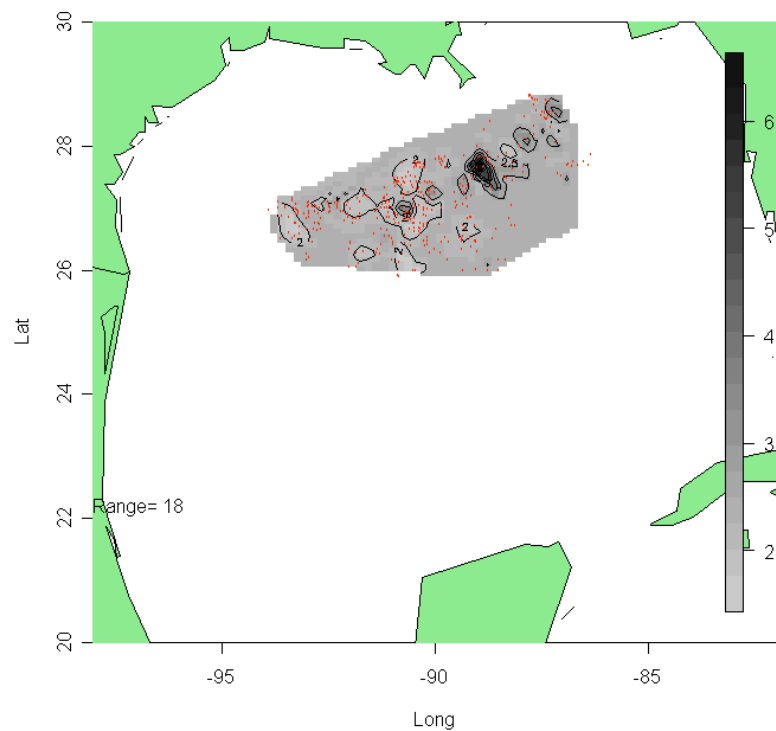
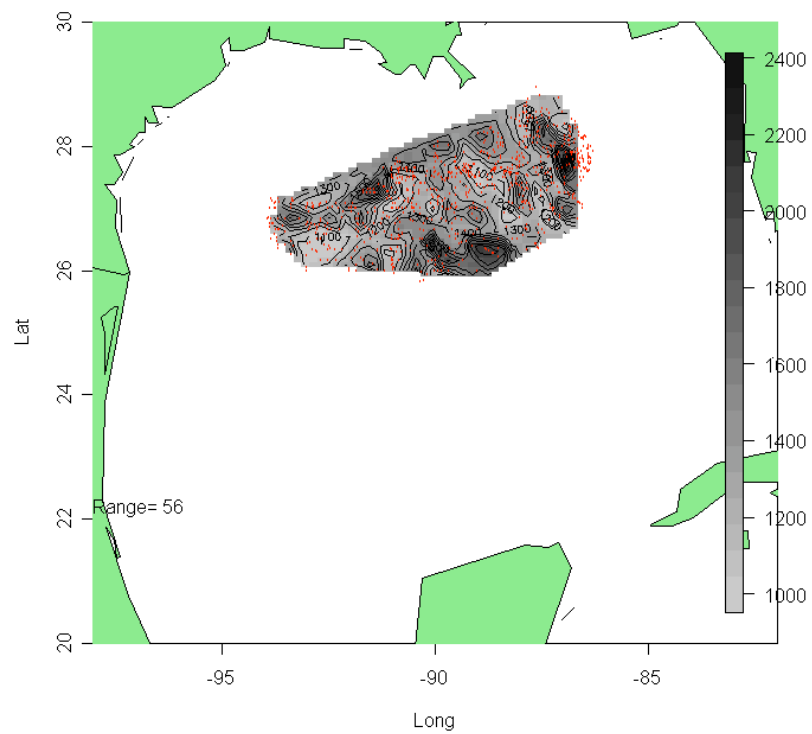
Lognormal Dolphinfish (19953 summer)**Lognormal Dolphinfish (19963 summer)**

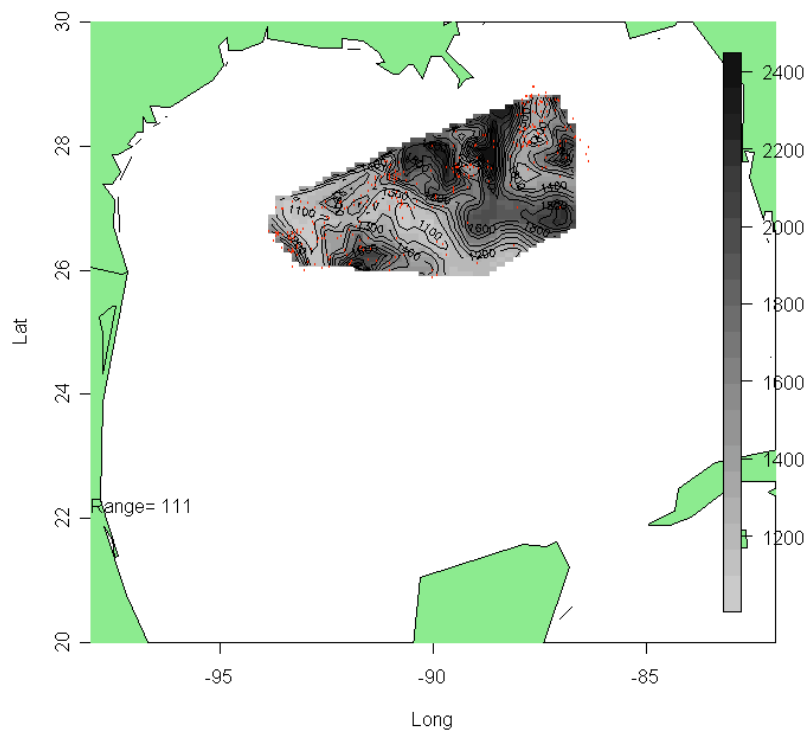
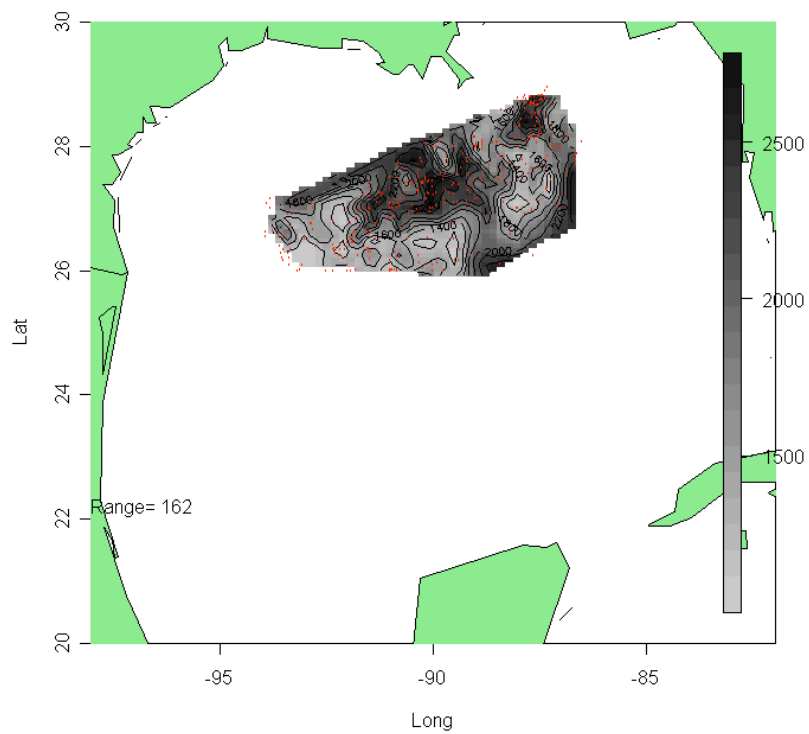


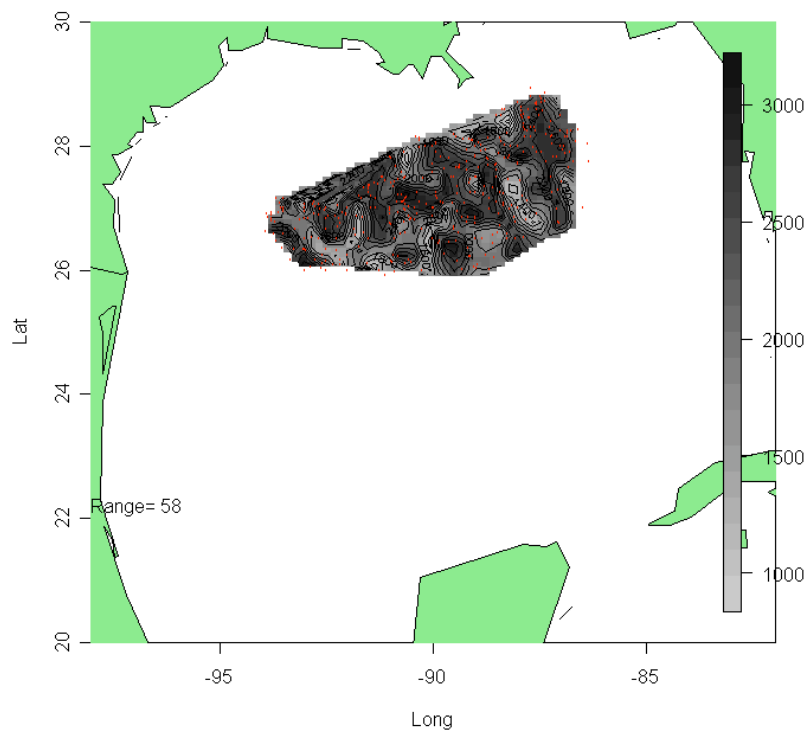
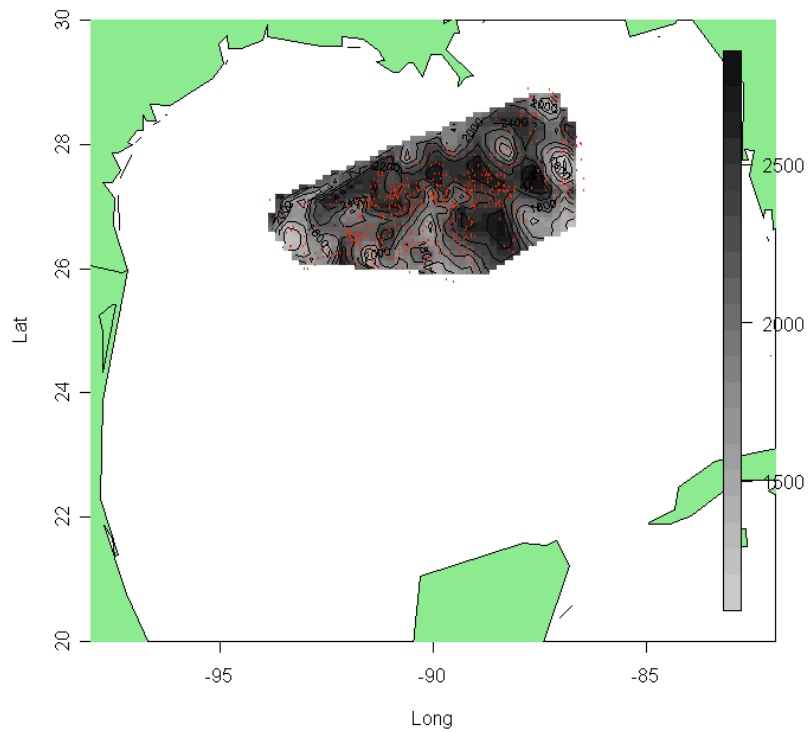


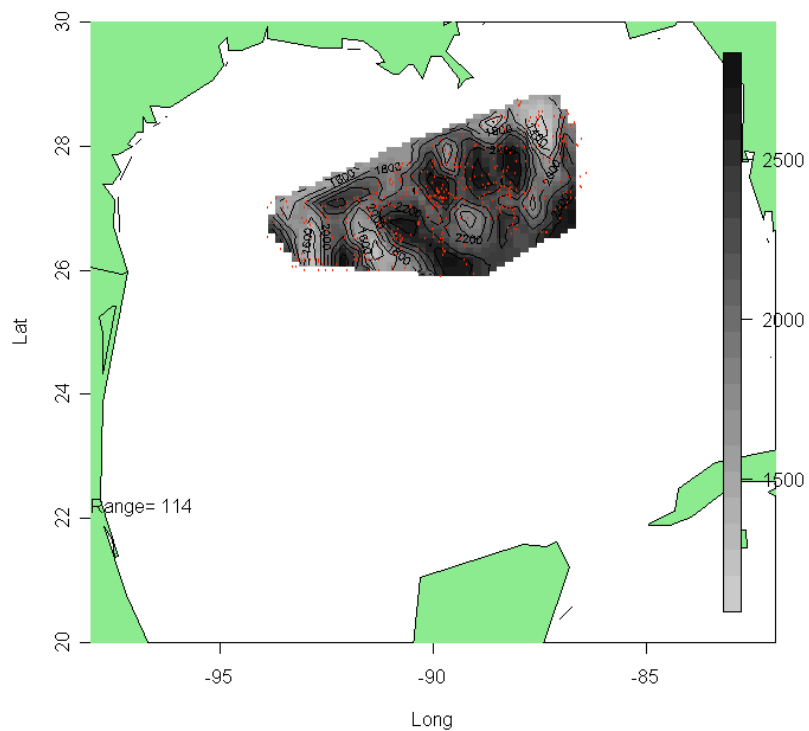
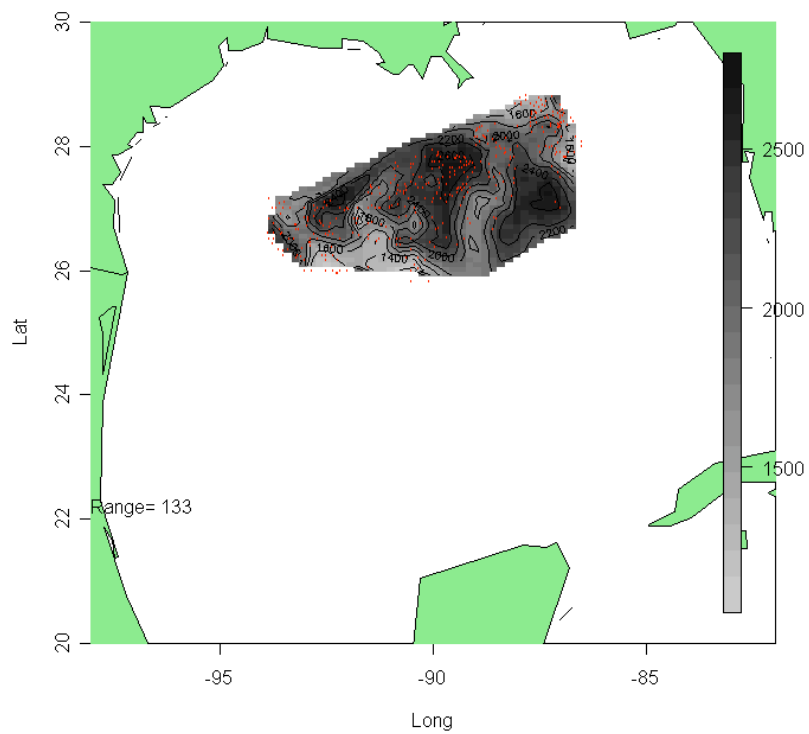


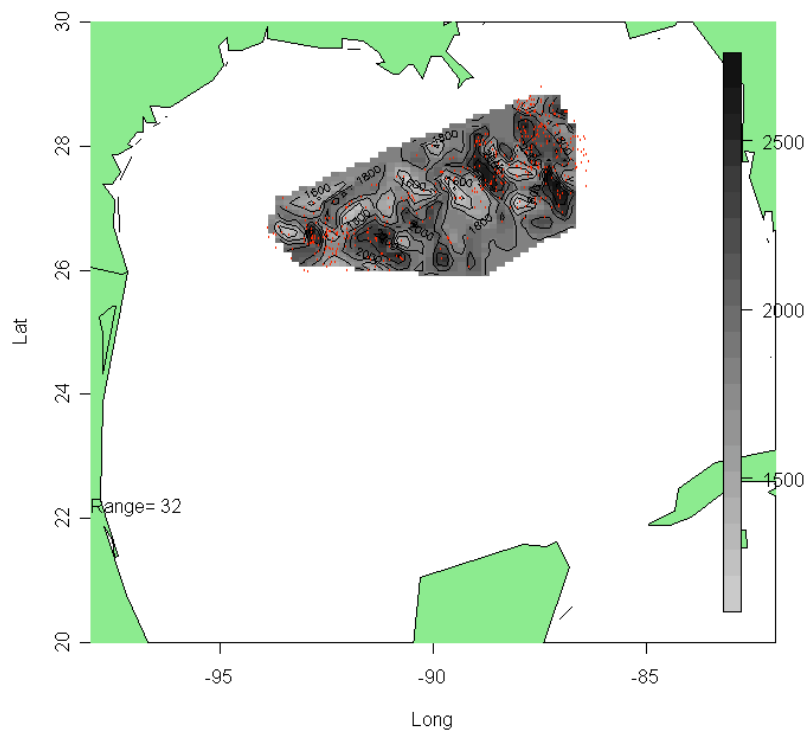
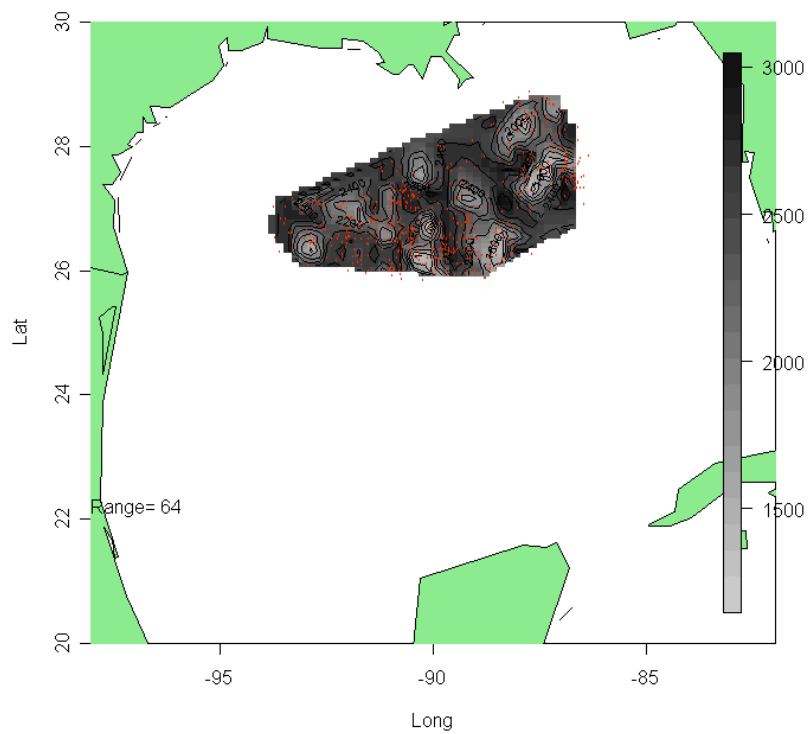


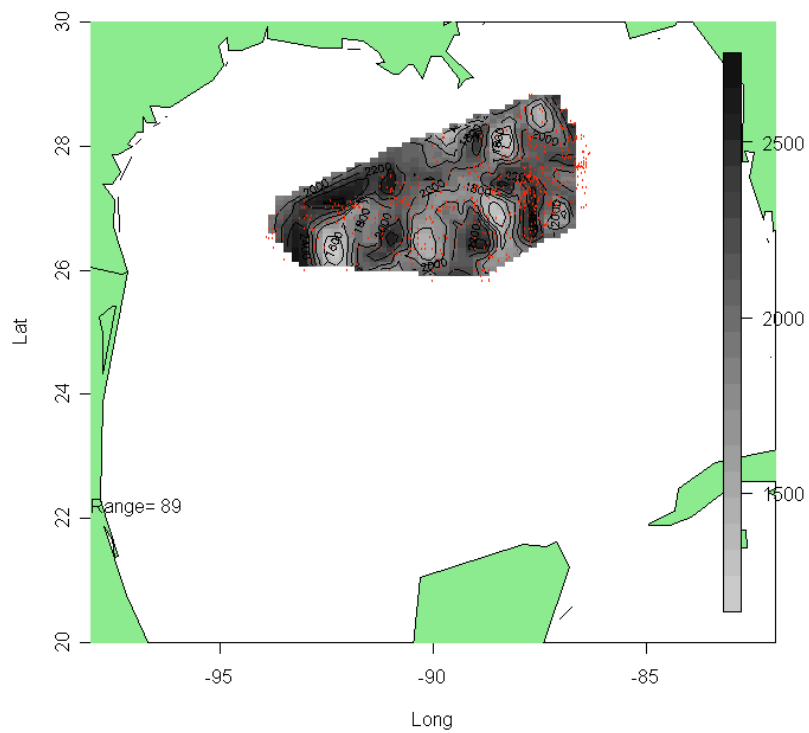
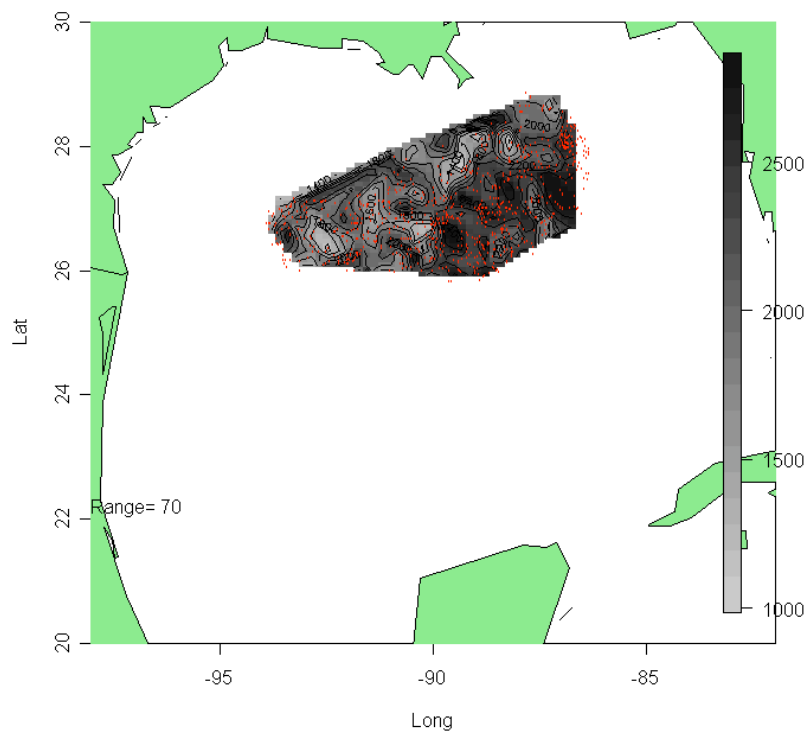
Lognormal Dolphinfish (20053 summer)**Indicator Dolphinfish (19873 summer)**

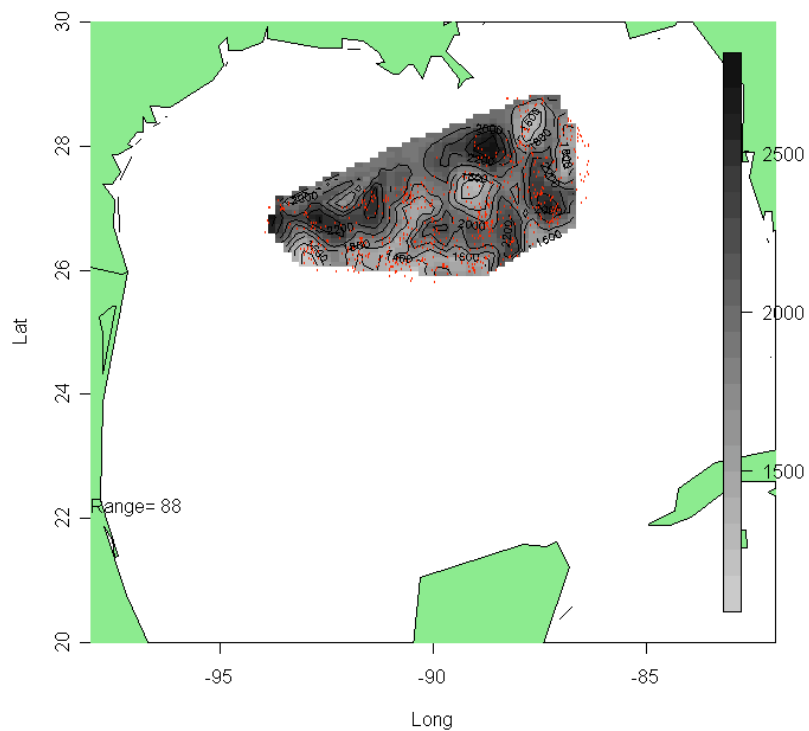
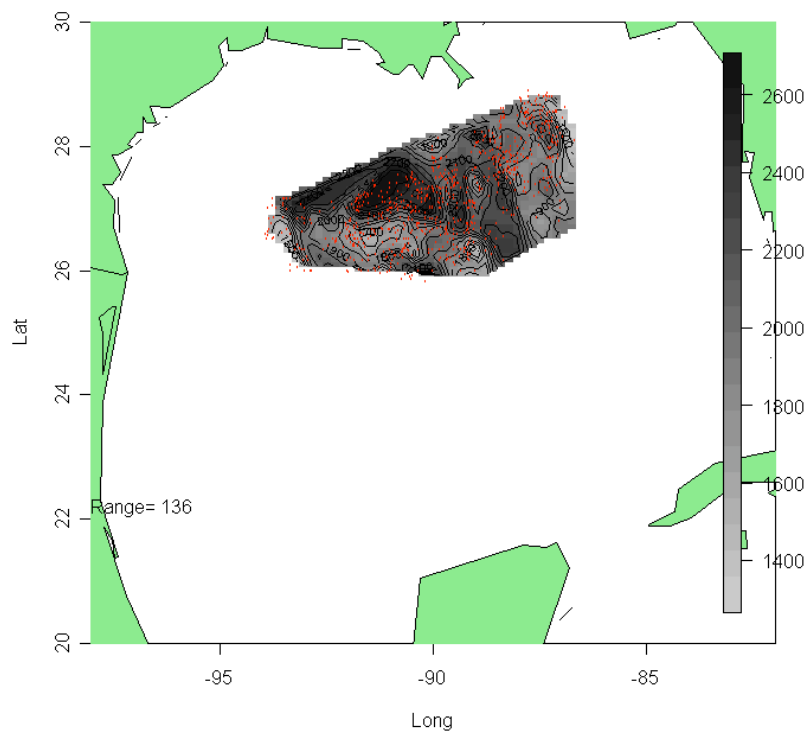
Indicator Dolphinfish (19883 summer)**Indicator Dolphinfish (19893 summer)**

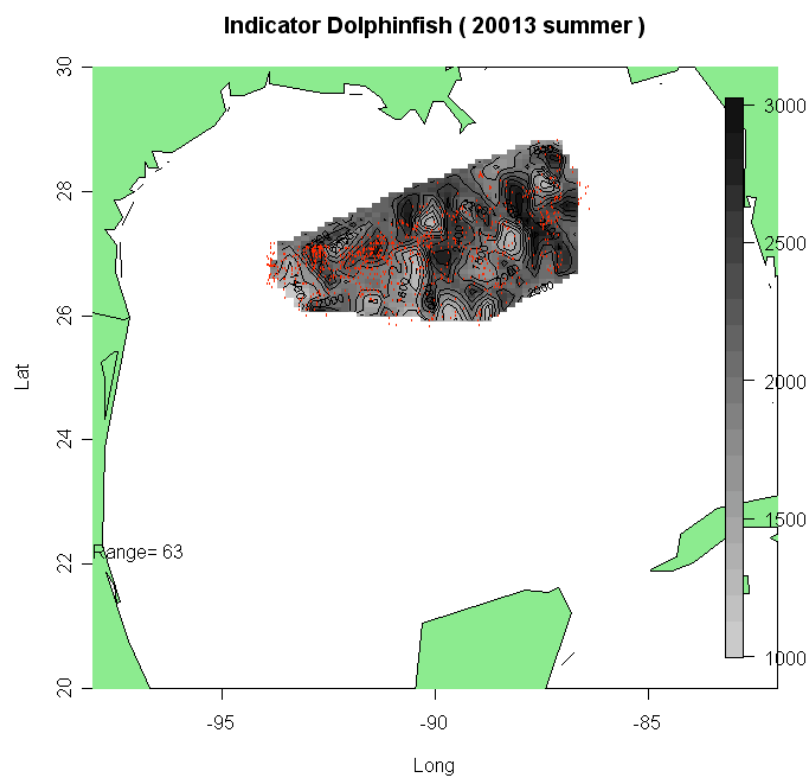
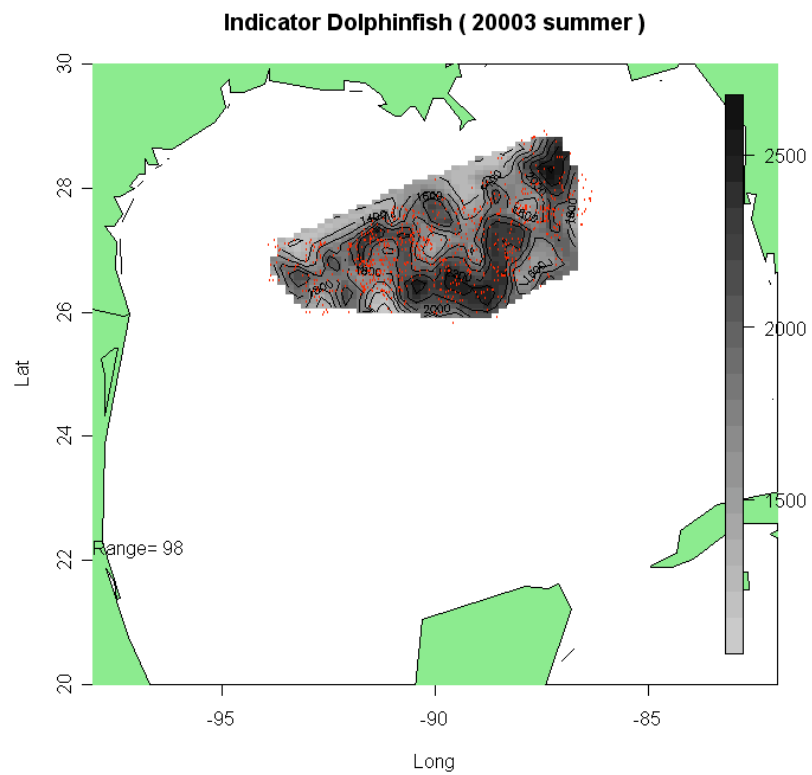
Indicator Dolphinfish (19903 summer)**Indicator Dolphinfish (19913 summer)**

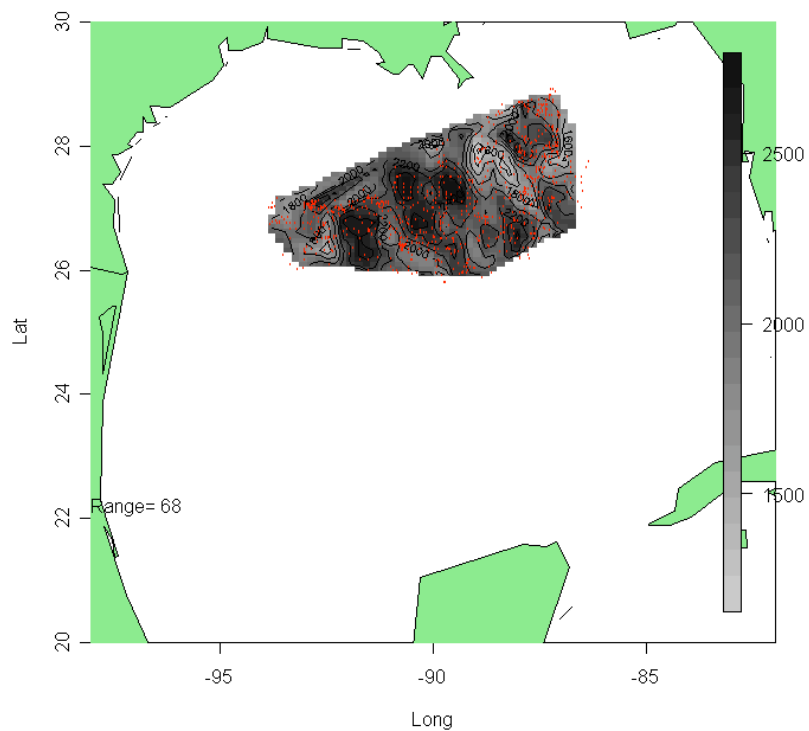
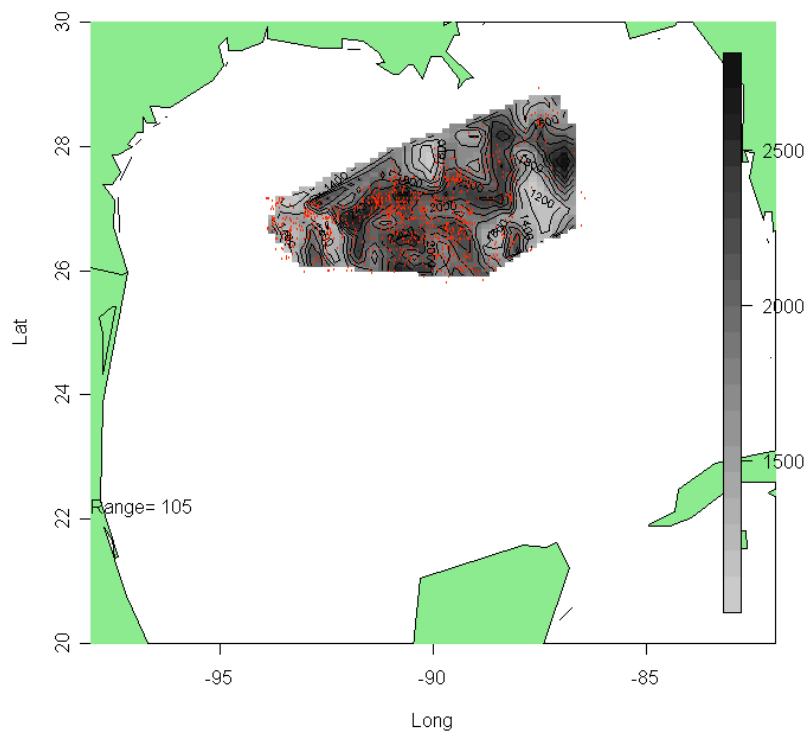
Indicator Dolphinfish (19923 summer)**Indicator Dolphinfish (19933 summer)**

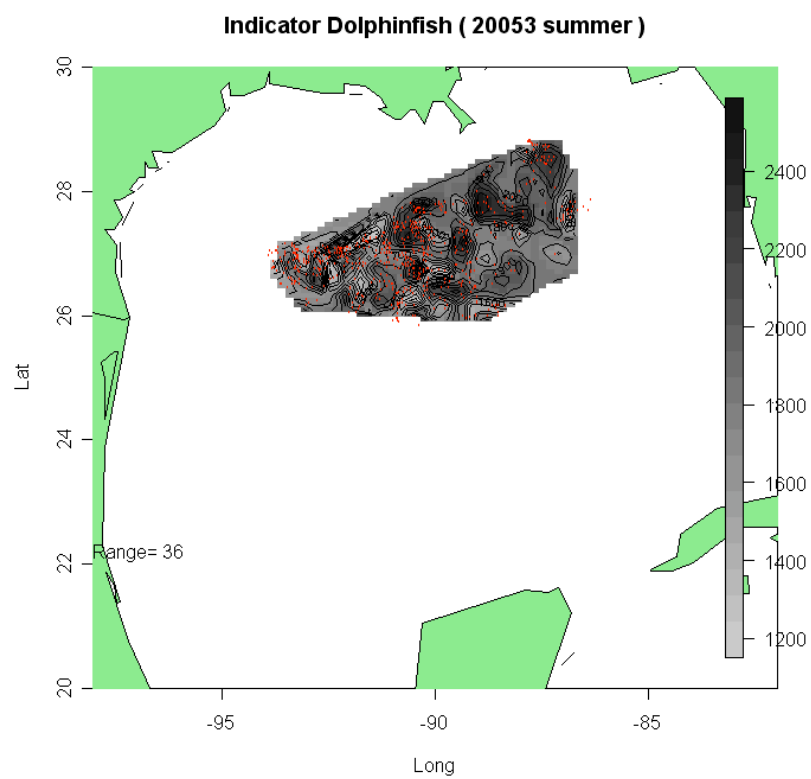
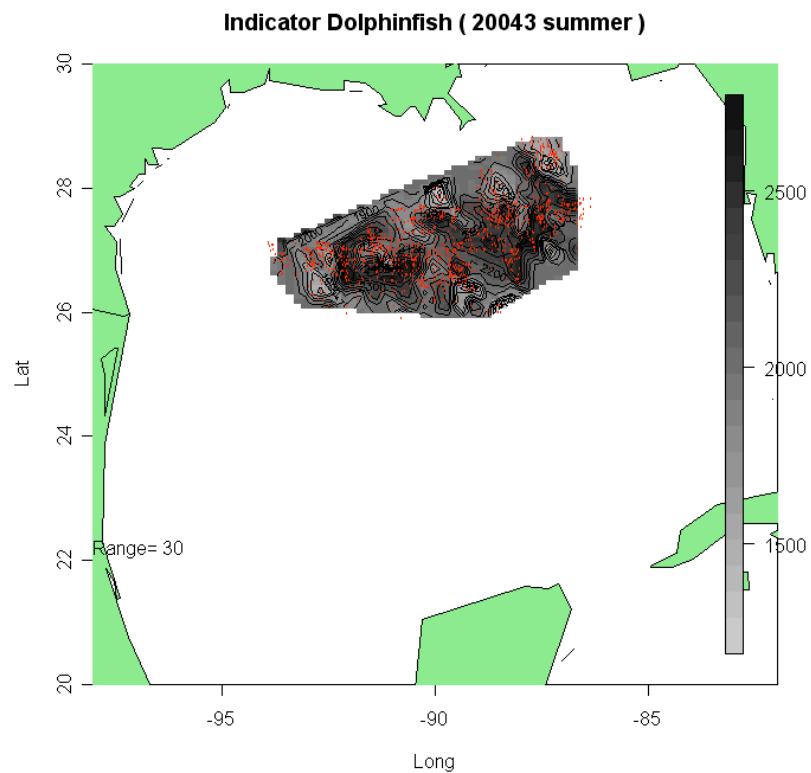
Indicator Dolphinfish (19943 summer)**Indicator Dolphinfish (19953 summer)**

Indicator Dolphinfish (19963 summer)**Indicator Dolphinfish (19973 summer)**

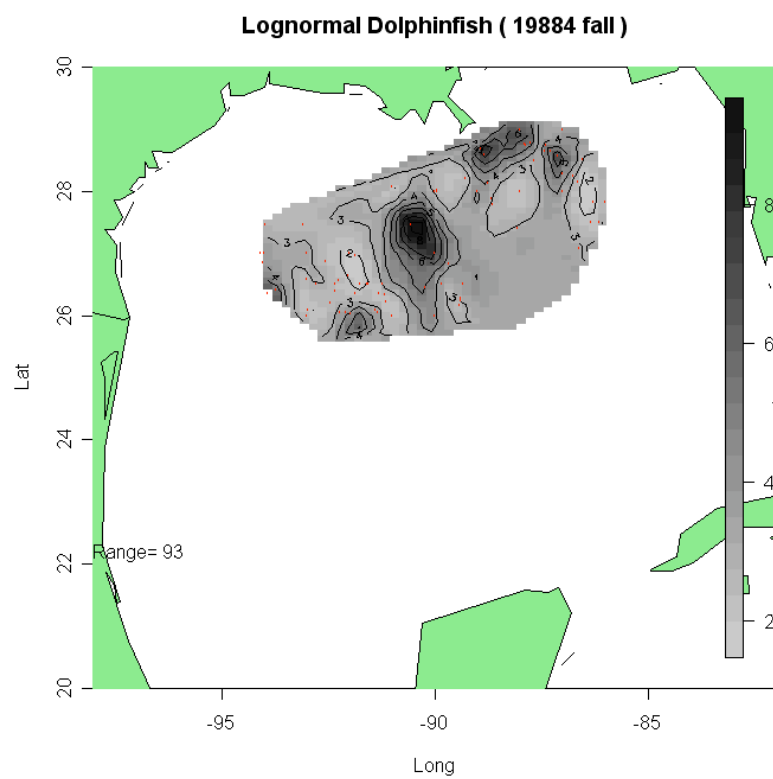
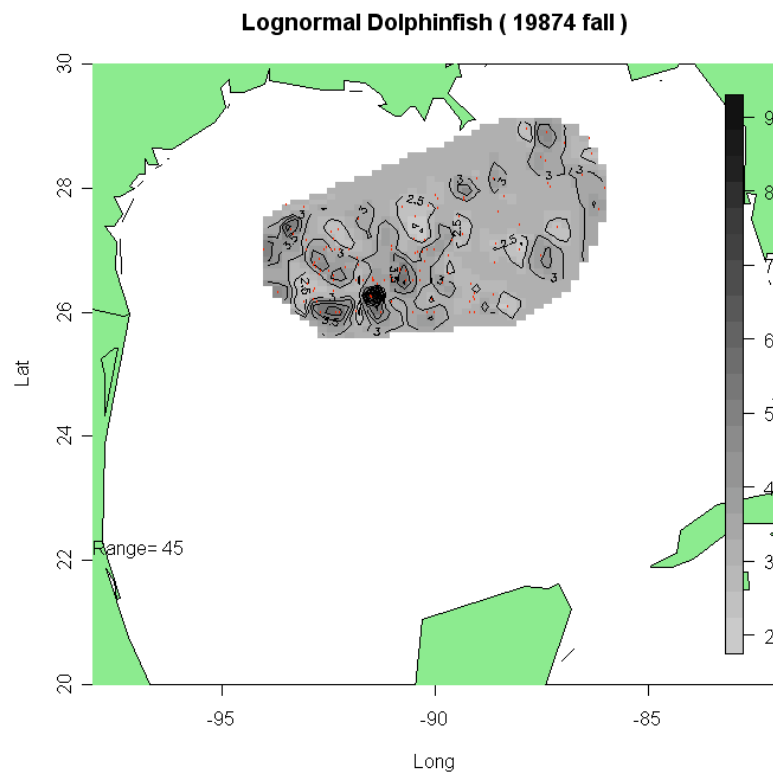
Indicator Dolphinfish (19983 summer)**Indicator Dolphinfish (19993 summer)**

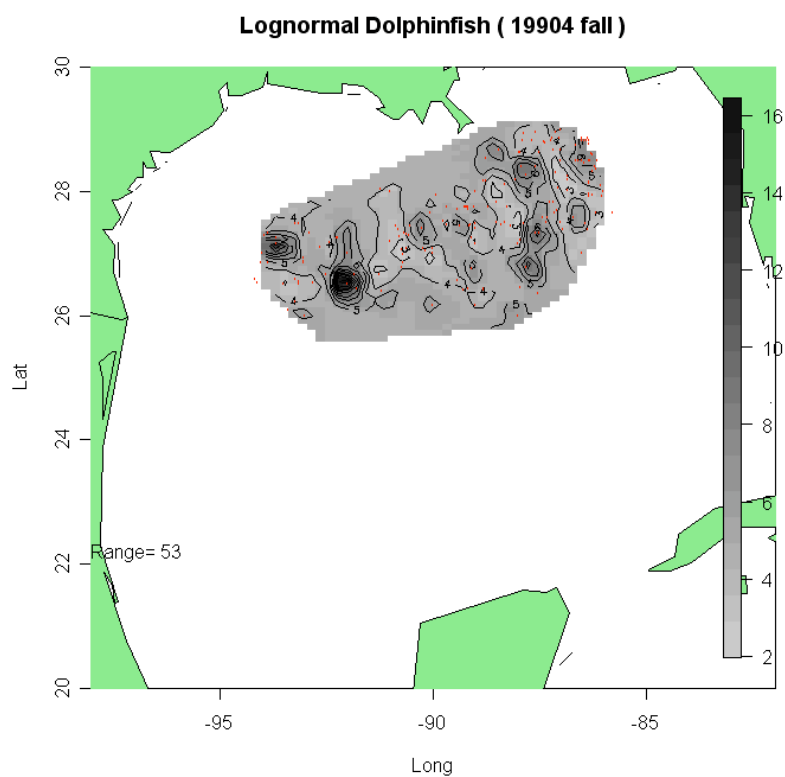
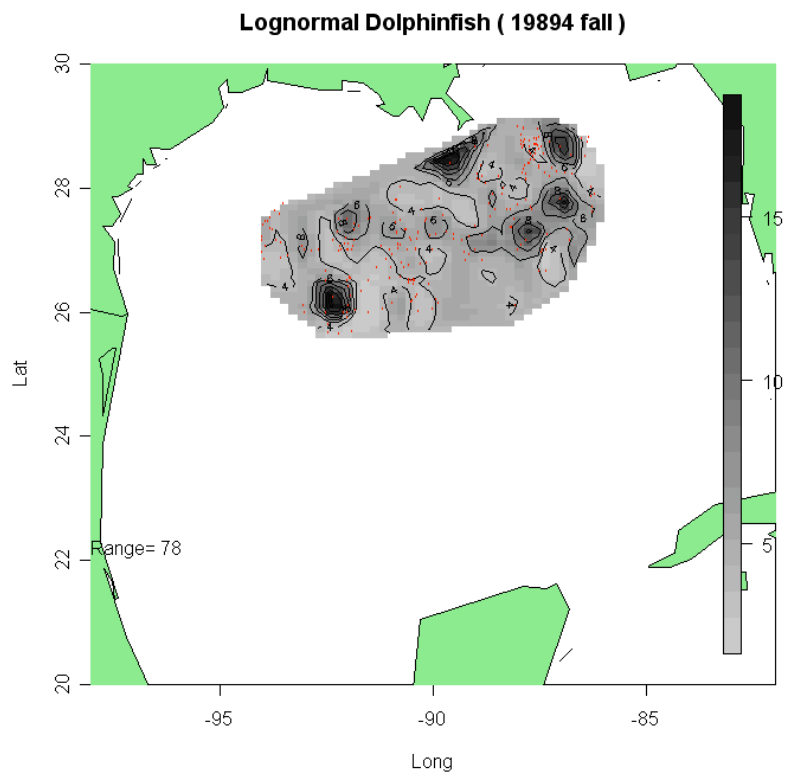


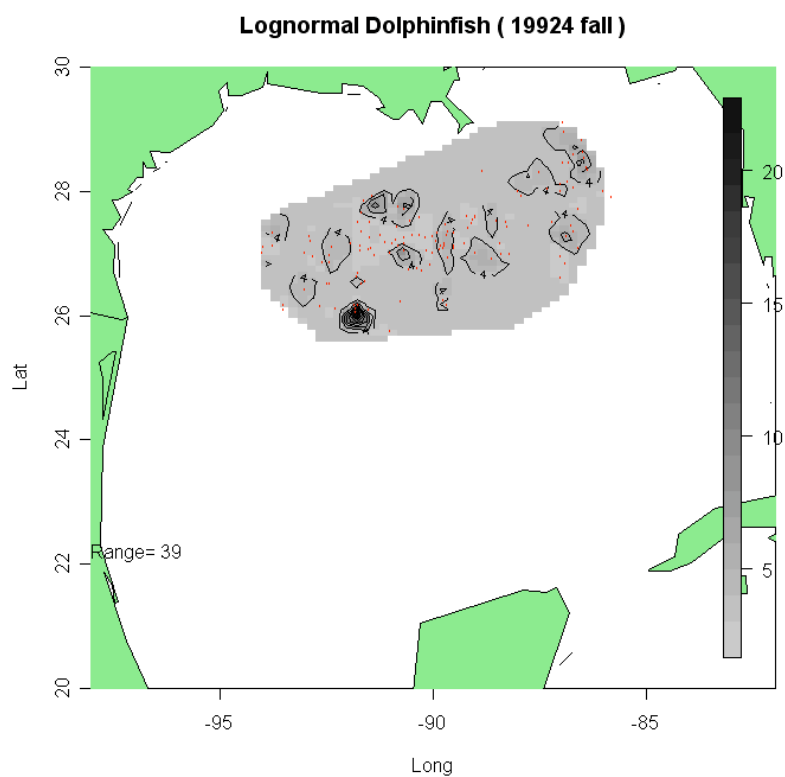
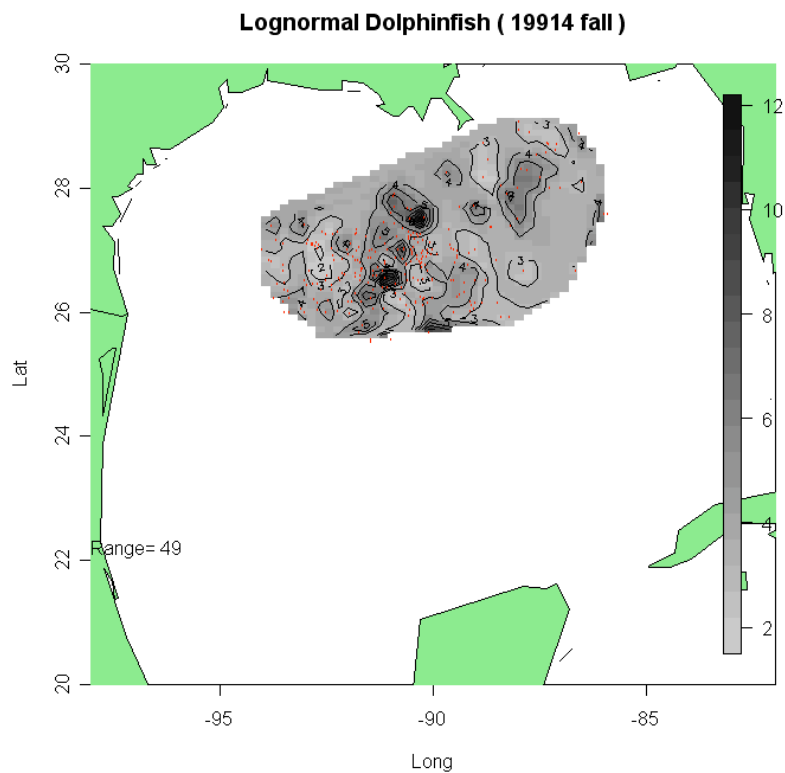
Indicator Dolphinfish (20023 summer)**Indicator Dolphinfish (20033 summer)**

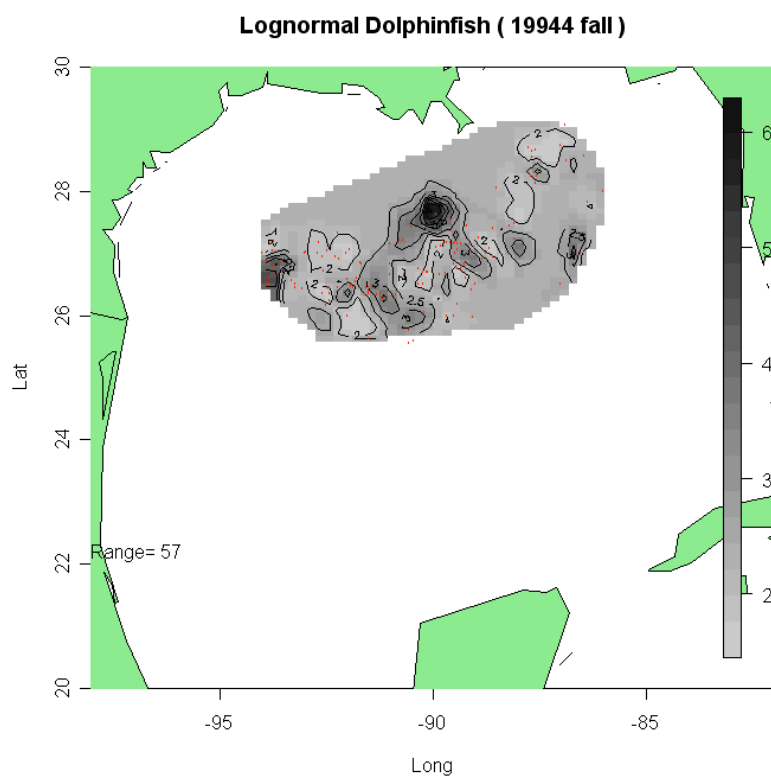
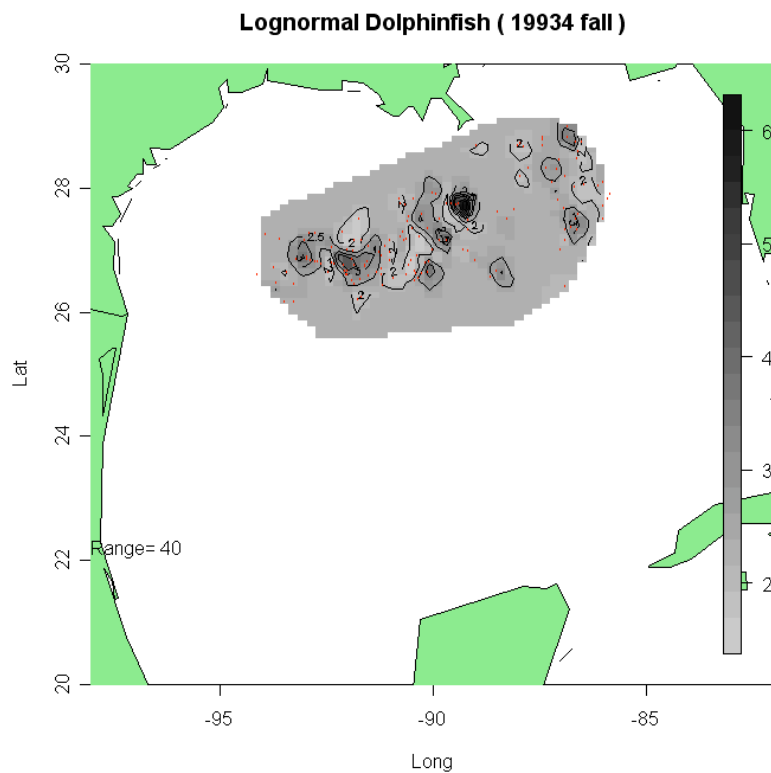


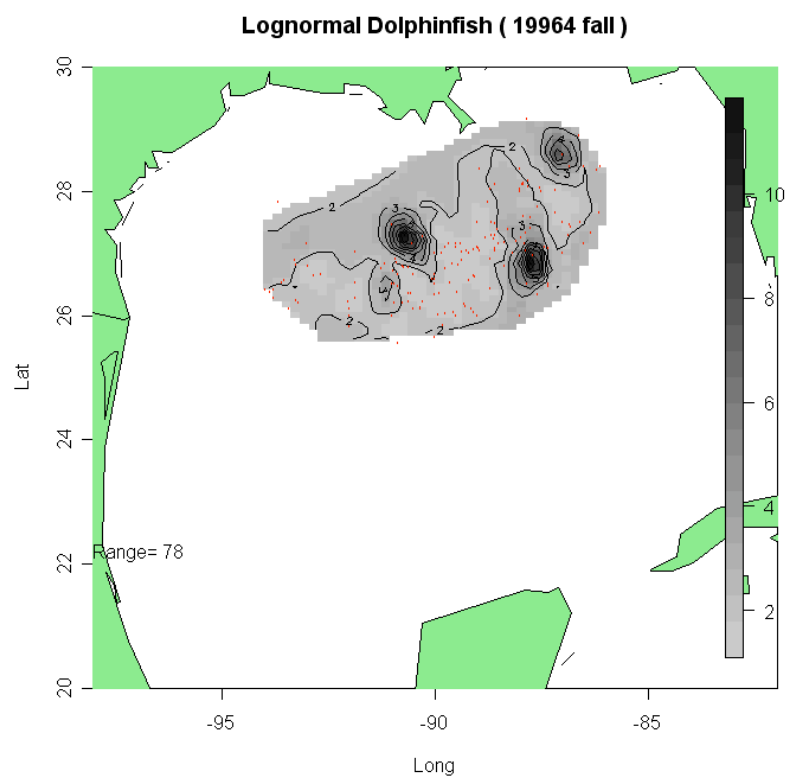
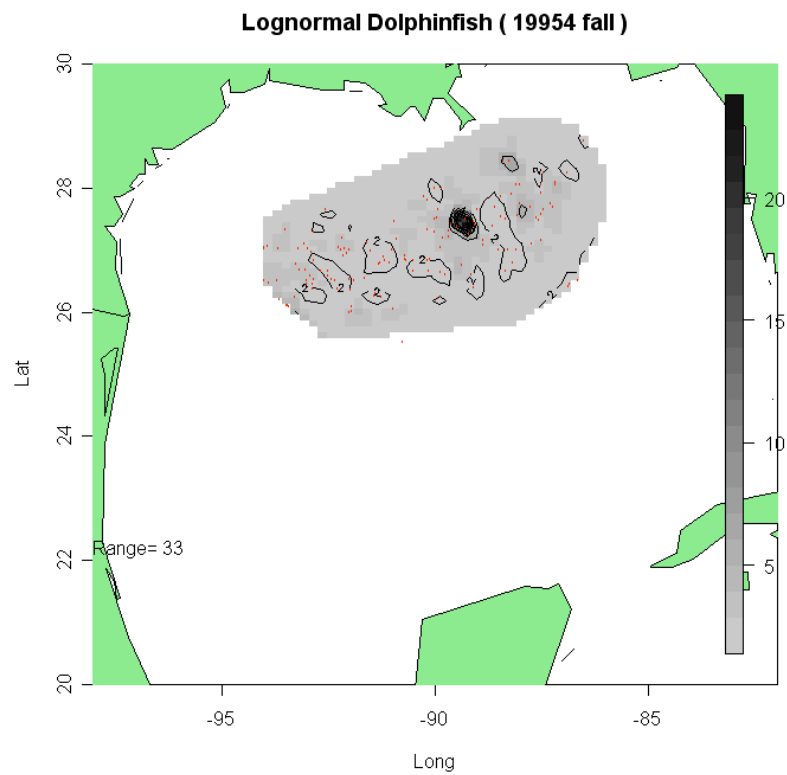
Fall Kriging Maps

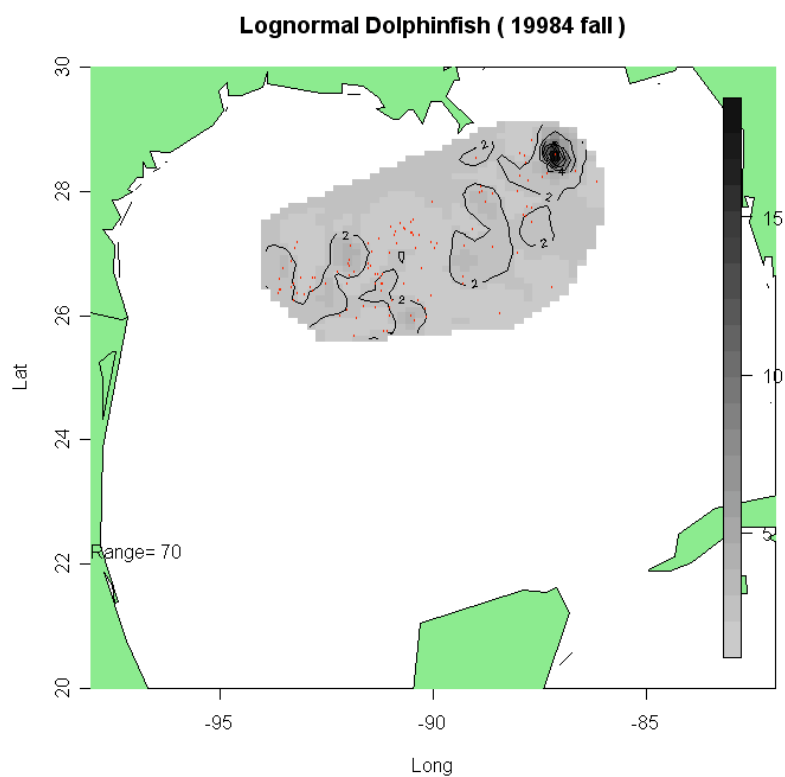
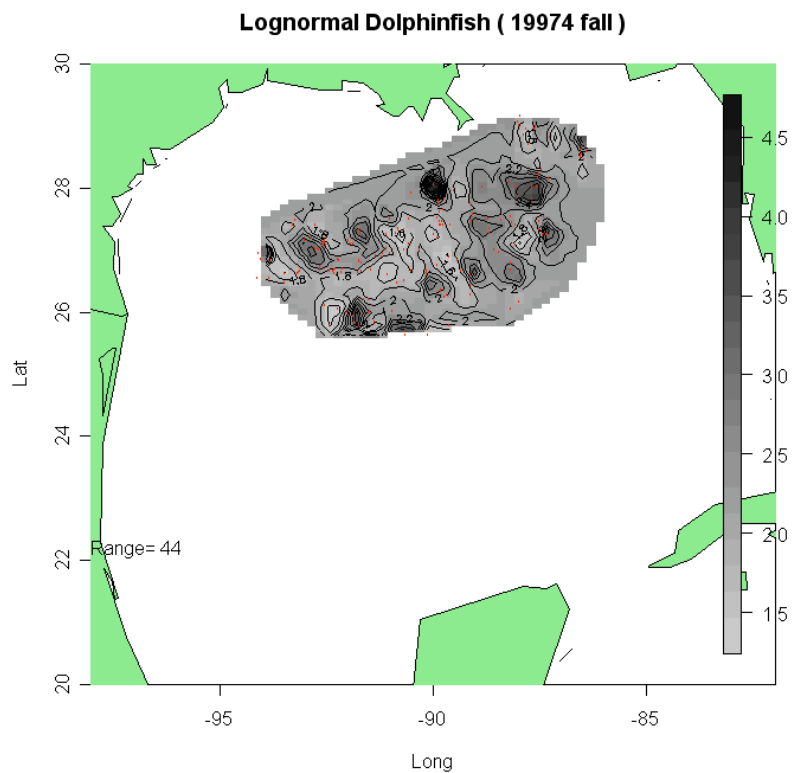


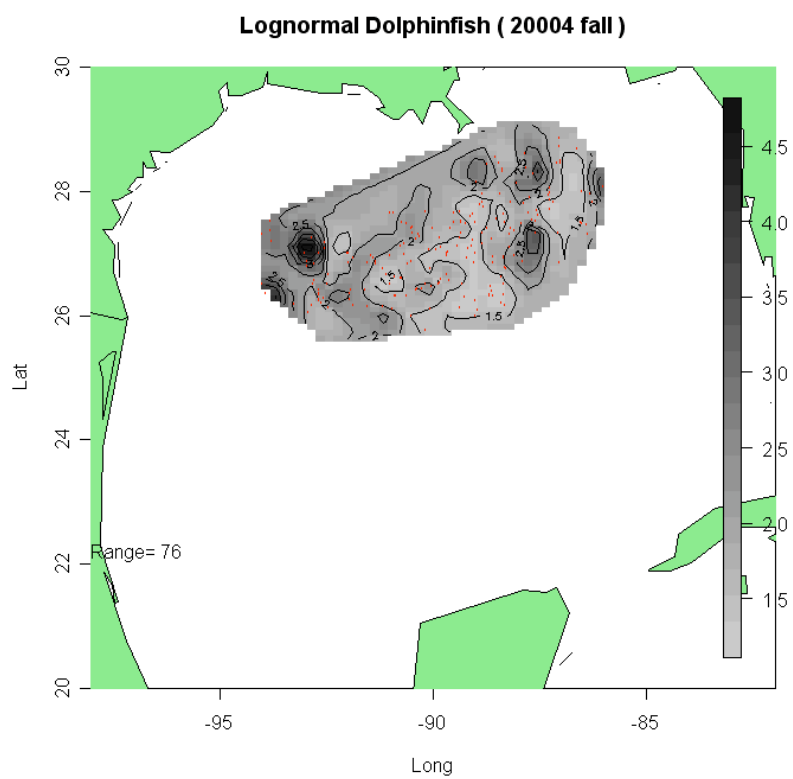
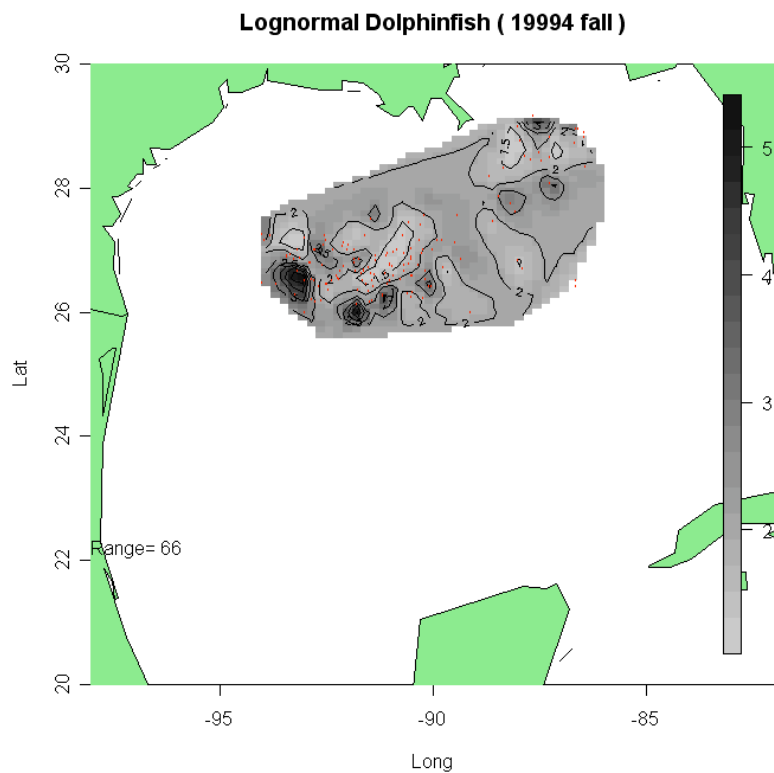


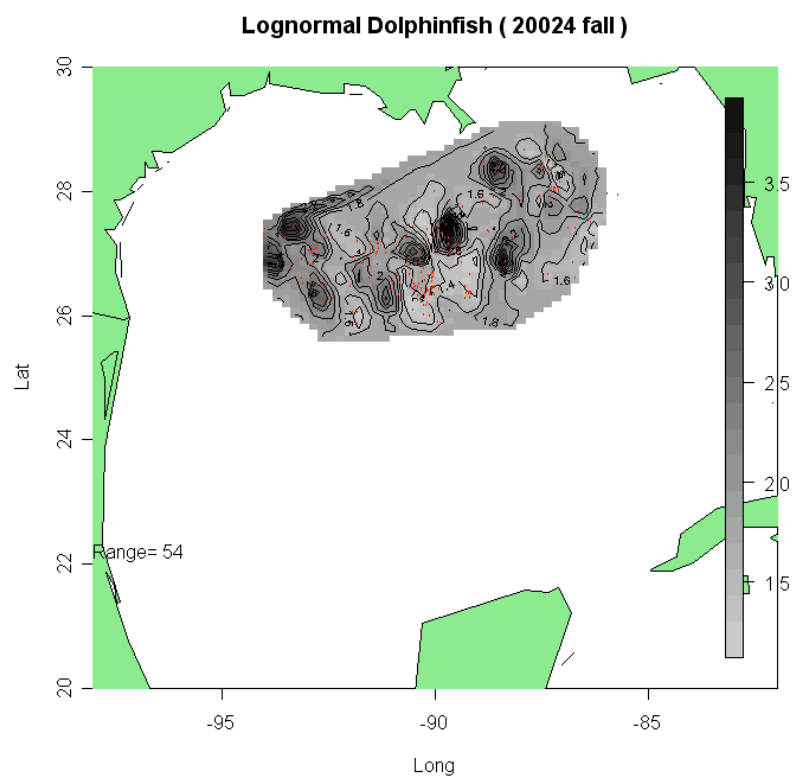
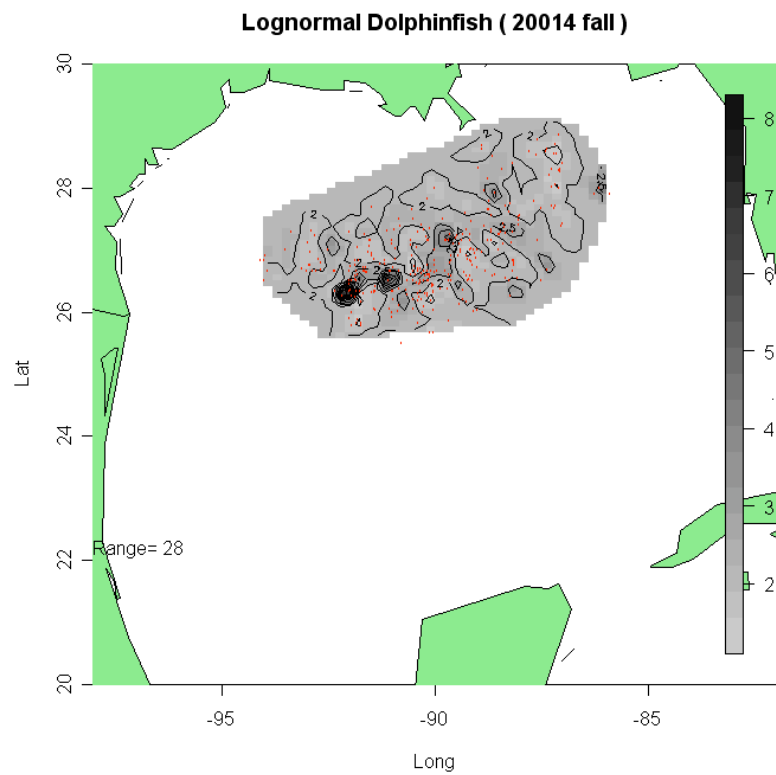


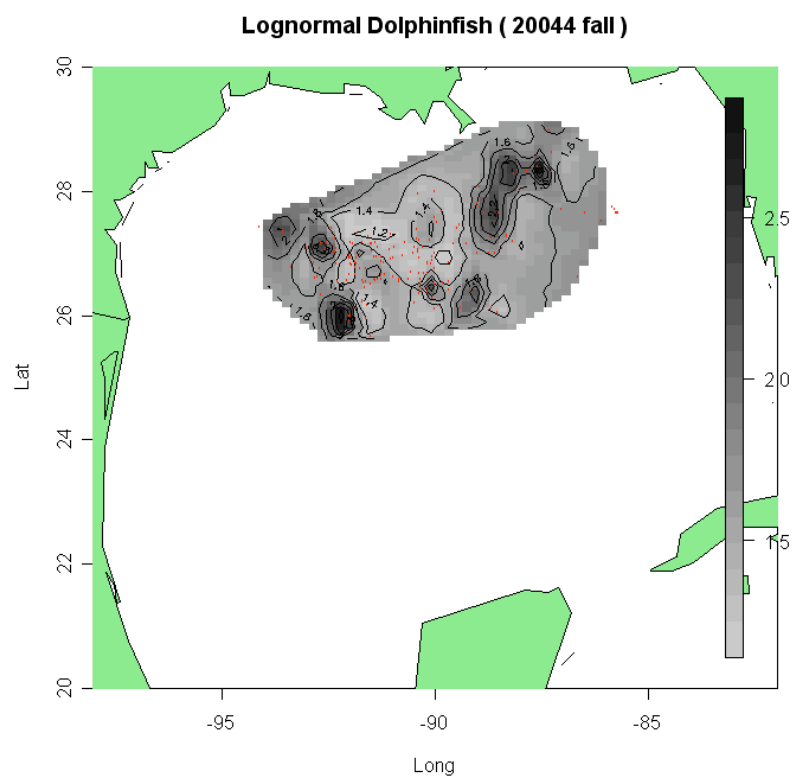
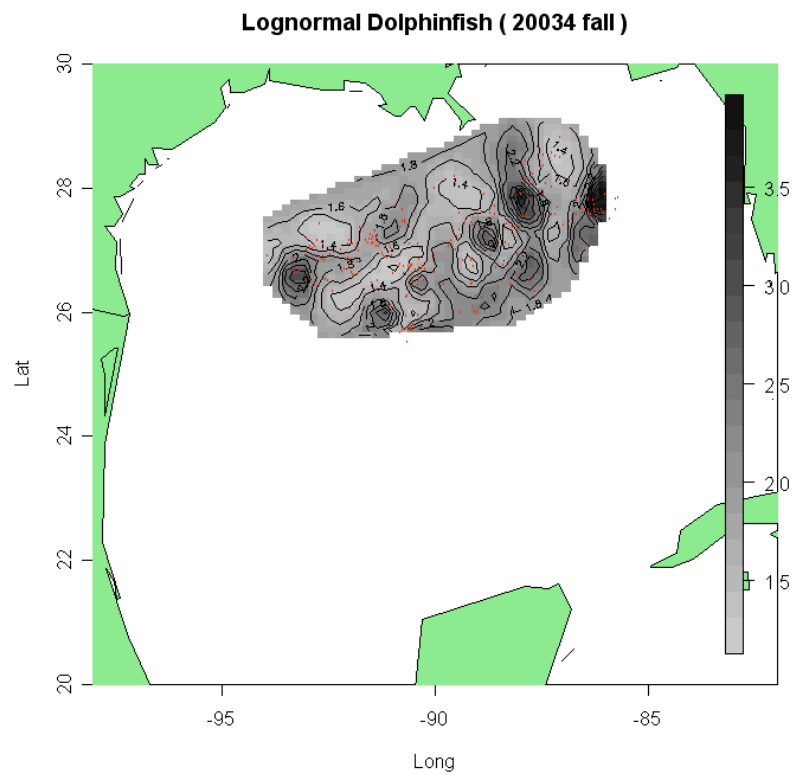


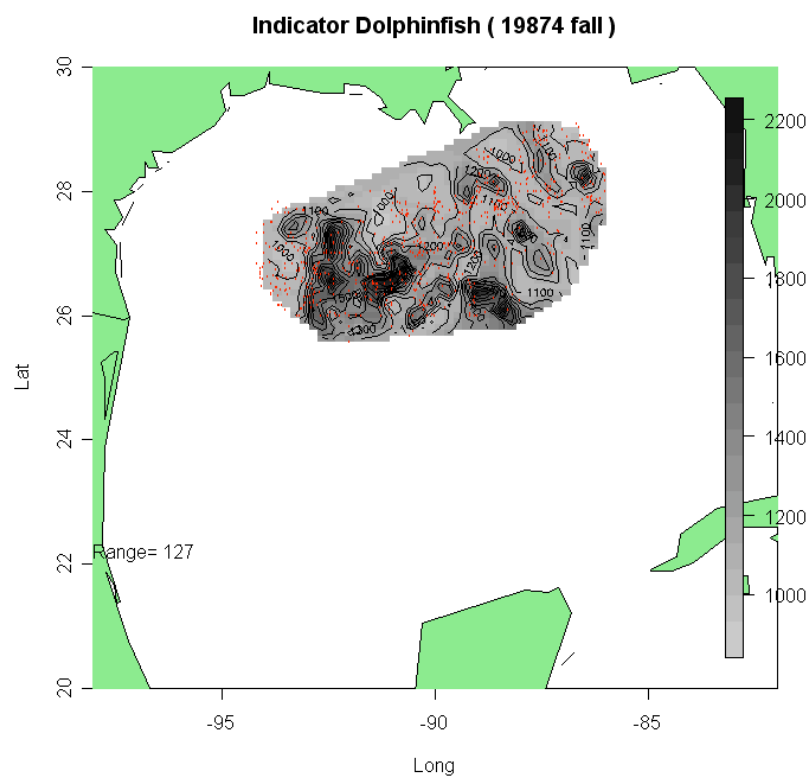
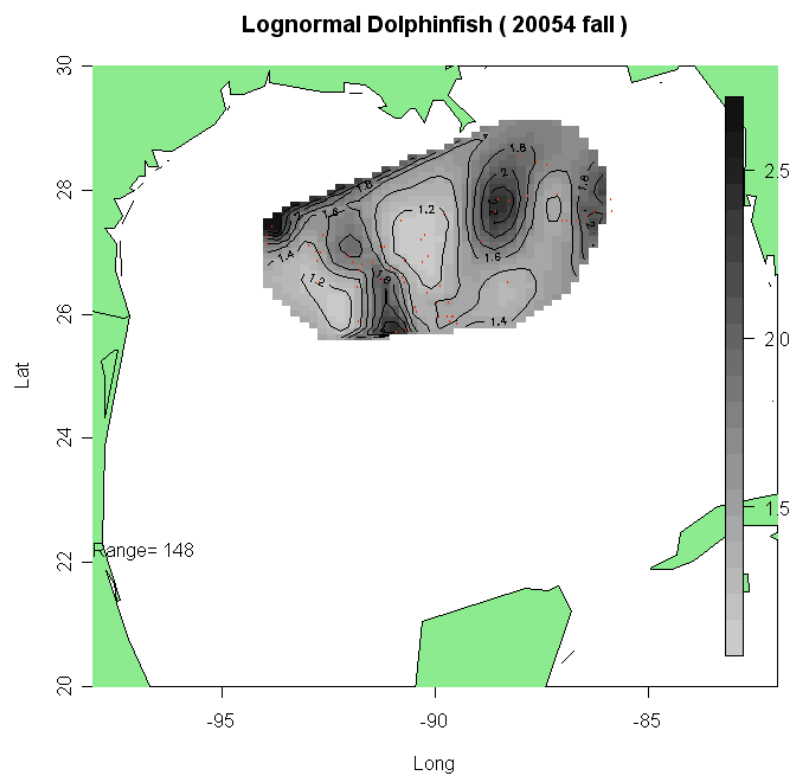


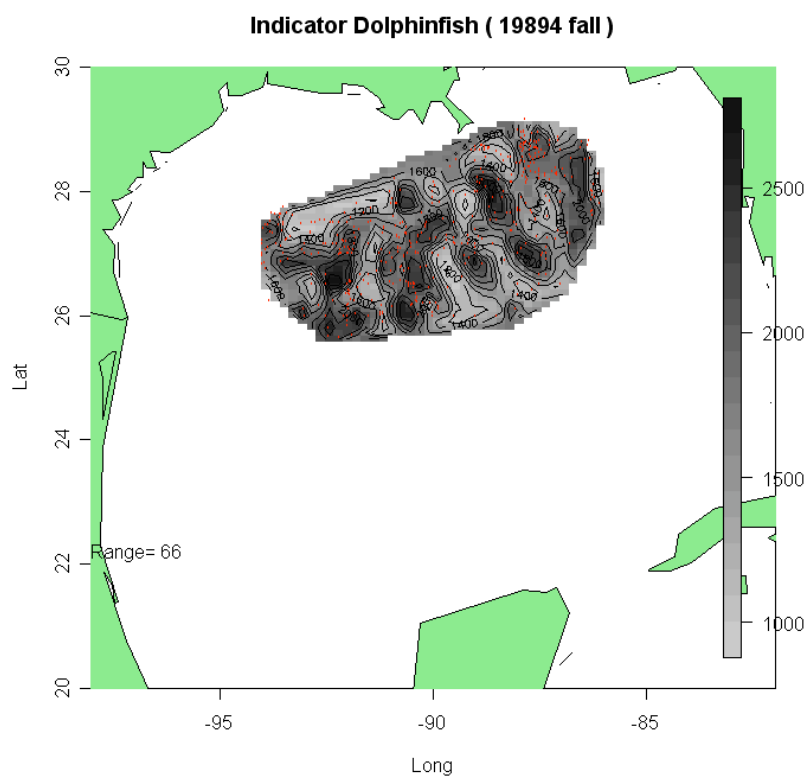
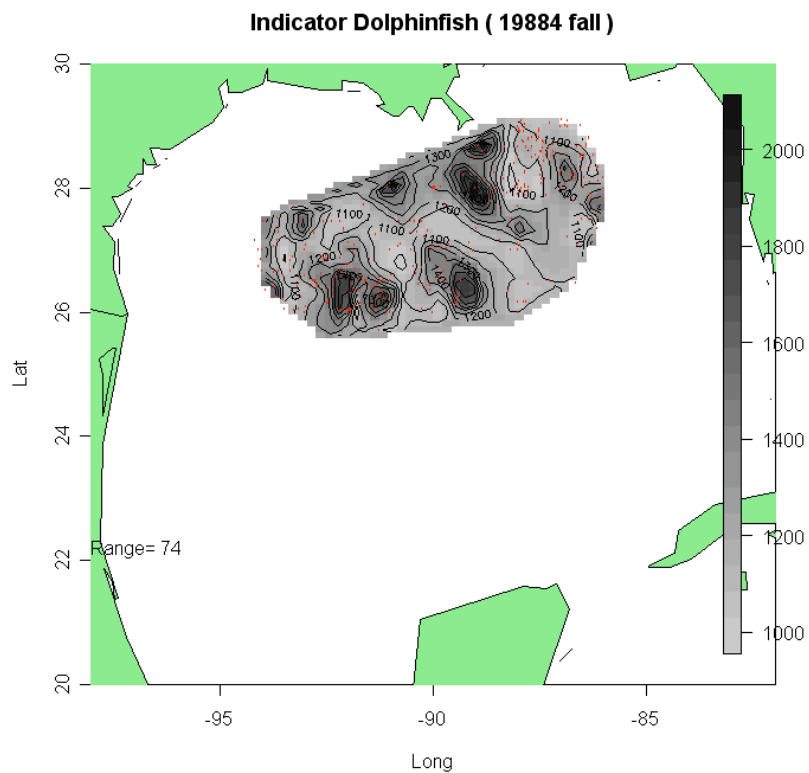


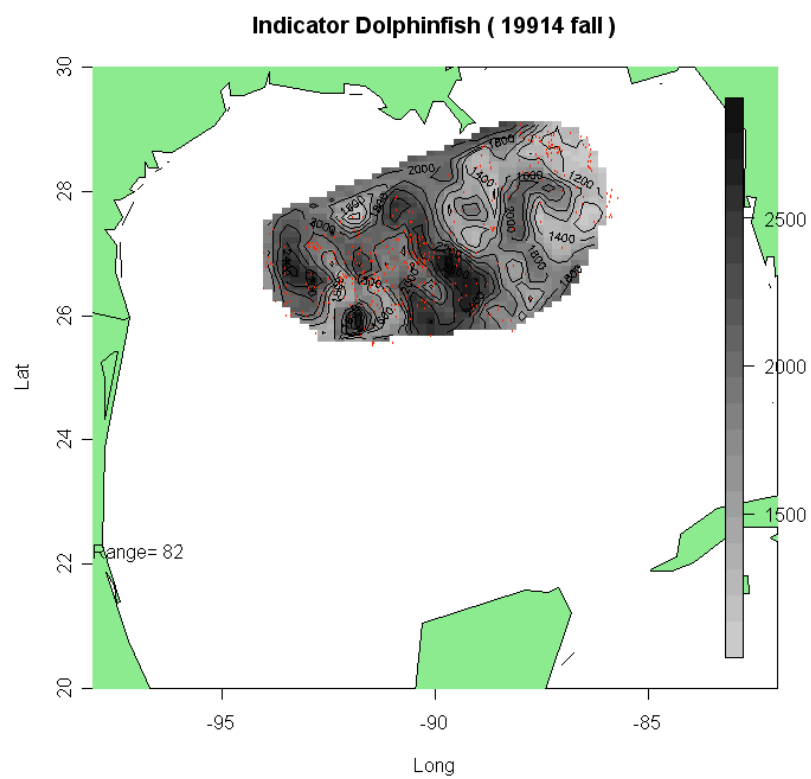
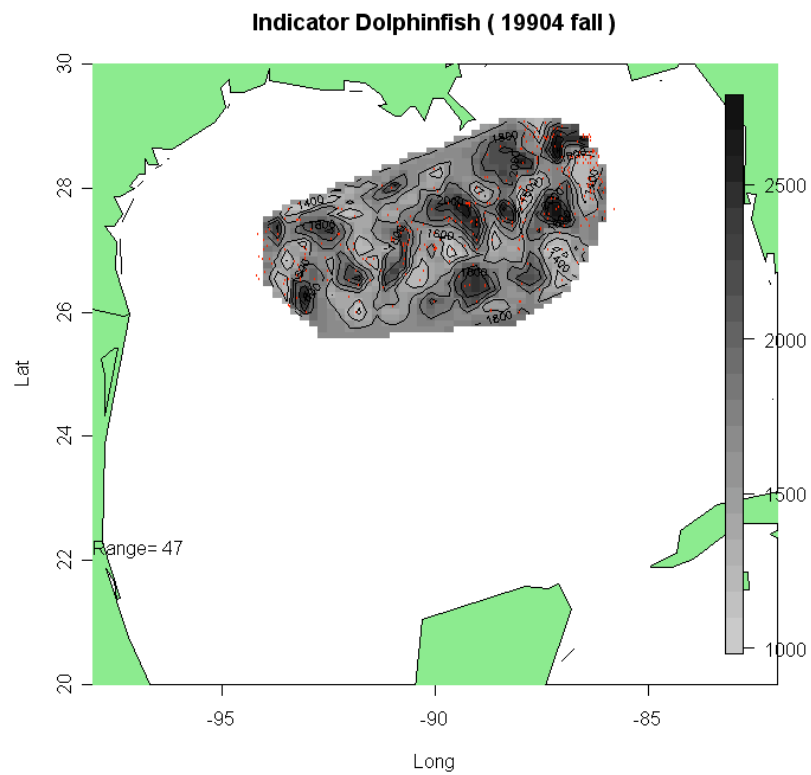


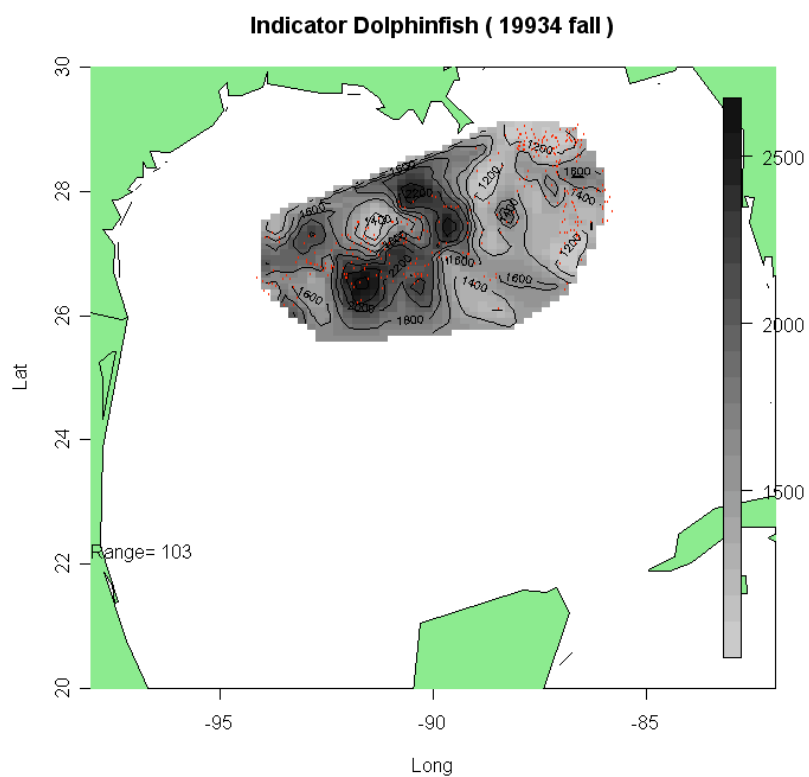
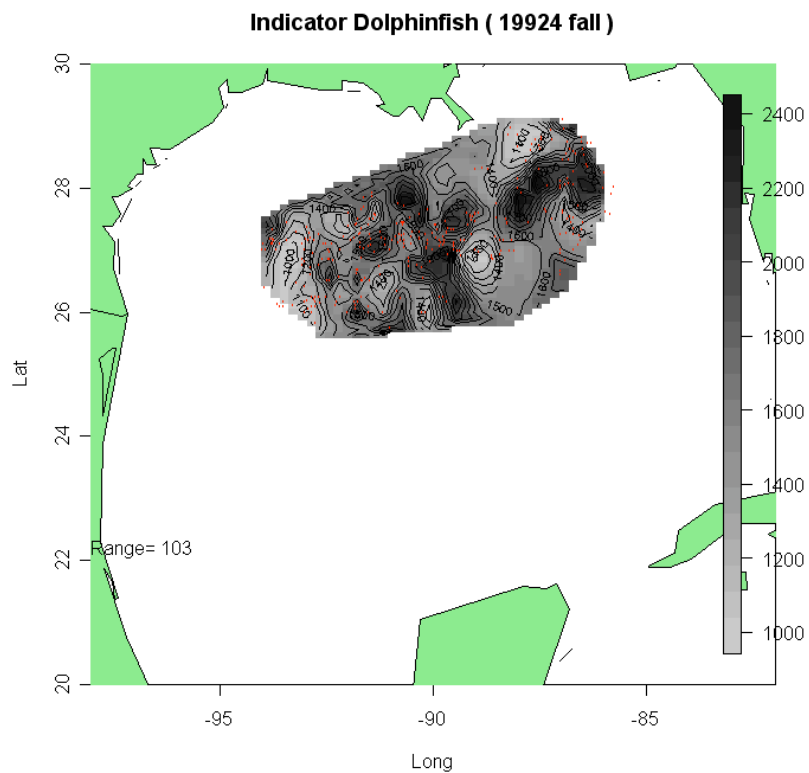


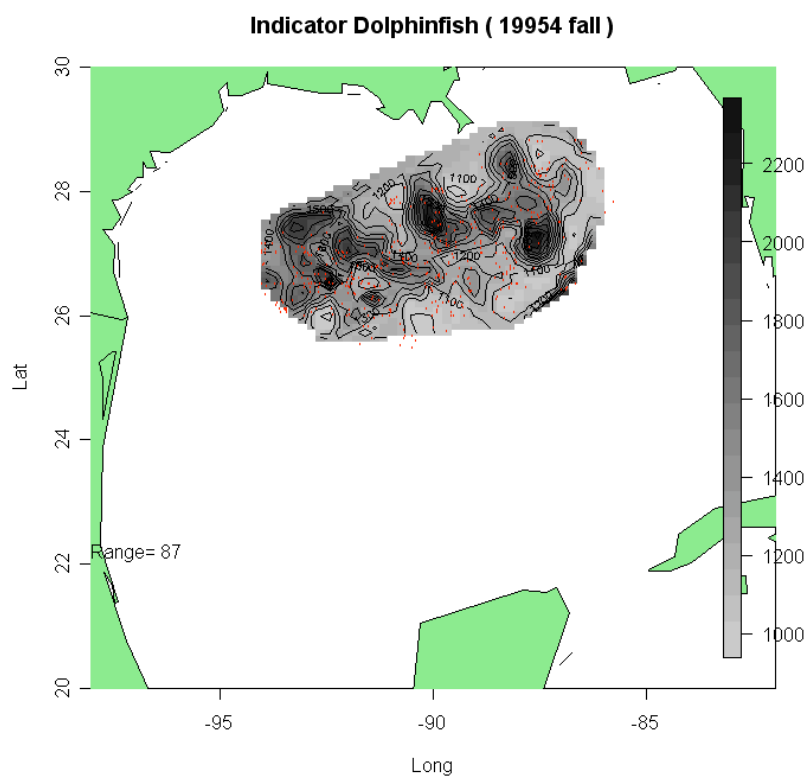
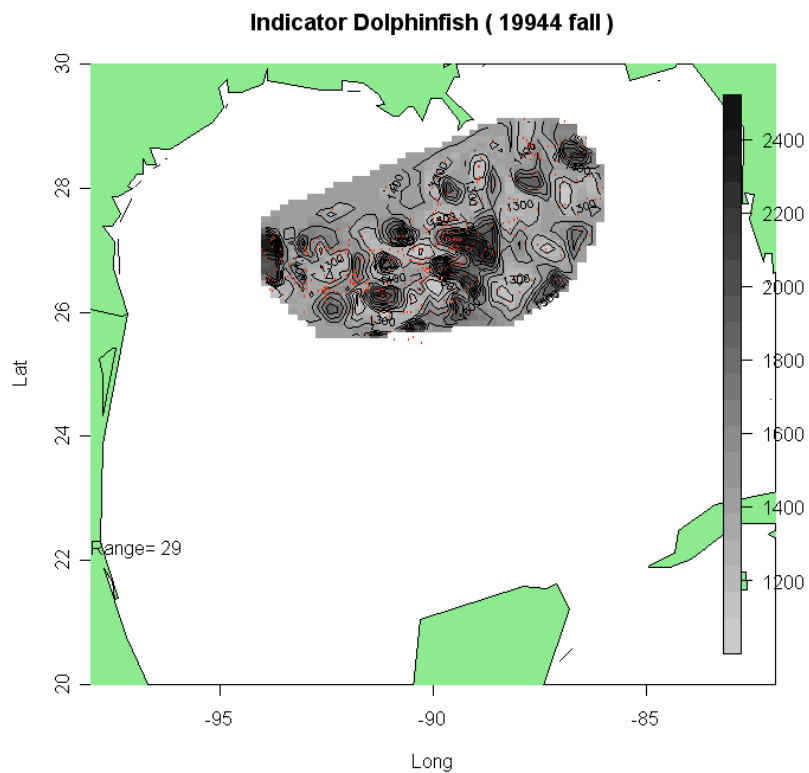


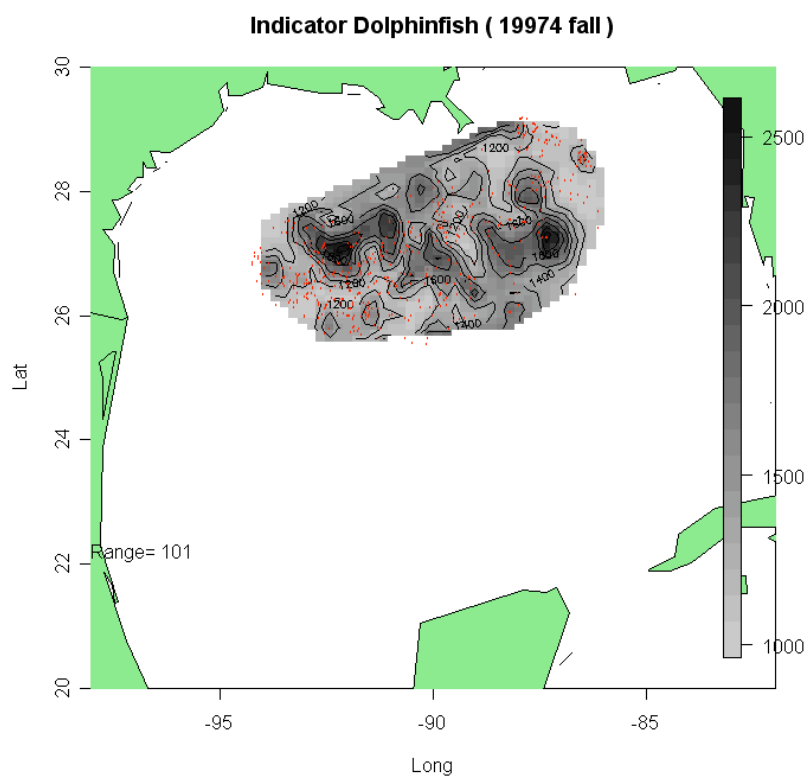
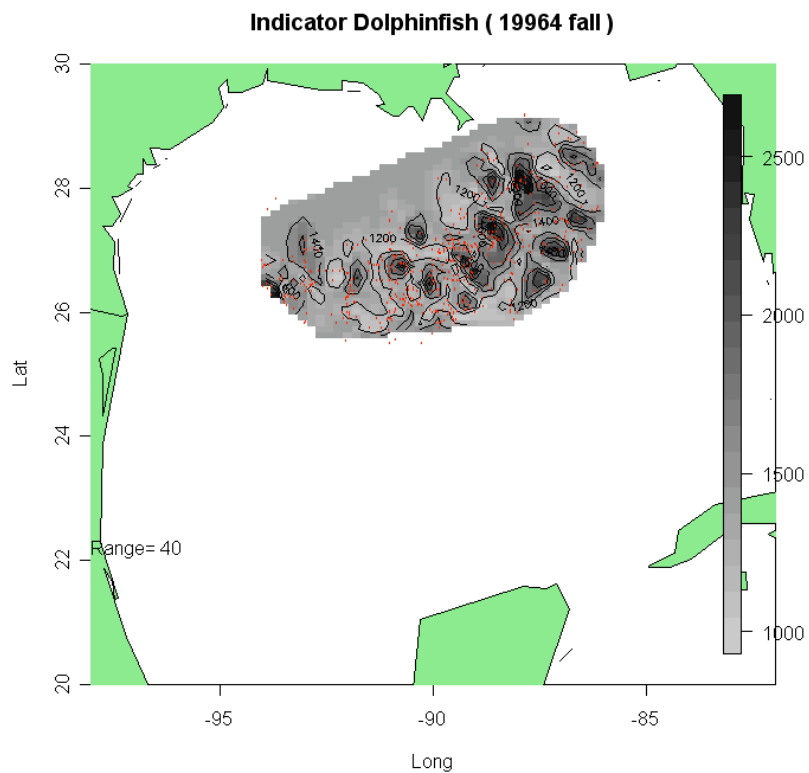


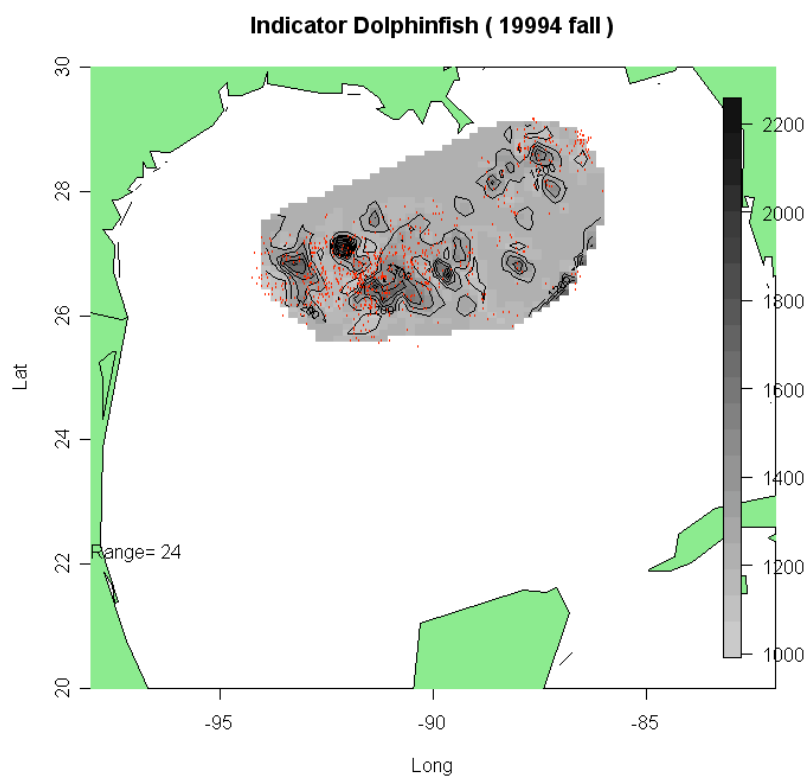
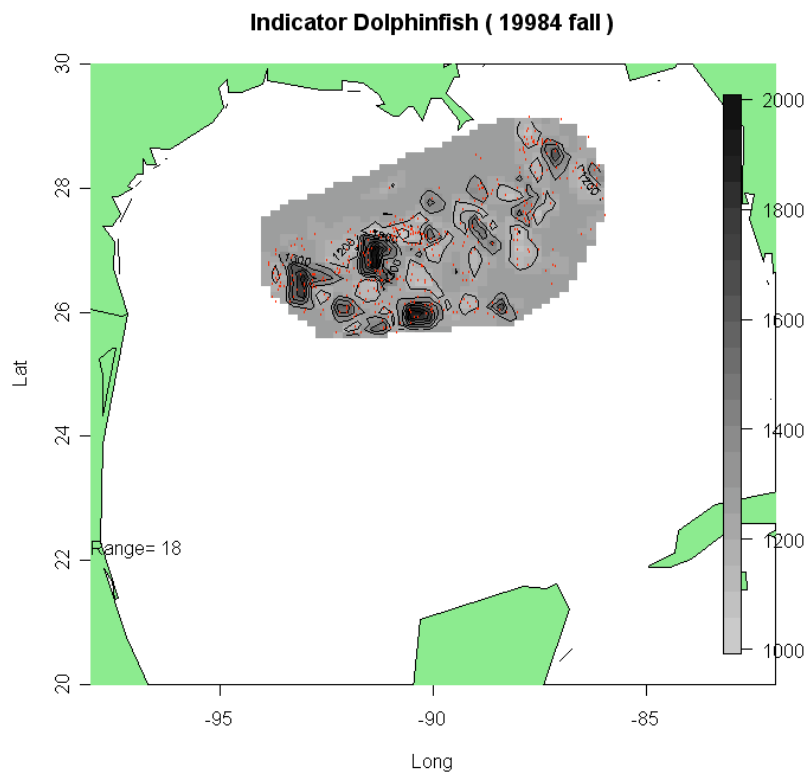


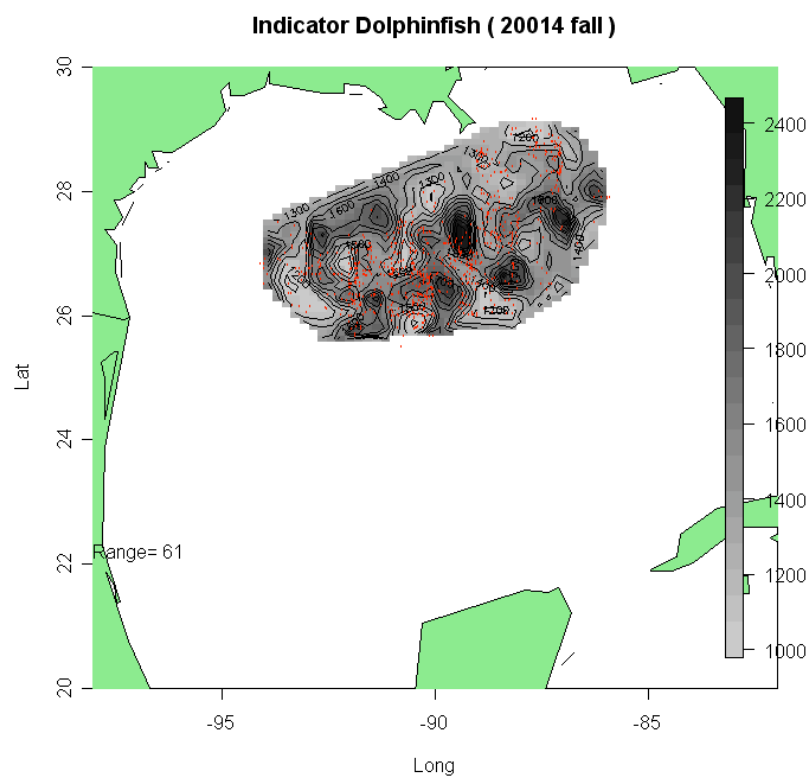
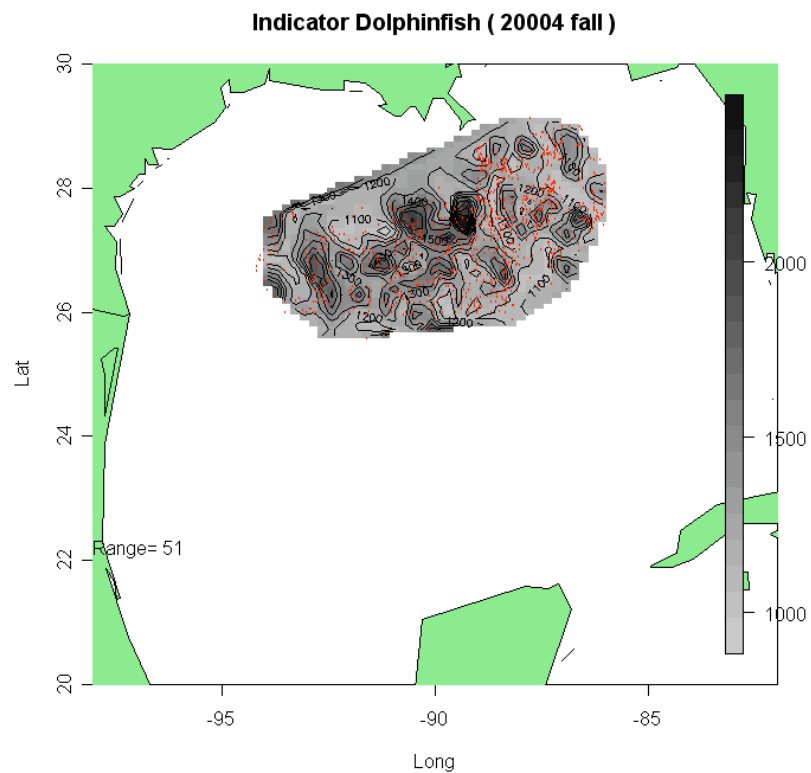


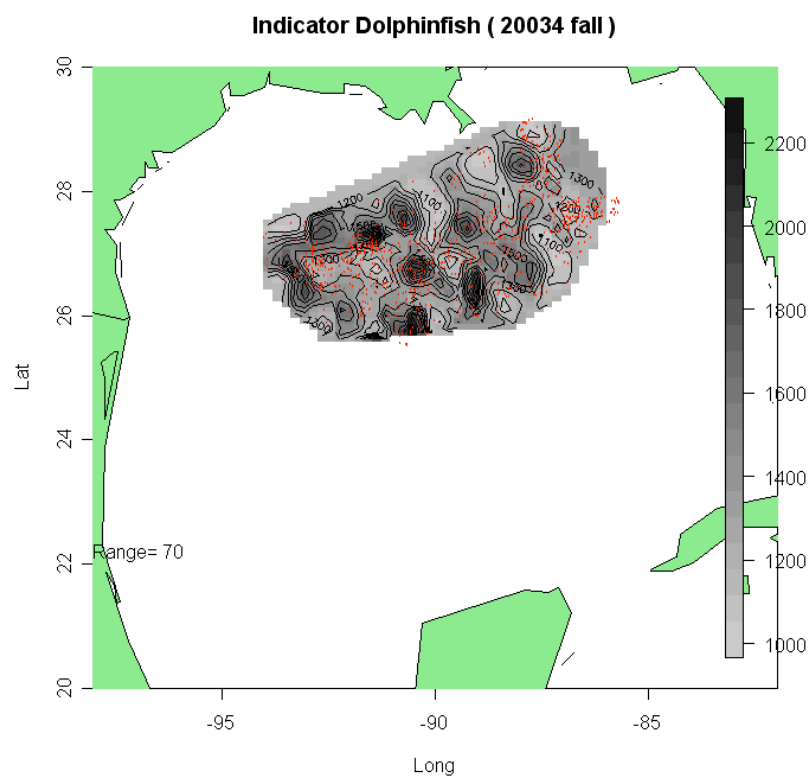
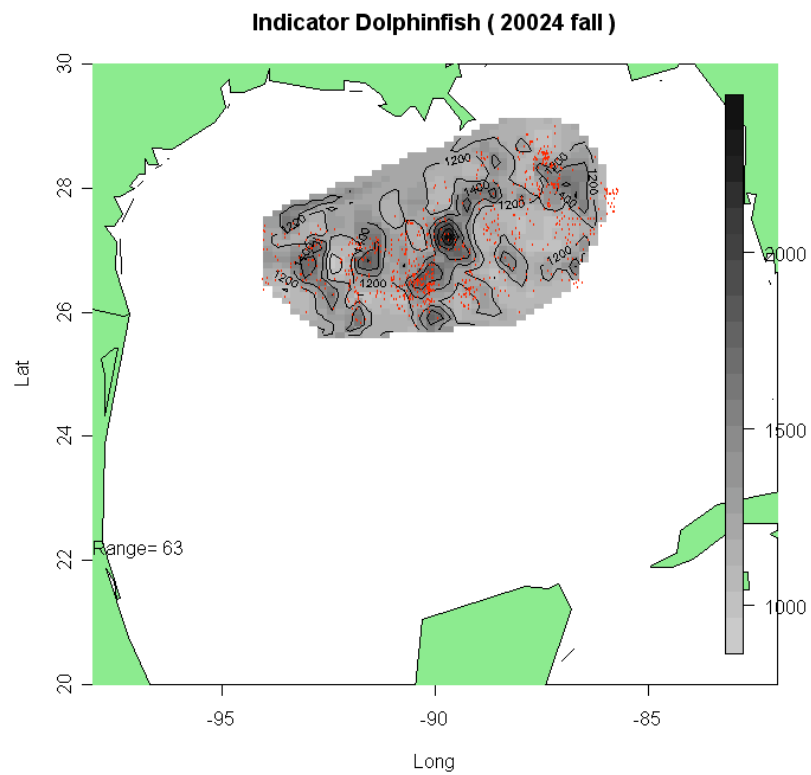


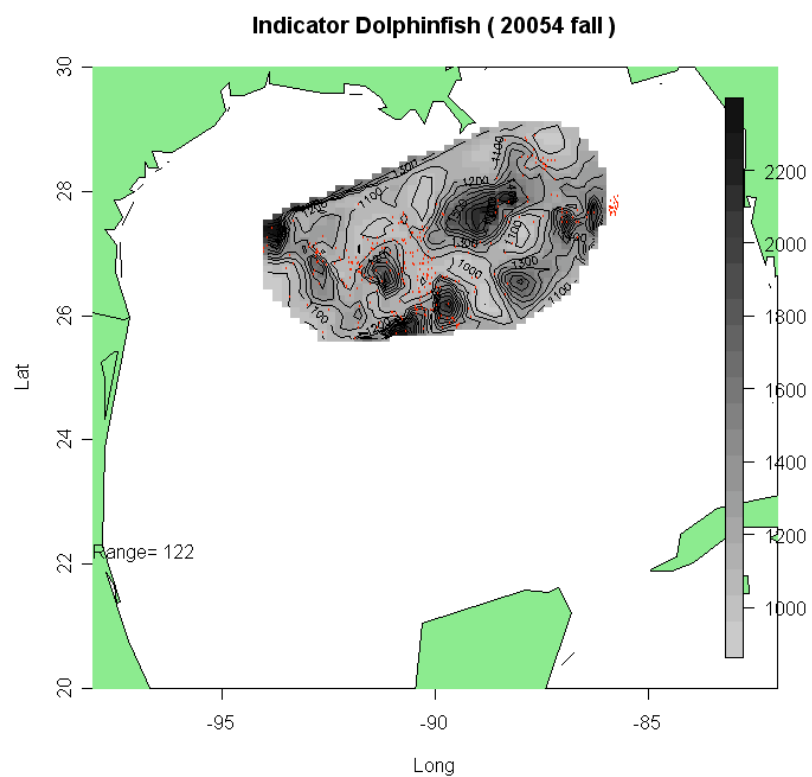
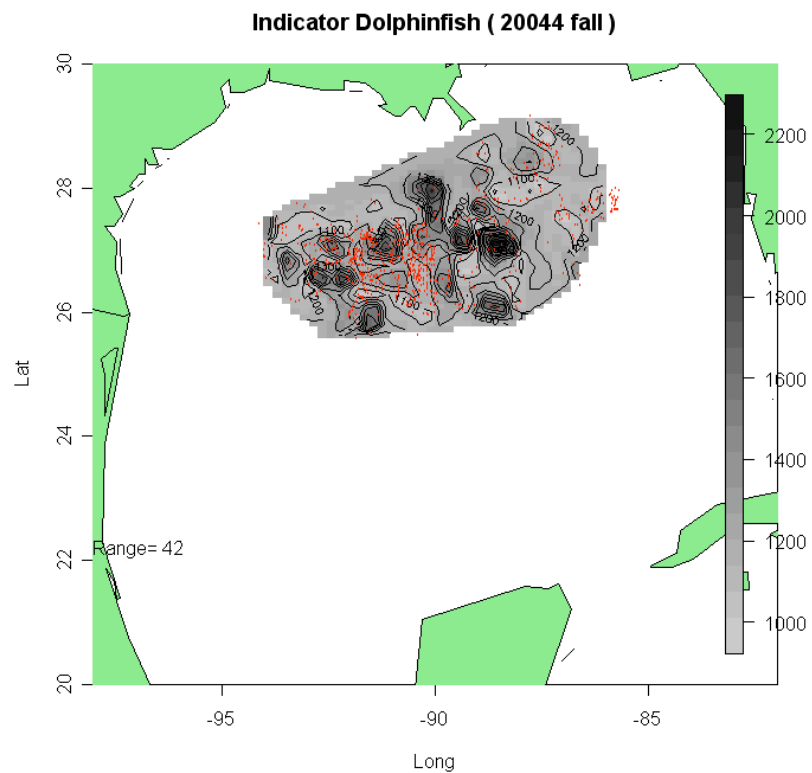




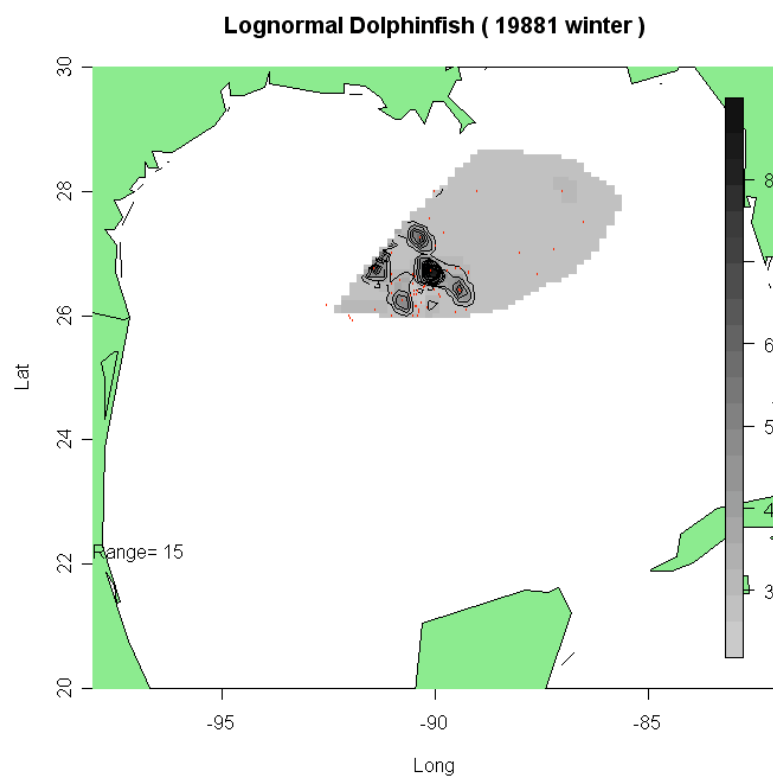
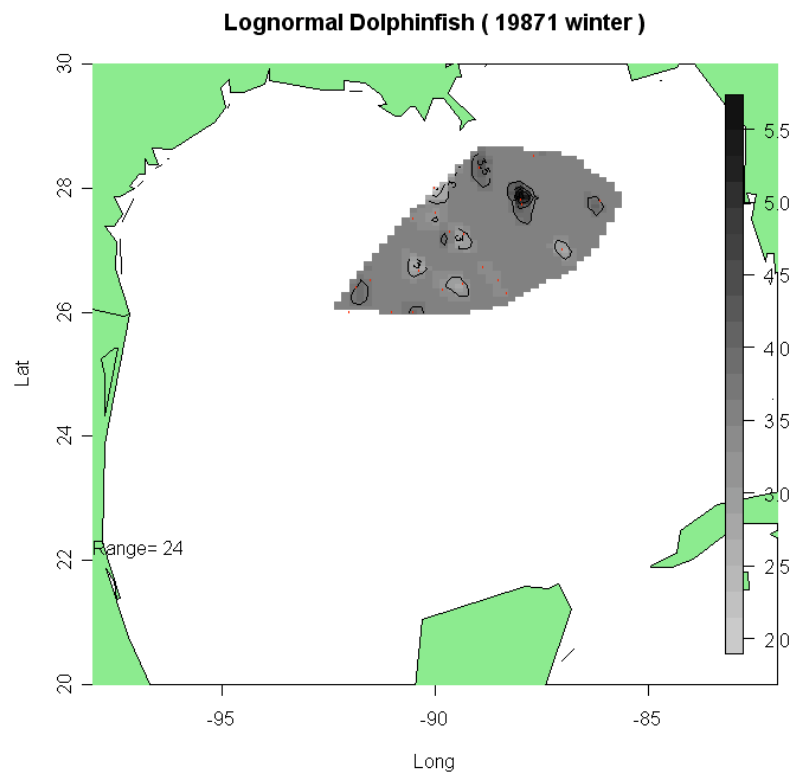


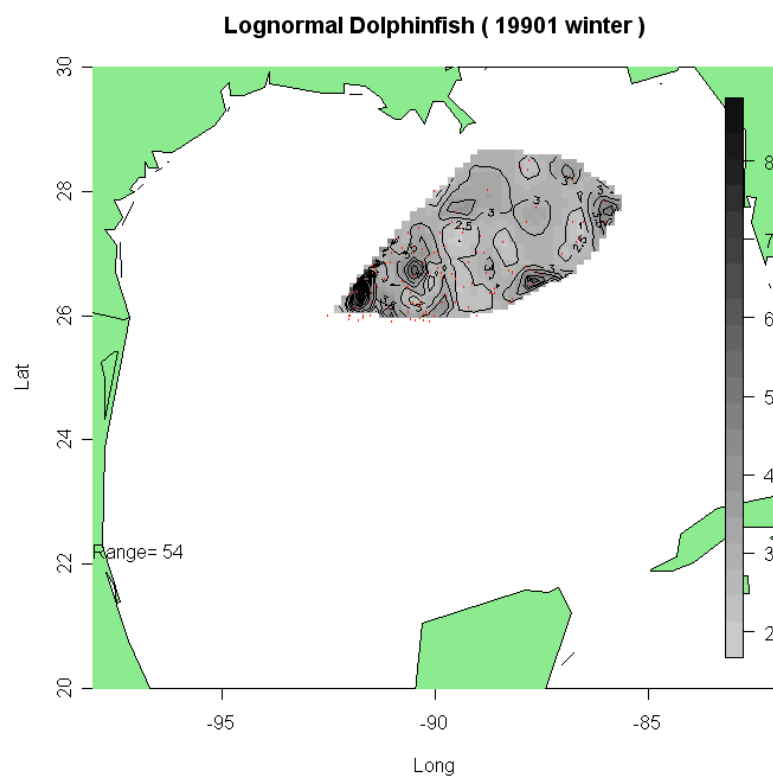
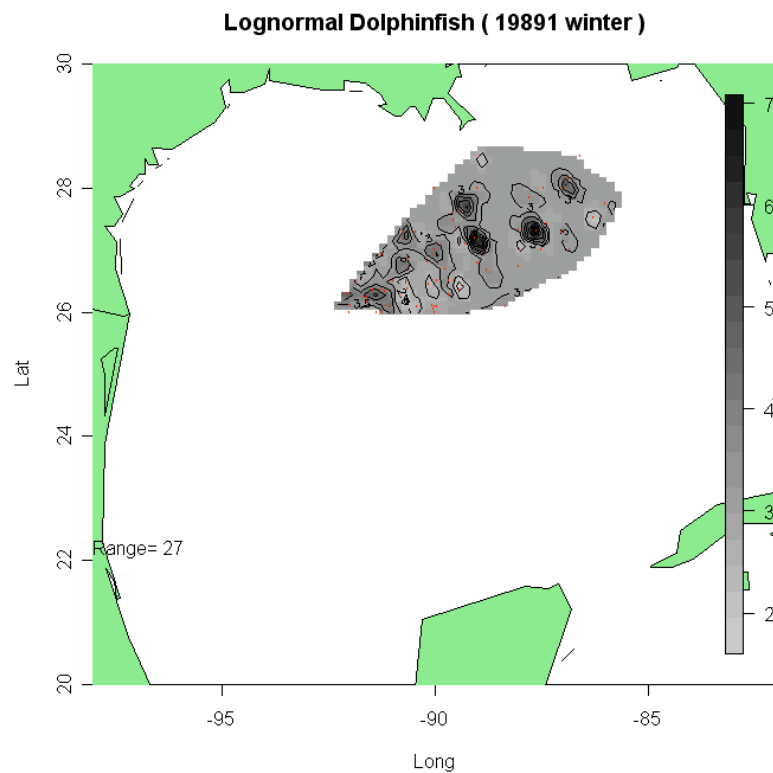


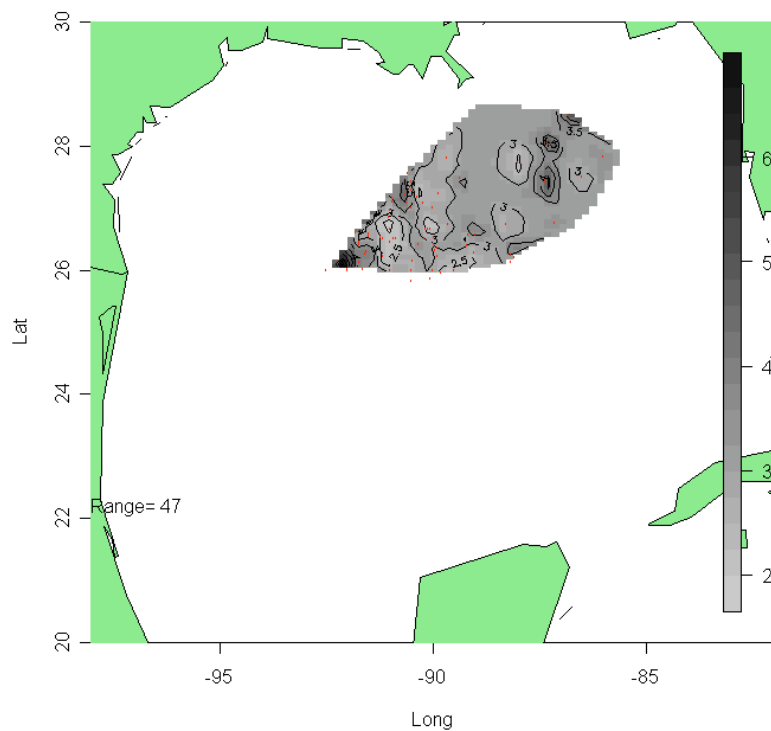
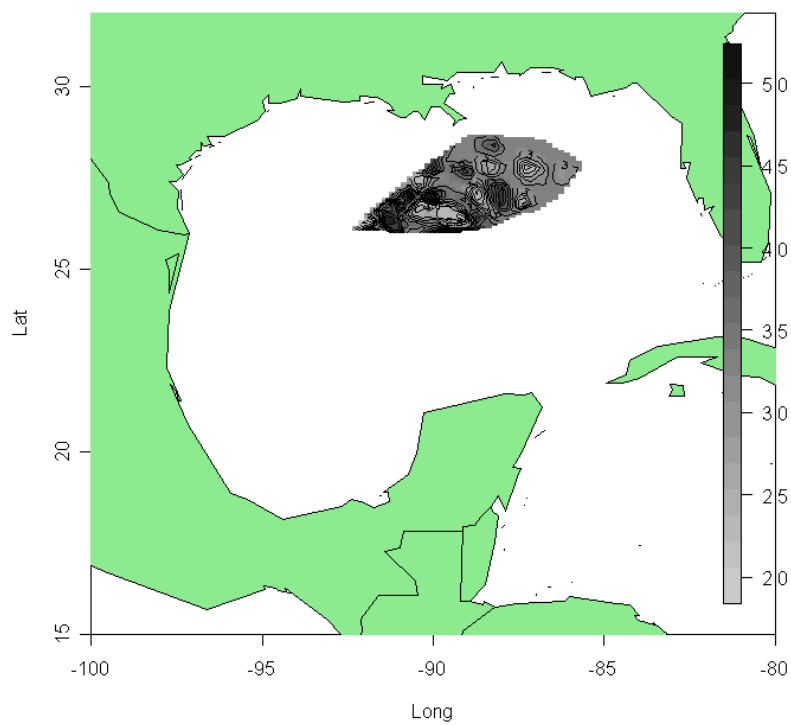


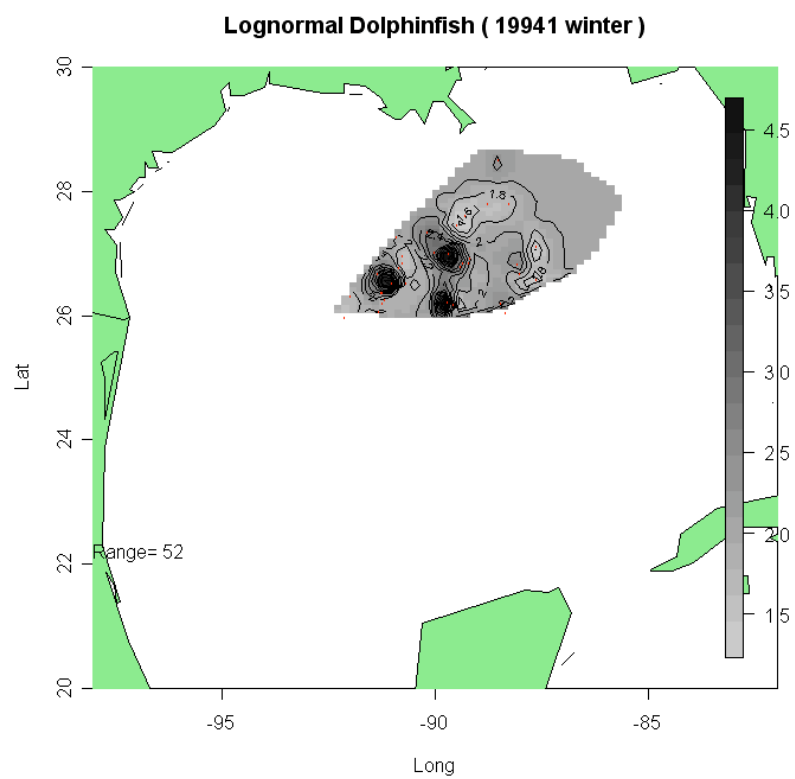
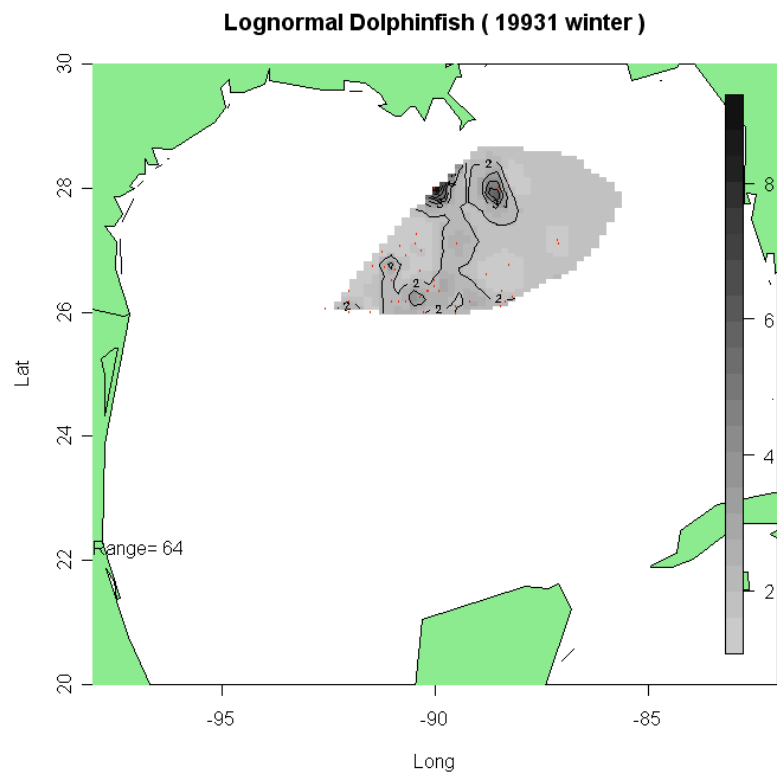


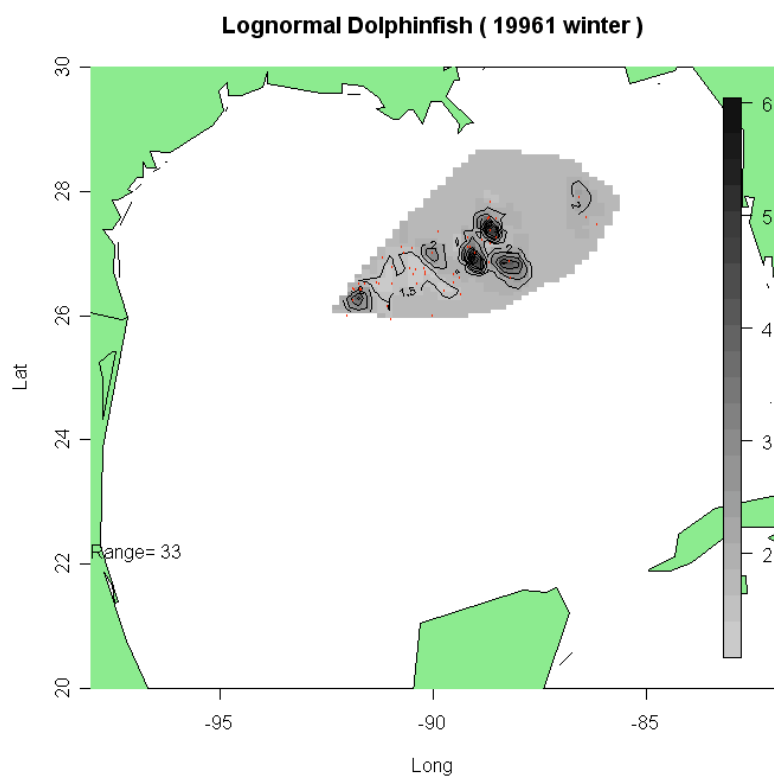
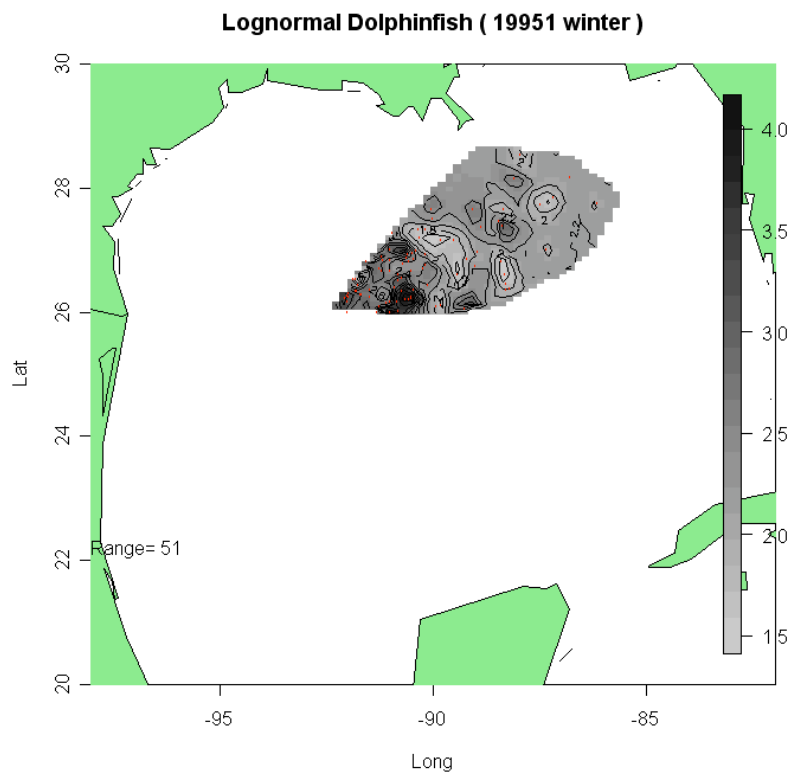
Winter Kriging Maps

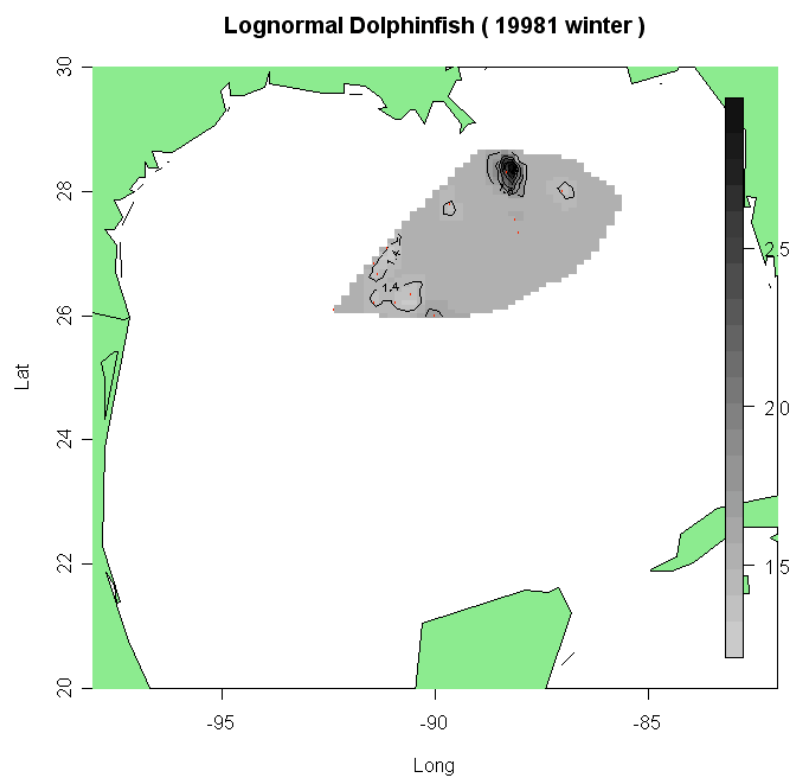
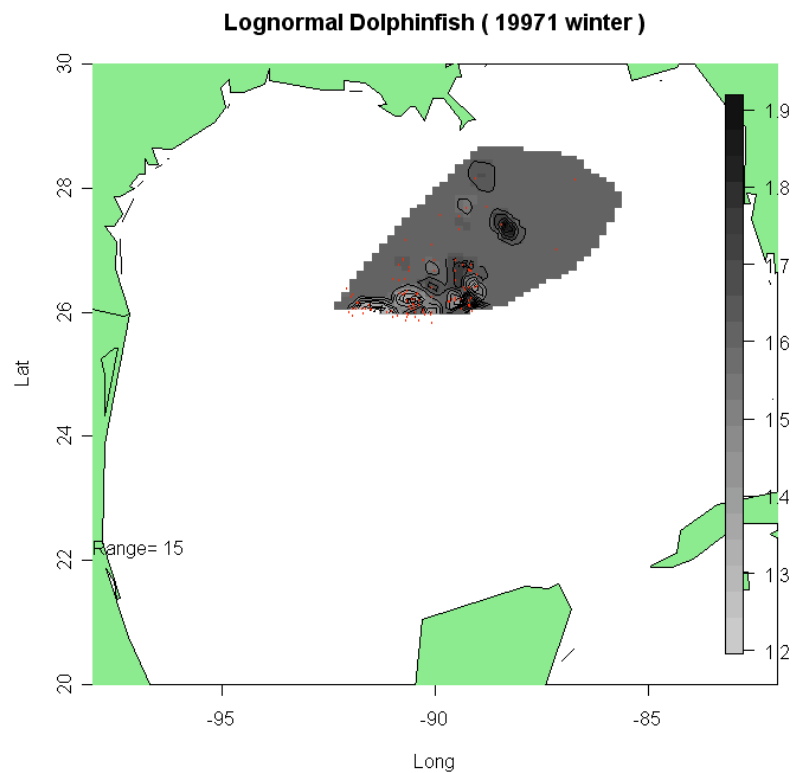


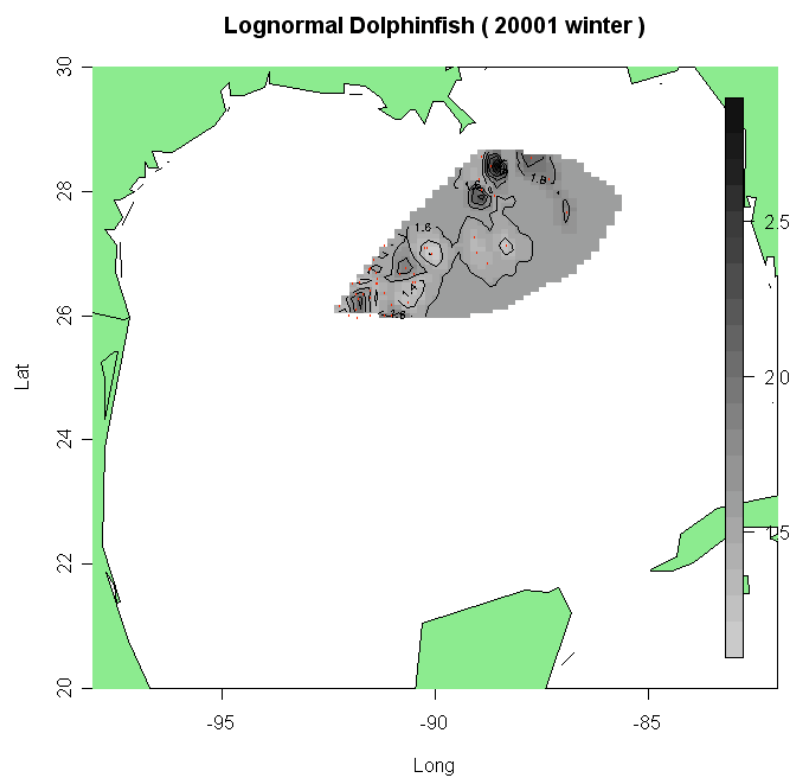
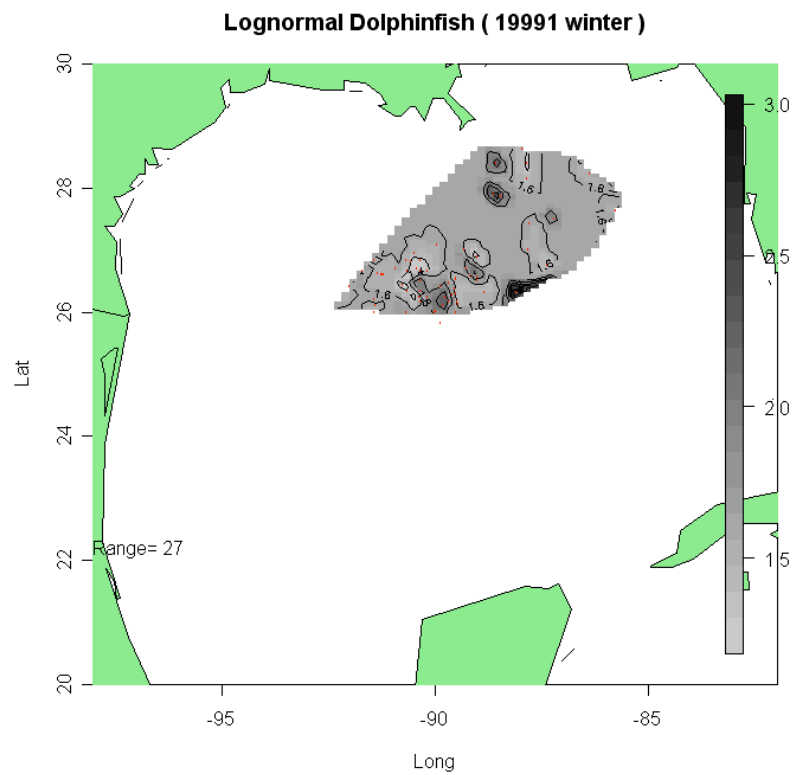


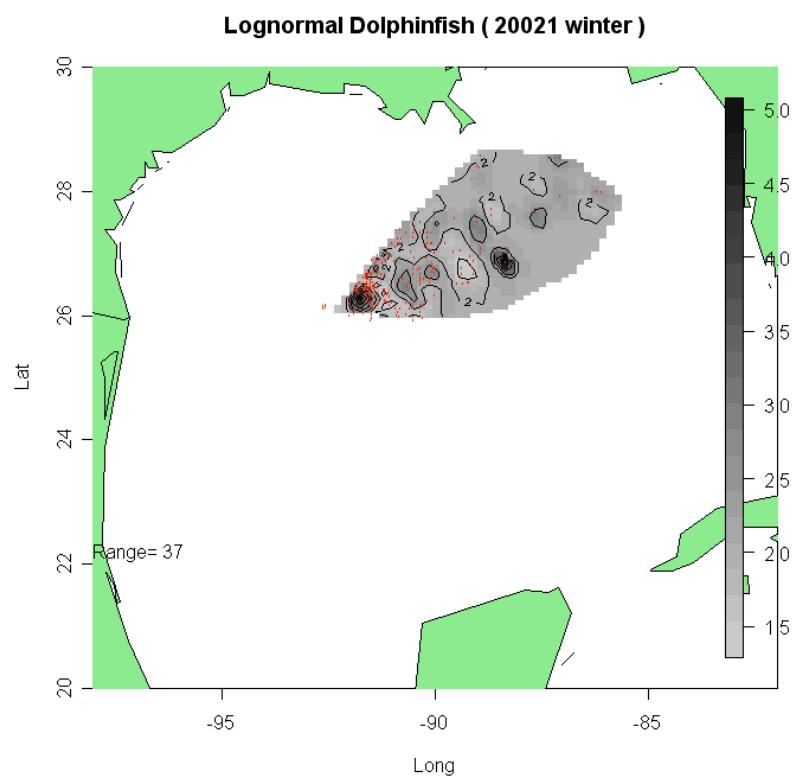
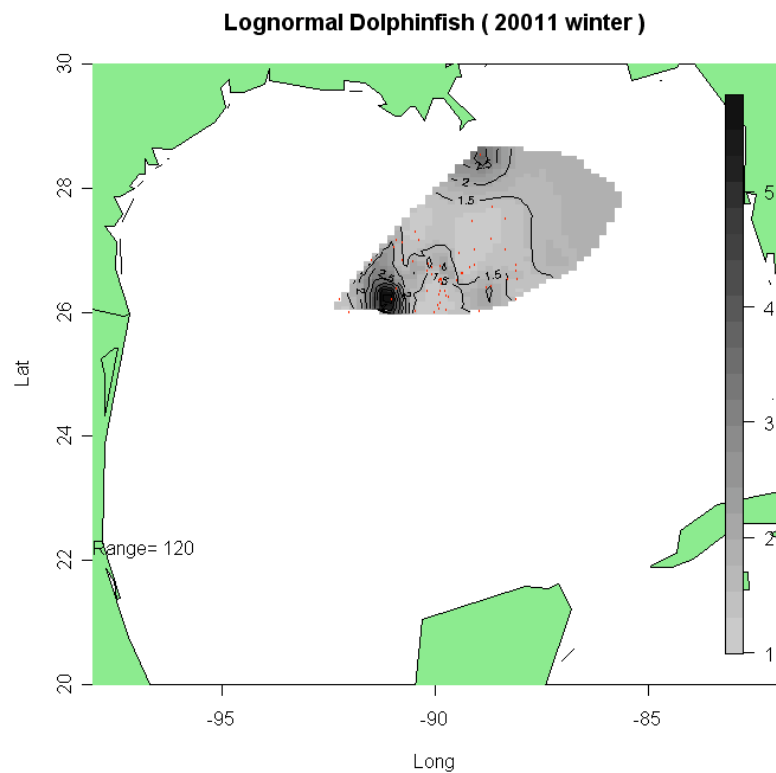
Lognormal Dolphinfish (19911 winter)**Lognormal Dolphinfish (19921 winter)**

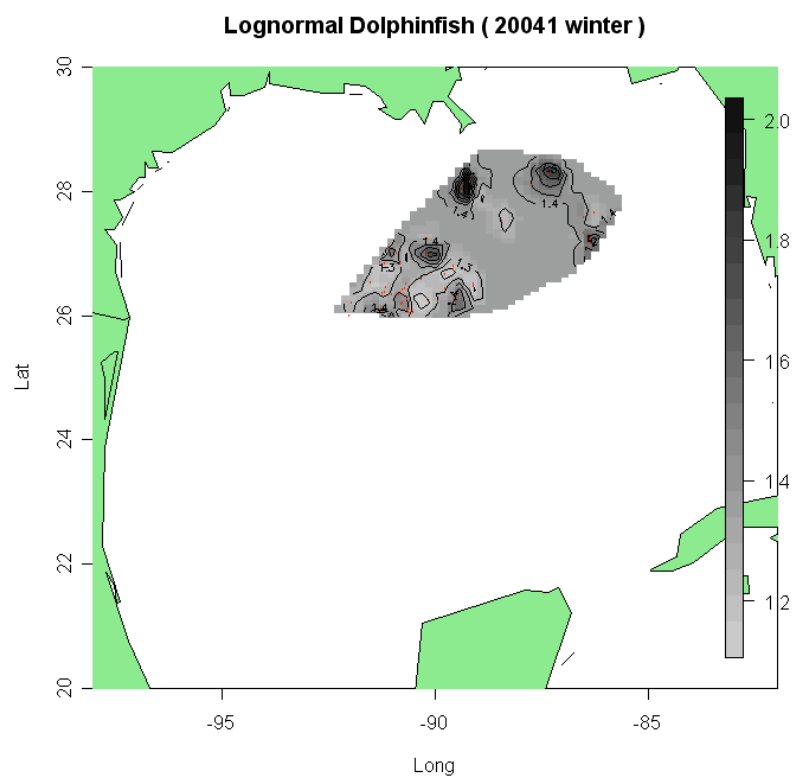
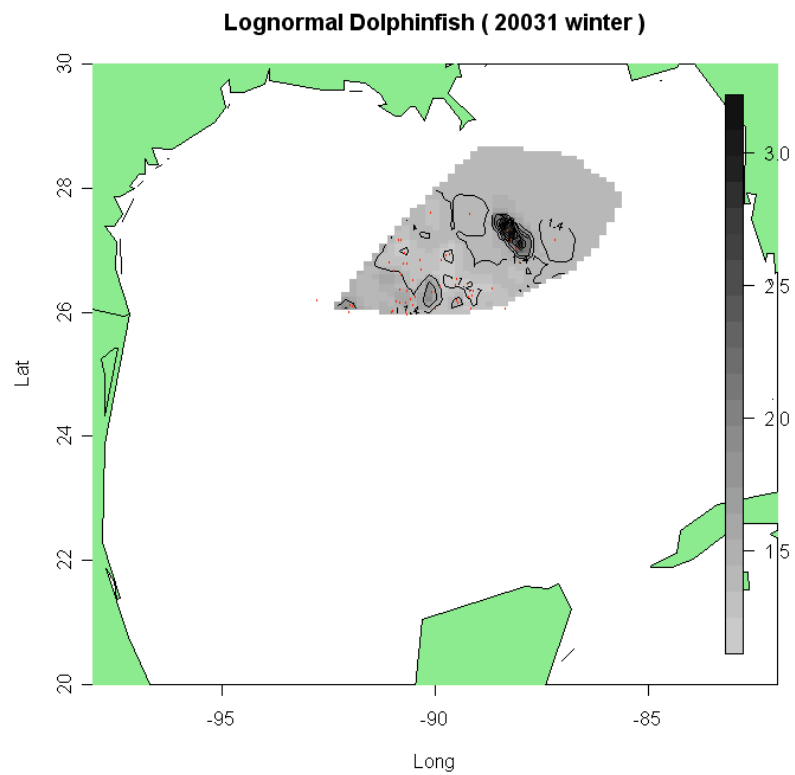


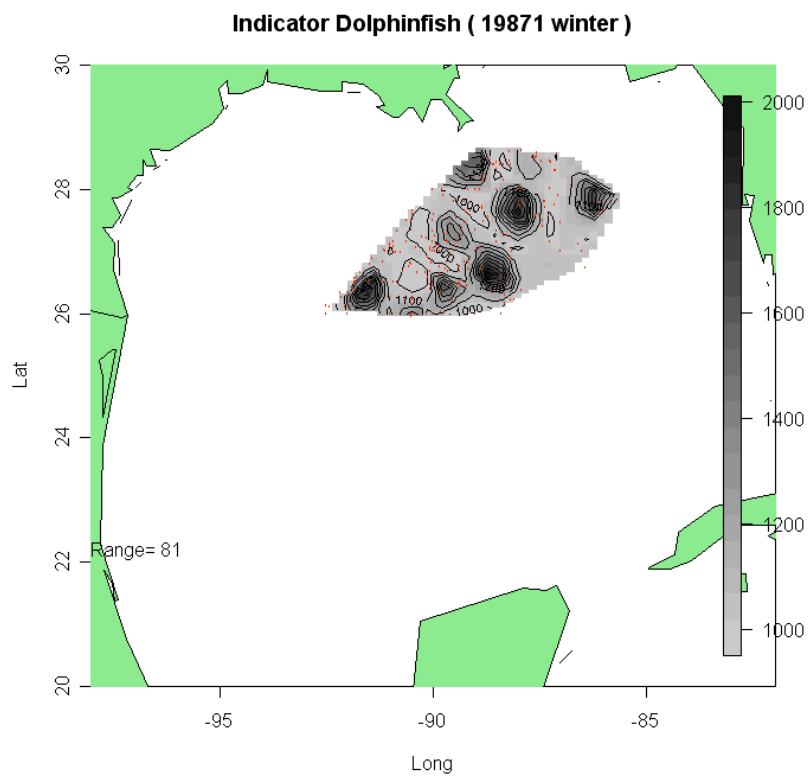
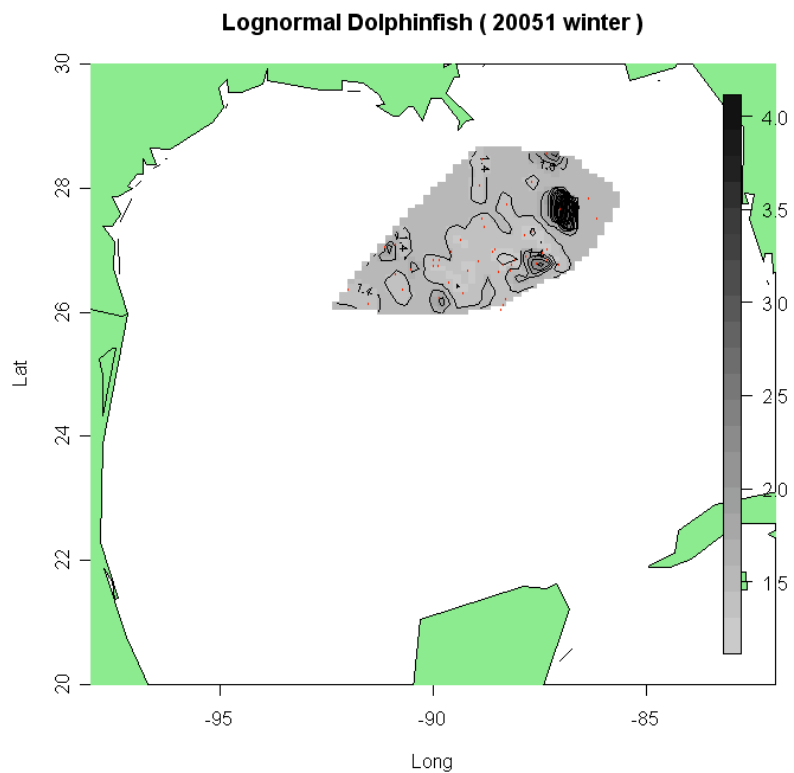


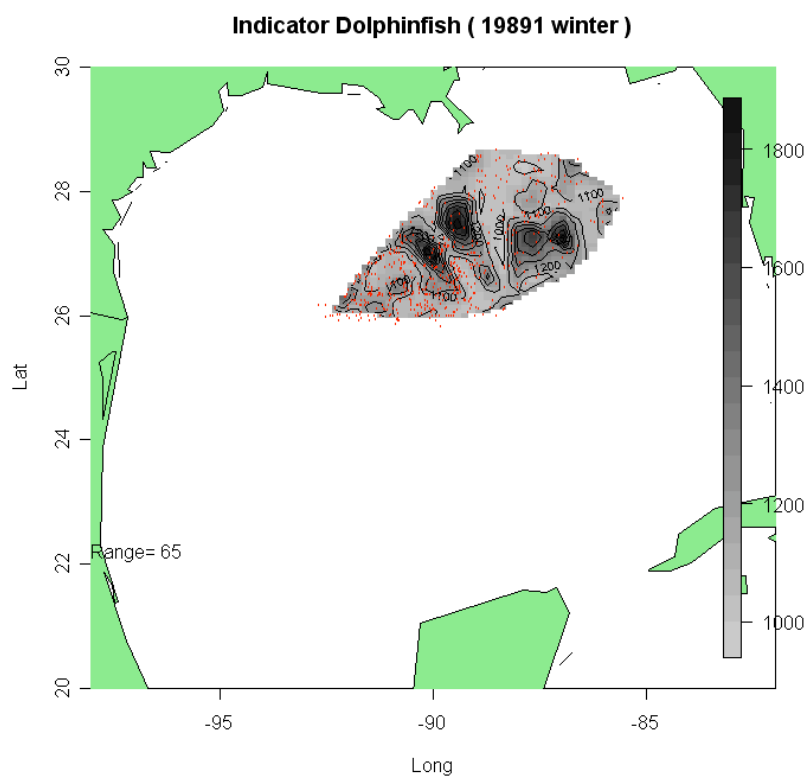
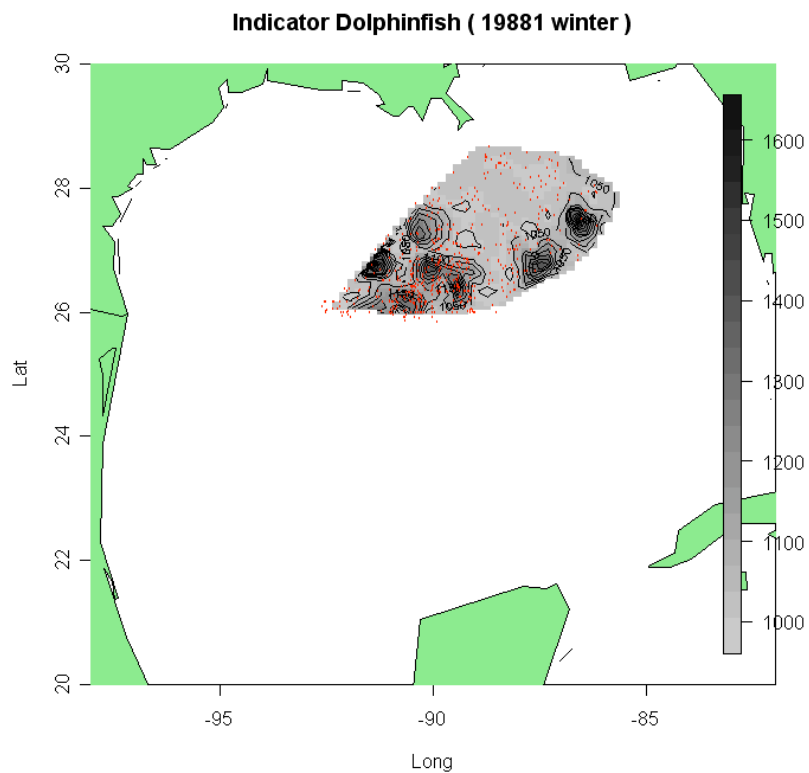


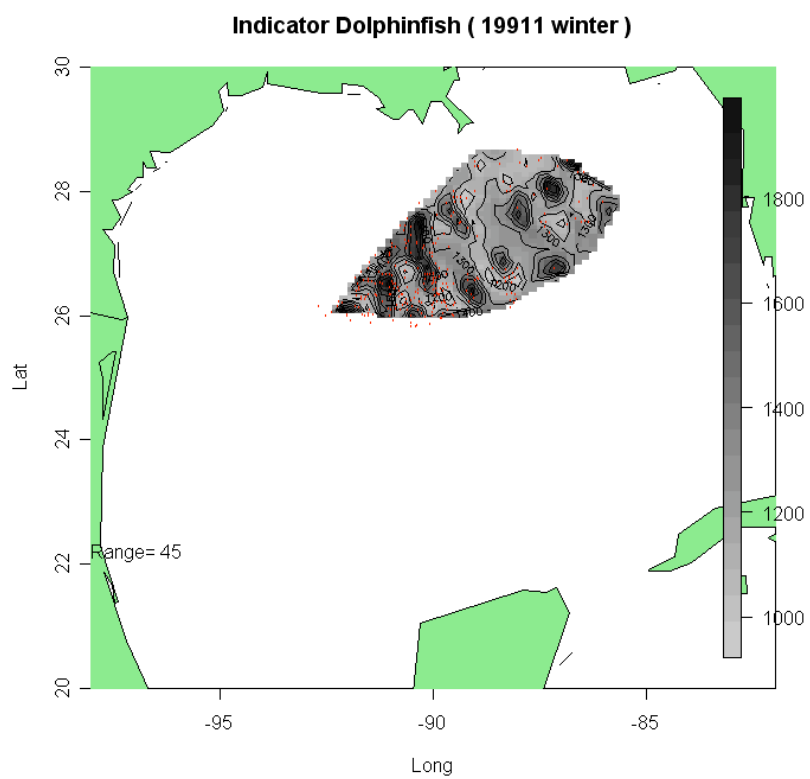
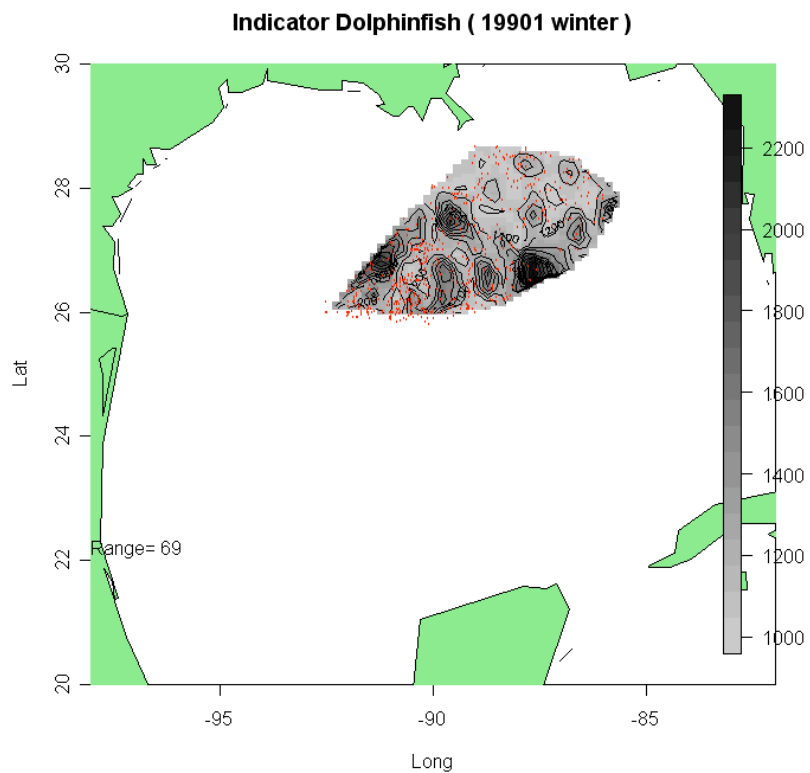


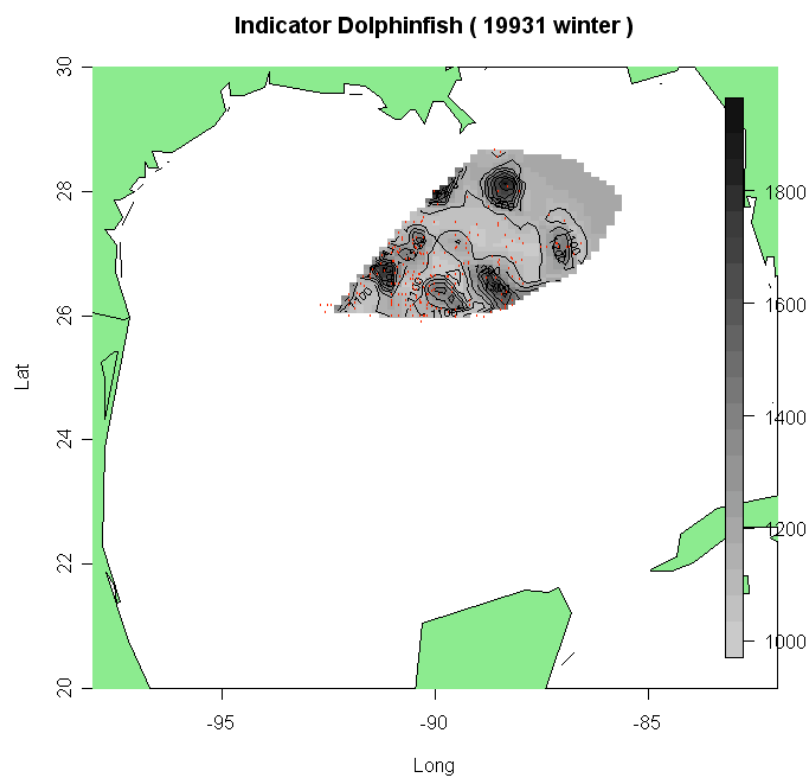
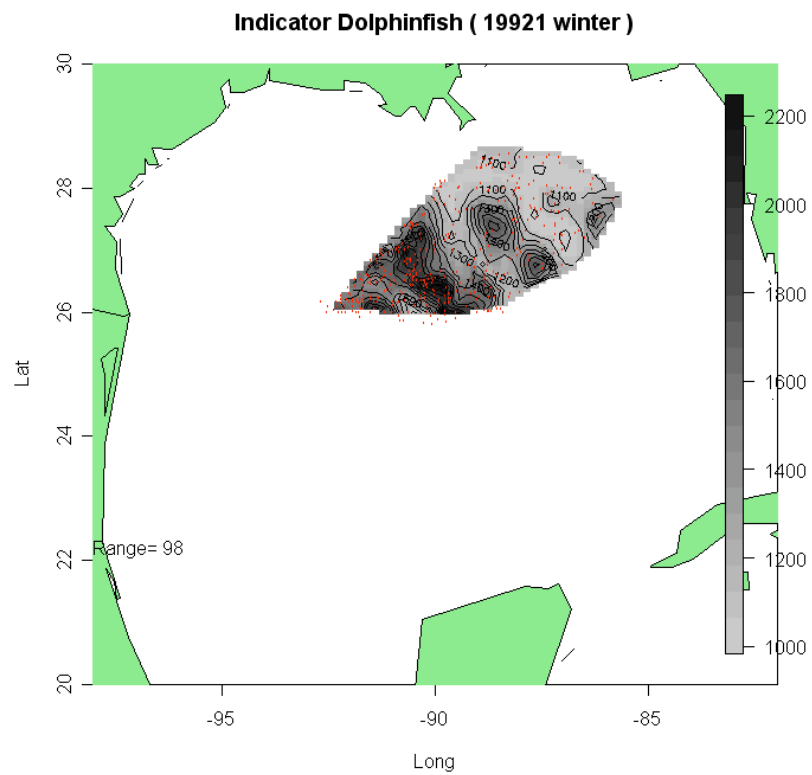


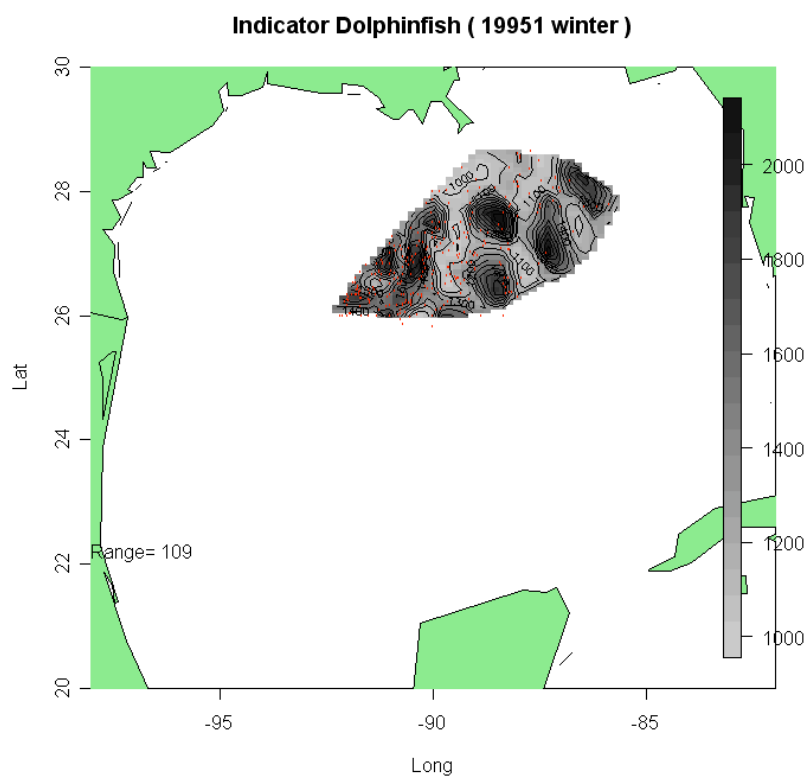
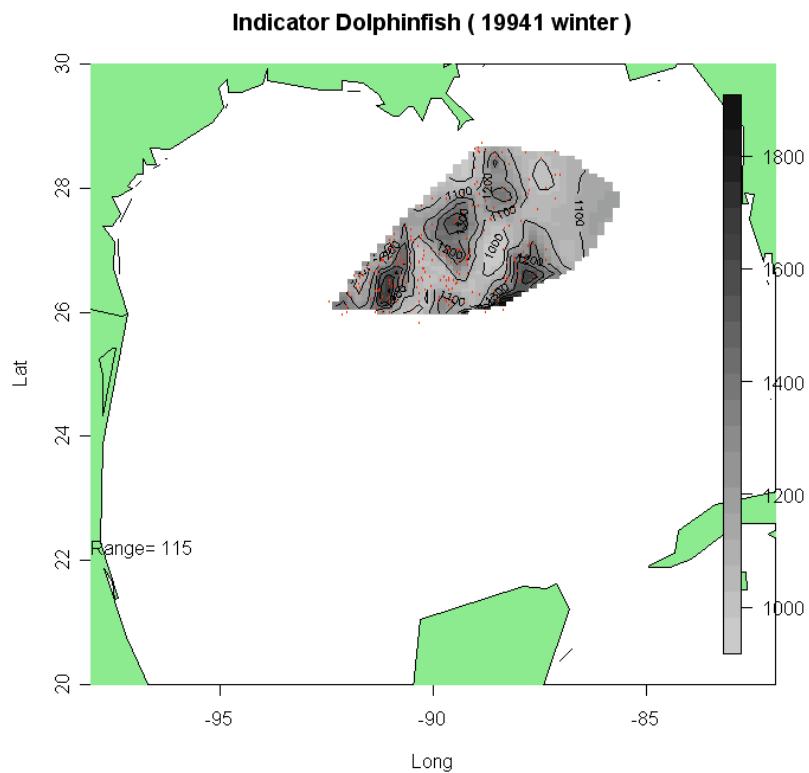


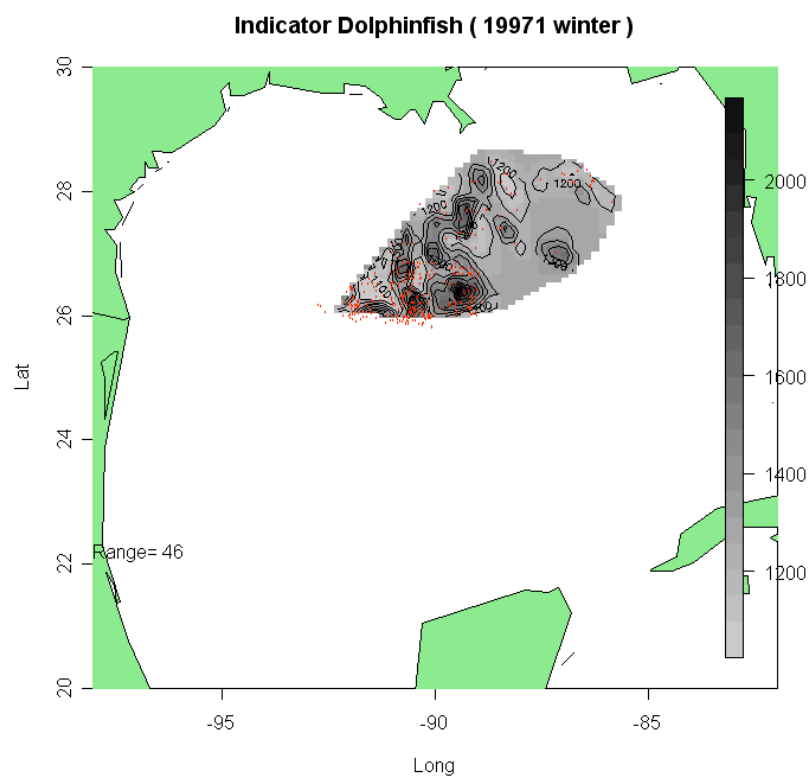
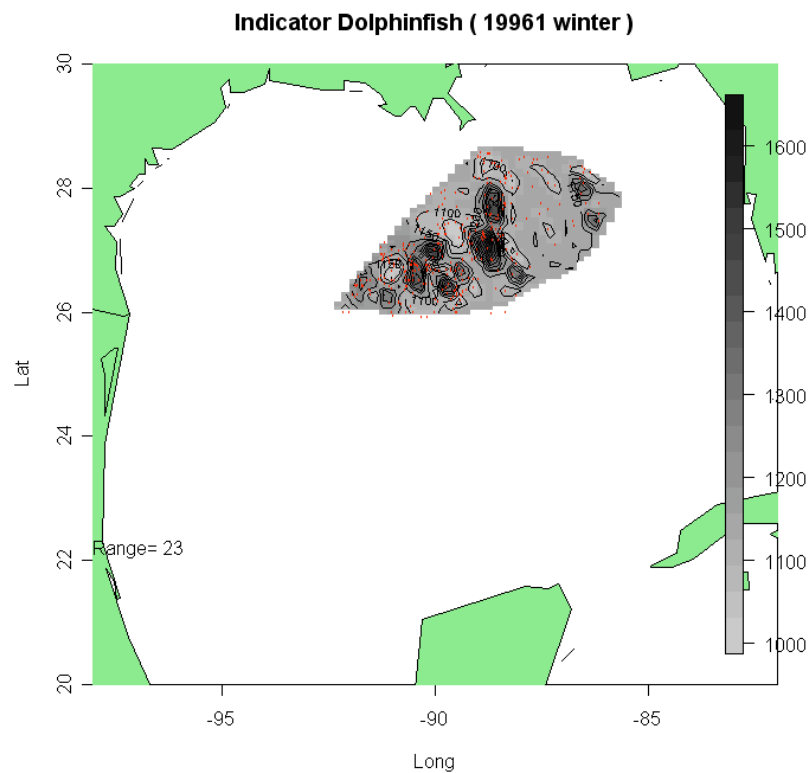


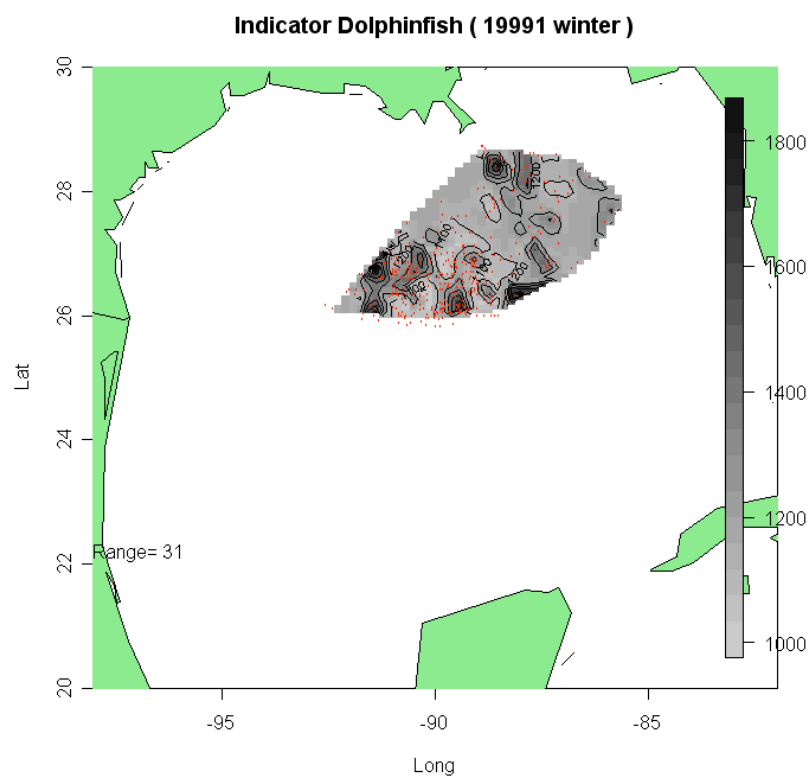
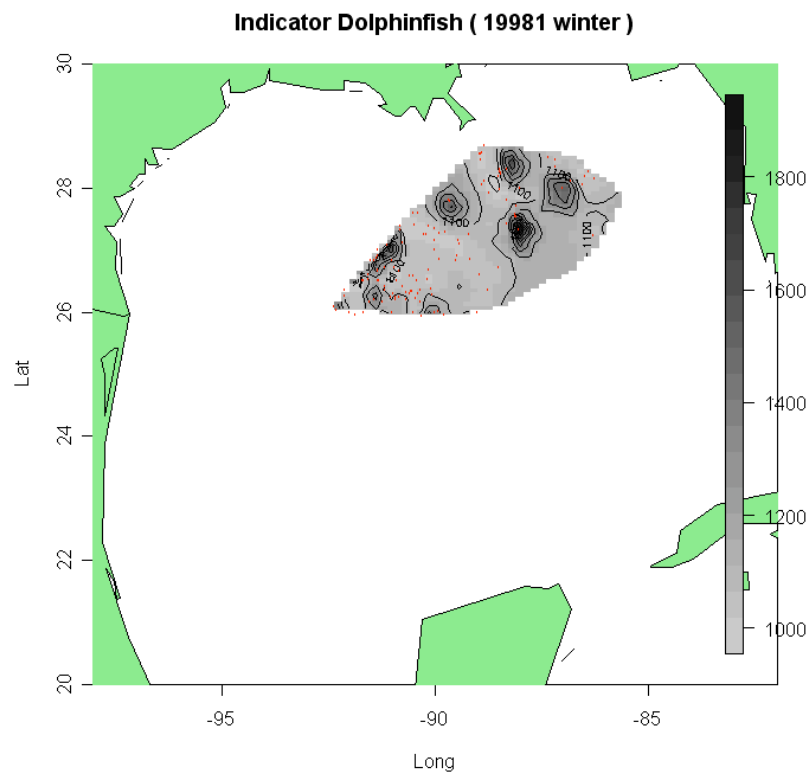


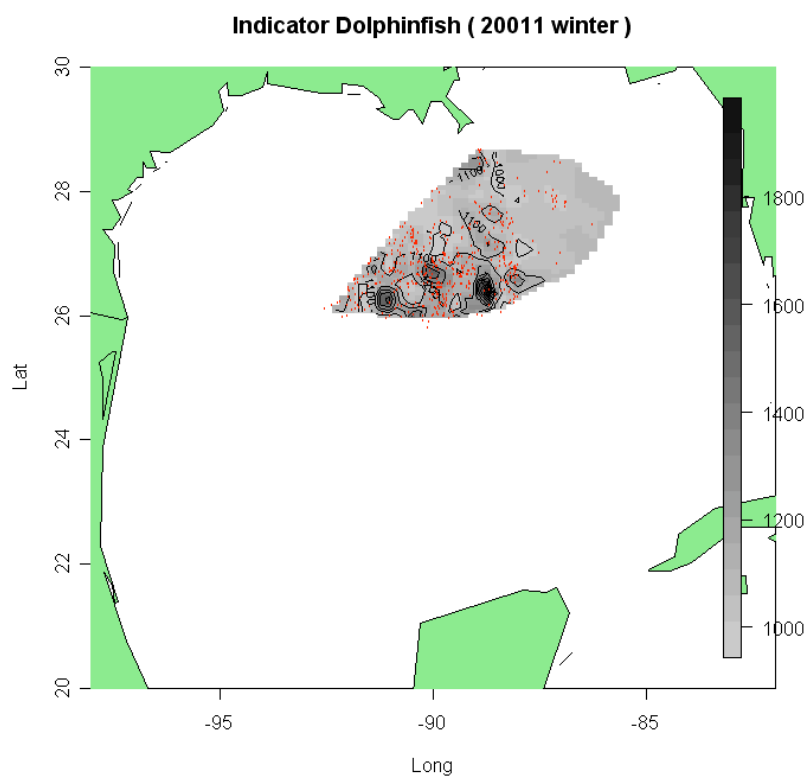
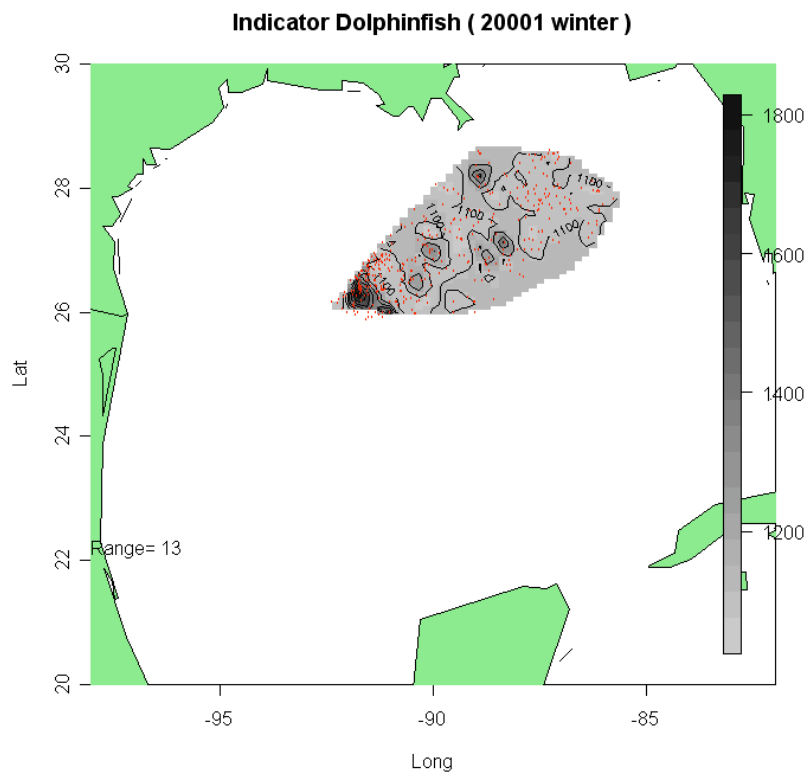


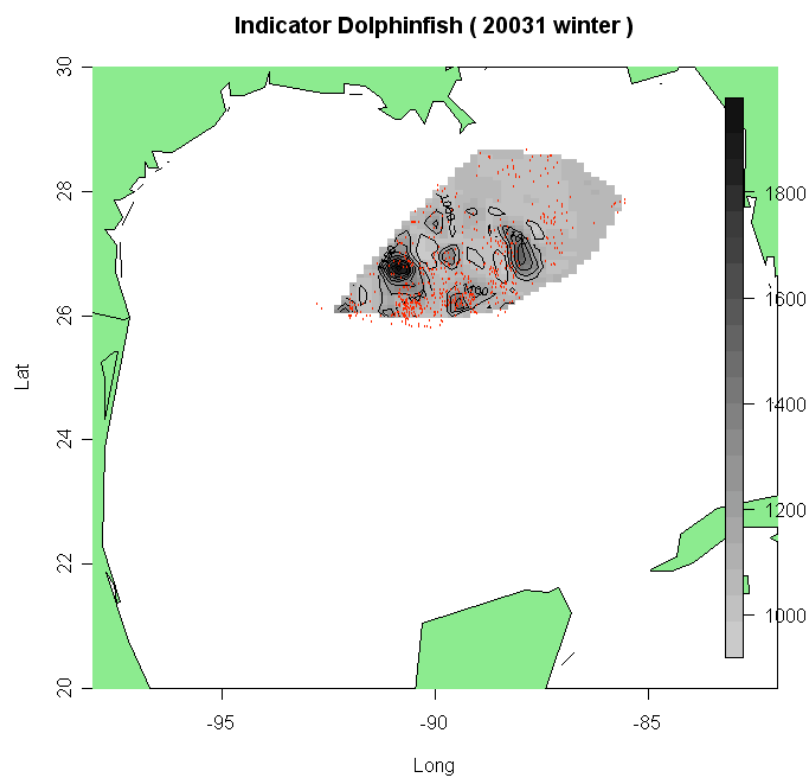
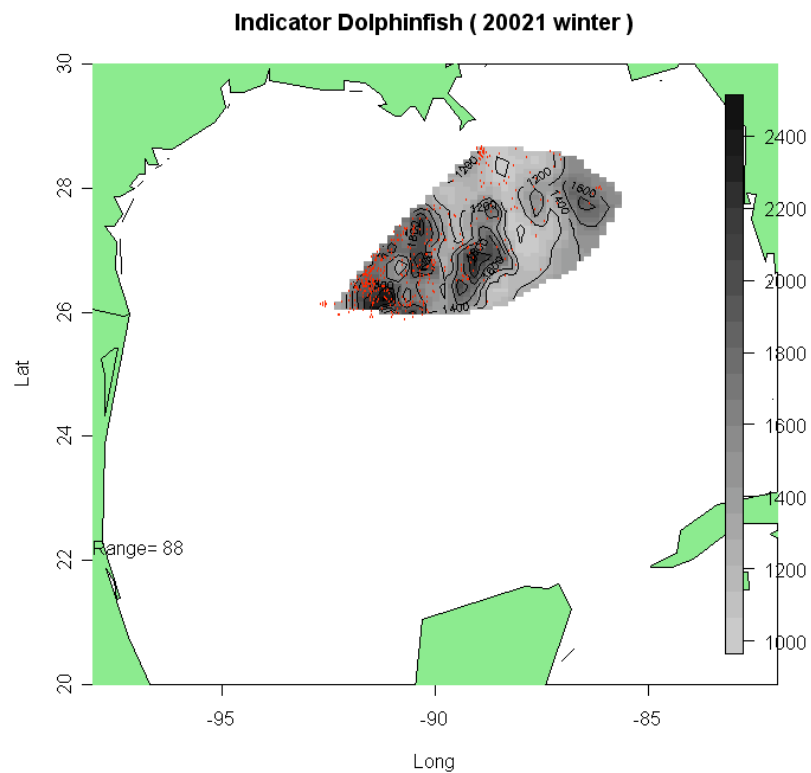


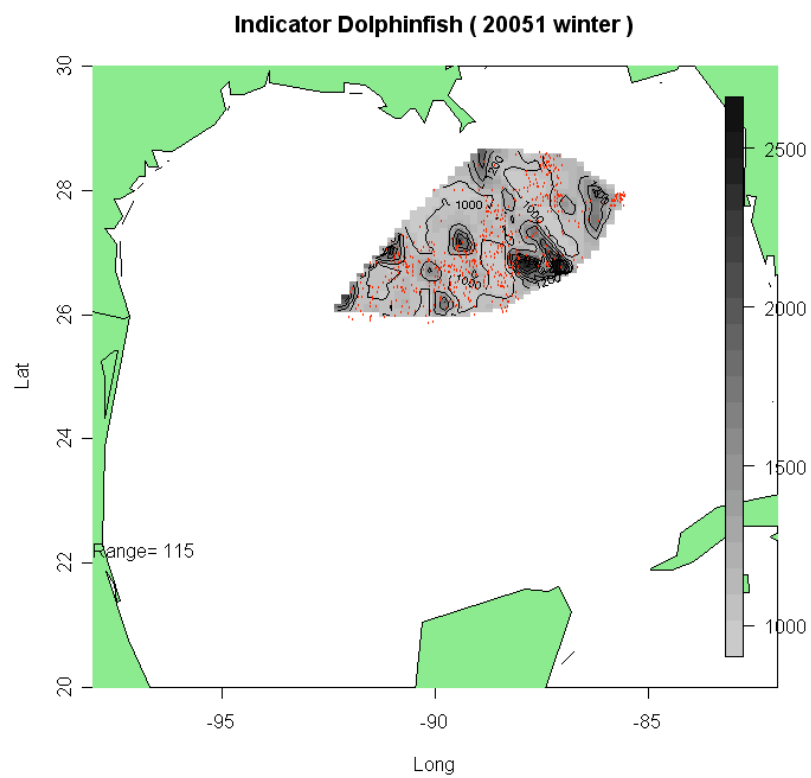
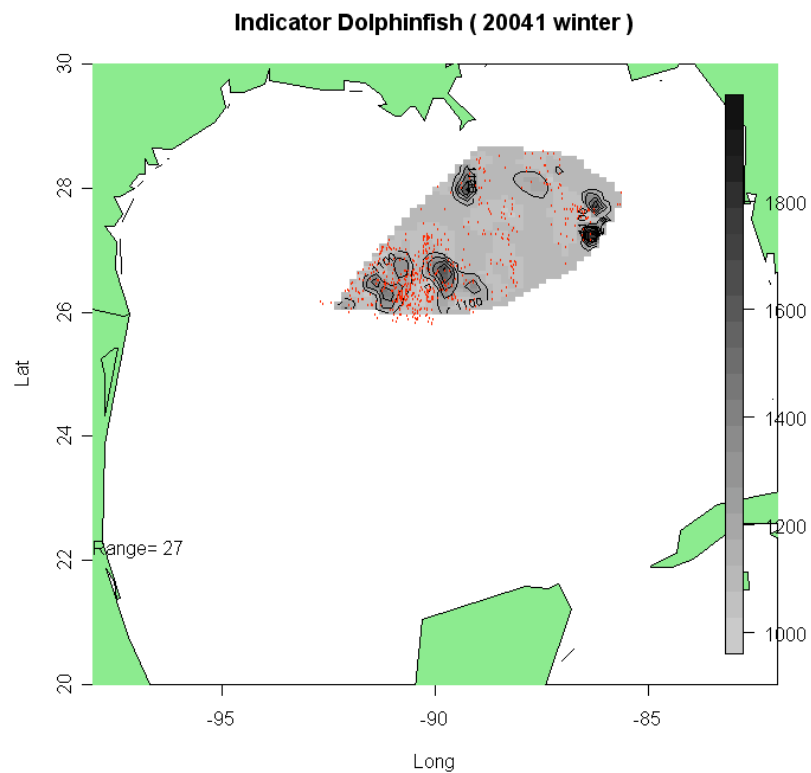












VITA

Kristin Marie Kleisner was born in Denver, Colorado, on August 27, 1978. Her parents are Jack Joseph Kleisner and Marie Paris Clements. She received her secondary education at F.W. Cox High School in Virginia Beach, Virginia. In September of 1996 she entered Lewis and Clark College in Portland, Oregon, where she completed one year before transferring to Portland State University in the same city. She graduated from Portland State University in May of 2000 with a double major: B.S. degrees in Biology and Environmental Science. She spent two years in Jackson Hole, Wyoming, before entering the division of Marine Biology and Fisheries at the Rosenstiel School of Marine and Atmospheric Science at the University of Miami where she was granted a Ph.D. degree in August 2008.

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