ESTIMATING ABUNDANCE INDICES FOR NAFO SUBAREA 2 + DIVISION 3K REDFISH VIA A SPATIOTEMPORAL MODEL

By © Natalie Fuller

A Thesis submitted to the School of Graduate Studies in partial fulfillment of the requirements for the degree of Master of Science in Fisheries Science (Stock Assessment)

Fisheries and Marine Institute

School of Fisheries

Memorial University of Newfoundland

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Abstract

Redfish (*Sebastes spp*.) are commercially important groundfish whose fisheries experienced some devastating collapses in the Northwest Atlantic of Canada. The stock on the Labrador Shelf (Northwest Atlantic Fisheries Organization Subarea 2 + Division 3K) is currently under a fishing moratorium but has experienced some recent population growth. Since there is currently no accepted assessment model for this stock, crucial decisions on when and how the fishery may reopen are determined by abundance indices. One big concern for this stock is the reliability of the abundance indices estimated from research surveys, especially with the partial and inconsistent survey coverage that has occurred over time. A possible solution for index standardization is via a spatiotemporal model, which utilizes spatial and spatiotemporal correlations to estimate trawl catches in unsampled areas based on sampled catches from neighbouring areas and years. In Chapter 1 I provide an overview of the redfish fishery and background on index standardization. In Chapter 2 I test different temporal and spatiotemporal structures for a model and use the best-performing model to predict catches in unsampled areas and therefore fill the gaps in survey coverage. I also quantify the uncertainties due to these predictions and generate new standardized survey abundance indices for the stock. There is also the possibility in the future of reductions in survey efforts in many regions in Subarea 2 + Division 3K, especially the near-shore and deep-water strata. Therefore, in Chapter 3, I test various survey configurations to assess the consequences of further reduction in sampling.

General Summary

Redfish is an important commercial fish complex with three species and multiple management zones (stocks) in the Northwest Atlantic Ocean. The fishery for the redfish stock off the Labrador shelf is currently closed due to substantial decreases in their abundance, but there has recently been population growth in this area. Stock management decisions (such as re-opening the fishery) are highly influenced by the trends in their estimated survey abundance indices. Currently, there is concern over the indices because of the substantial data gaps caused by under-sampled areas in the research surveys. This thesis explores using a model that incorporates spatial and spatiotemporal correlations to improve estimates in under-sampled regions and across the entire zone. Chapter 1 describes the background of the redfish fishery and methods to estimate their abundance. Chapter 2 presents the results from the model, and Chapter 3 explores how survey design potentially influences the model estimates.

Acknowledgements

Thank you to my supervisors, Dr. Jin Gao and Dr. Noel Cadigan, for their help. Specifically, thank you, Dr. Jin Gao, for her patience and guidance throughout the entire process and Dr. Noel Cadigan, for agreeing to move from being on my committee to taking on a co-supervisor role and providing his vital advice and insights. Thank you, Dr. Paul Regular, for supplying the data and answering my questions. Thank you to everyone else who provided me with helpful feedback and suggestions. I am thankful for the funding provided by The Ocean Frontier Institute and Ocean Choice International.

Thank you to all my friends and my family for the consistent support. I am continuously thankful to my parents for everything they have done to support my dreams and provide a safe space to land. I want to express my deep gratitude to all my friends and colleagues in Newfoundland who made St. John's feel like home while I was here.

Co-Authorship Statement

This thesis was the result of a collaborative effort. I developed the design of the project, performed the analyses, interpreted the results, and wrote the manuscript. Dr. Jin Gao helped conceptualize and create the project and provided revisions to the analysis and the manuscript. Dr. Noel Cadigan provided critical revisions to the analyses and the manuscript. Dr. Paul Regular from Fisheries and Oceans Canada provided the unpublished groundfish survey data utilized in the research.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

1.1. Introduction

In this Chapter, I provide an overview of redfish (*Sebastes spp.*) biology and the history of their commercial fishery in Northwest Atlantic Fisheries Organization (NAFO) Subarea 2 + Division 3K (SA2+Div.3K). I highlight the importance of abundance indices in fisheries management. I also provide an overview of the current management strategies and potential utilization of spatiotemporal modelling to produce new standardized stock abundance indices for fisheries management decisions.

1.2. Redfish Fishery Background

1.2.1. Redfish Background

In the Northwest Atlantic, 'redfish' characterizes a three species complex: *Sebastes mentella* (Travin, 1951), *S. fasciatus* (Storer, 1854) and *S. marinus* (synonymous with *S. norvegicus* (Ascanius, 1772); Gascon, 2003). These species are managed together as they are hard to distinguish visually (Fisheries and Oceans Canada, 2001; Power, 2001). Redfish live on both sides of the Atlantic Ocean, ranging in the Northwest from the coast of New Jersey to Baffin Island (Fisheries and Oceans Canada, 2001; Gascon, 2003). *S. marinus* distribution is mainly limited to the Flemish cap, whereas *S. mentella* and *S. fasciatus* have slightly different distributions; *S. mentalla* mostly ranges from the Gulf of St. Lawrence northwards, and *S. fasciatus* predominantly ranges from the southern Grand Banks southwards to the Gulf of Maine

(Gascon, 2003). They are found in cool waters (3-8°C), along banks and deep channels, typically at depths between 100-700 m, with *S. mentella,* usually found deeper than *S. fasciatus* (Fisheries and Oceans Canada, 2001; Gascon, 2003).

Within species, there are many different redfish ecotypes and populations, terms used for distinguishing groups of medium and low levels of reproductive isolation, respectively (Benestan et al., 2021). For *S. mentella,* multiple distinct ecotypes have been identified at different depths or locations, with moderate genetic differentiation between them (Benestan et al., 2021). For *S. fasciatus*, a unique population only exists within Bonne Bay, with the distribution of four other identified ecotypes of the species more overlapping (Benestan et al., 2021). However, sampling for genetic analysis has been limited; therefore, improving the understanding of species/ecotype distribution and characteristics (e.g., growth and recruitment) has been identified as a top priority for redfish research (Cadigan et al., 2022).

Many biological characteristics of redfish make them sensitive to overfishing and cause slow recovery (Cadigan et al., 2022). Redfish are a long-lived species, with a maximum age between 30 and 50 years for *S. fasciatus* and between 60 and 75 years old for *S. mentella* (Campana et al., 1990; Devine & Haedrich, 2011). They are slow-growing and mature at old ages (8-10 years old) (Fisheries and Oceans Canada, 2012), with variation in their estimated size at maturity depending on the population; lower estimates of this size are between 22-24 cm (Sévigny et al., 2007), and higher estimates are between 38-39 cm (Magnússon & Magnússon, 1995). They reach their minimum legal harvesting size (22 cm) on average between 6 to 8 years old (Fisheries and Oceans Canada, 2012). Males mature 1-2 years earlier than their female counterparts of the same species and 3-5cm smaller than when females mature (Sévigny et al., 2007).

Redfish have internal fertilization (Sévigny et al., 2007) and produce live pelagic larvae that can disperse over large distances (Valentin et al., 2015). These pelagic larvae must migrate through the cold intermediate layer when they become demersal, which may affect their survival and recruitment (Cadigan et al., 2022). The mating season occurs in the fall (Sep.- Dec.), and then the females carry the developing young until they are released in the spring (Apr.- Jul.) (Fisheries and Oceans Canada, 2012; Gascon, 2003). *S. mentalla* release their young a month earlier than *S. fasciatus* (Gascon, 2003). Fecundity depends on female size but ranges between 15, 000 to 107, 000 larvae (Fisheries and Oceans Canada, 2012). Recruitment success is highly variable and shows episodic patterns, where strong cohorts may occur from 5 to more than 12 years apart (Gascon, 2003; Sévigny et al., 2007). There is still much unknown about redfish mating, embryogenesis, and larval survival (Cadigan et al., 2022).

The diet of larger redfish is generally composed of crustaceans and fish (Sévigny et al., 2007). The Labrador shelf redfish have variable diets, but amphipods, shrimp, myctophids and euphausiids appear to be consistent prey (Fisheries and Oceans Canada, 2020). Redfish larvae mainly eat fish eggs and invertebrates, with larger larvae feeding on copepods and euphausiids (Fisheries and Oceans Canada, 2012). There seems to be little difference in the diets of *S. mentalla* and *S. fasciatus* (Sévigny et al., 2007).

Diet composition data from Labrador shelf groundfish species indicate that redfish is a frequent but not dominant prey for Atlantic Cod, Greenland Halibut and occasionally American Plaice (Fisheries and Oceans Canada, 2020). They represented up to 20% of Greenland Halibut diet in the late 1980s and a maximum of 30% in 2010 (Fisheries and Oceans Canada, 2020). From 1990 to 1996, Hammill and Stenson (2000) found that redfish in the Gulf of St. Lawrence were shown to be an important part of harp seal diet composition; however, more recently, redfish were rarely found in harp seal stomachs (Sévigny et al., 2007). On the eastern Scotian Shelf, haddock, pollock and grey seals are redfish predators (Fisheries and Oceans Canada, 2012).

1.2.2. SA2+Div3K Redfish Stock History and Management

There are nine separate redfish management zones in the Northwest Atlantic: South Greenland. (Div. 1F), Northeastern Newfoundland and Labrador Shelf (SA2+Div.3K), Flemish Cap (Div. 3M), Grand Banks (Div. 3LN), Southern Grands Banks (Div. 3O), Gulf of St. Lawrence (Unit 1 - Gulf of St. Lawrence (Unit 1 - Div. 4RST, 3Pn4Vn [Jan. to May]), Laurentian Channel (Unit 2 - Div. 3Ps4Vs4Wfgi, 3Pn4Vn [June to Dec.]), Scotian Shelf (Unit 3 – Divisions 4WdegklX) and Gulf of Maine (SA 5) (Gascon, 2003). A redfish fishery by Canadian and international fleets has been prosecuted in NAFO SA2 + Div.3K (Northeastern Newfoundland shelf and Labrador shelf, referred to for simplicity as the Labrador shelf from this point on) since the late 1940s (Fisheries and Oceans Canada, 2020; Figure 1.1). After the closure of fisheries for other groundfish stocks in the 1990s, there was renewed interest in redfish fisheries (Gascon, 2003).

The highest recorded catch in SA2+Div.3K was 187,000 t in 1959 (Fisheries and Oceans Canada, 2001, 2020; Power, 2001). Based on data presented by Power et al. (2001), Canada only made up 21% of the nominal removals from 1960 to 2002 of redfish in SA2+Div.3K. A total allowable catch (TAC) quota of 30,000 t was placed on the fishery in 1974 (Fisheries and Oceans Canada, 2001, 2020; Power, 2001). The TAC subsequently increased and decreased in the following years until a moratorium was declared in 1997 (Fisheries and Oceans Canada, 2001, 2020; Power, 2001). The reported removals were between 30 t to 7,500 t during 1987 to 1997 (Fisheries and Oceans Canada, 2020). A fishing mortality proxy has been low (<1%) since 2006 (Fisheries and Oceans Canada, 2020). Discards ranged between 15 t to 700 t annually between 1980-1996, and during 1997-2015 they varied from 50 t to 600 t, with an average of <300 t (Fisheries and Oceans Canada, 2020). The redfish biomass index substantially increased from 2003 to 2011 (Fisheries and Oceans Canada, 2020). The biomass index declined from 2011 to 2015 but was approximately half of the pre-collapse (1978-1990) levels (Fisheries and Oceans Canada, 2020; Healey & Parrill, 2018). This trend is seen in design-based biomass indices for Divisions 2J3K (Figure 1.2). The recruitment of redfish <15 cm from 2000 to 2015 was above the long-term average, with the highest recruitment abundance in 2014 (Fisheries and Oceans Canada, 2020).

One limitation to the management of the Labrador Shelf stock is that there is currently no accepted assessment model for the stock. Most redfish stocks in the Northwest Atlantic use trends in their survey indices and catches, and their size compositions, for their assessment, but a few stocks have assessment models (Cadigan et al., 2022). The episodic and unpredictable nature of redfish recruitment has caused many challenges in managing redfish stocks (Gascon, 2003). Additionally, their episodic recruitment has raised questions about the suitability of limit reference points (LRPs) for redfish (Fisheries and Oceans Canada, 2020). Many factors have been examined regarding recruitment success, such as temperature, oceanographic conditions, and the presence of prey/predators; another aspect discussed has been juvenile bycatch (Gascon, 2003).

A Bayesian-fitted state-space production model was tested by Fisheries and Oceans Canada to create limit reference points (LRPs) for NAFO SA2+Div.3K redfish (Fisheries and Oceans Canada, 2012). However, neither the production model nor the derived LPRs were used in the latest assessment due to concerns over the input data and model rationale, specifically issues with separating species in surveys commercial catch data (Fisheries and Oceans Canada, 2020). No other LPRs were accepted because of concerns about episodic recruitment, species separation and data input (Fisheries and Oceans Canada, 2020). Without accepted LRPs, and because of the declines in biomass during 2011-2015, it was recommended that any reopening be done with a precautionary approach (Fisheries and Oceans Canada, 2020; Healey & Parrill, 2018). With no accepted assessment model, trends in abundance indices will be highly influential in management decisions regarding reopening; therefore, the indices need to be reliable.

1.2.3. Bycatch

Juvenile redfish bycatch is a concern across the Northwest Atlantic; this is especially true in the shrimp fishery, where a small mesh size is used. Additionally, redfish have a physoclistous swim bladder (a swim bladder not connected to the intestinal tract) and therefore suffer high mortality when brought to the surface due to the swim bladder busting from rapid changes in pressure (Benoît et al., 2013). Since the moratorium, removals of redfish from bycatch and discards have averaged around 500 t annually in NAFO SA2+Div.3K (Fisheries and Oceans Canada, 2020). A large proportion of redfish bycatch is juveniles. An estimated 2.5 million redfish were caught as bycatch in 2000, with 80% being juveniles, 12-18 cm long and approximately 4-6 years old (Power, 2001). In 2021, there was a substantial amount (amounts currently unpublished) of juvenile redfish bycatch in the shrimp trawls in Shrimp Fishing Area 4 (SFA4), which overlaps with Division 2G redfish (Courtney D'Aoust, 2021). Understanding the juvenile distribution of redfish may help limit the potential bycatch of juveniles in future shrimp fisheries.

1.2.4. Stratified Random Sampling Research Surveys

An important purpose of research vessel (RV) bottom trawl surveys is to sample fish abundance by conducting tows along or close to the seafloor for a standardized time or distance (Kimura & Somerton, 2006). A time-series of surveys produce information on trends in distribution, abundance, or population structure for stock assessments. In the Northwest Atlantic, stratified-random sampling (SRS) with proportional allocation to strata area is the standard practice for RV surveys (Cadigan, 2011). Strata are delineated based on biological or hydrographic considerations; depth was especially important in the NAFO stratification design (Doubleday, 1981).

Stratified random groundfish trawl surveys have been conducted by Fisheries and Oceans Canada (DFO) annually in the fall (usually Oct-Dec) since 1977 in parts of the NAFO SA2+Div.3K. In 1995, DFO switched the vessel, trawl gear, and other survey protocols (i.e., tow durations) they used for their groundfish surveys from the MV Gadus Atlantica with the Engel 145 Otter trawl to the more efficient CCGS Teleost with the Campelen 1800 shrimp trawl. Comparative fishing trials were conducted in 1995, and equations were developed to convert catches at length between the two fishing methods (Warren, 1996). The trials found that the Campelen trawl increased the catchability for all redfish size groups, but particularly for individuals less than 30 cm (Power & Orr, 2001). Survey catches prior to 1995 were converted to Campelen equivalents using the estimated conversion factors. However, there was high uncertainty in the conversion estimates (Warren, 1996), and therefore there is still uncertainty about how comparable the converted catches prior to 1995 (with the Engel trawl) are to those obtained with the Campelen trawl since then. This conversion factor uncertainty was especially high for juvenile redfish, which could potentially have more effect on the uncertainty of estimates for these size classes.

Since the start of the surveys in 1977, the survey coverage across NAFO SA2+Div.3K has been inconsistent. Divisions 2J and 3K have been sampled annually from 1977 to 2020. Prior to 1996, surveys covered depths from 100 to 1,000 m, but in 1996 coverage increased to 1,500 m (Fisheries and Oceans Canada, 2020). Division 2H was irregularly surveyed from 1978 to 2010 but has been surveyed annually since 2010. In addition, some years missed sampling deeper strata (>700 m), which is important habitat for redfish (Fisheries and Oceans Canada, 2020). Division 2G was sporadically surveyed with varying spatial coverage from 1978 to 1999 and has not been sampled since (Fisheries and Oceans Canada, 2020).

This inconsistent sampling creates substantial survey coverage gaps (Figures 1.3 – 1.6). In the future, there is also a potential plan to drop deep-water strata and near-shore strata entirely, which could miss the major distribution ground for redfish. This potential further reduction in sampling effort is due to the depth limitations of a new research vessel and time constraints

(Personal communication with Dr. Paul Regular). Additionally, one or two large catches can dominate redfish survey results due to redfish forming dense aggregations (Fisheries and Oceans Canada, 2020). Large aggregations causing "big catches" can greatly influence survey abundance indices and increase the uncertainty in abundance estimates. This is a prevalent problem for fisheries assessment (Kimura & Somerton, 2006). Much research (e.g., Berg et al., 2016; Ducharme-Barth et al., 2022; Gavaris & Smith, 1987; Kimura & Somerton, 2006; Smith & Hubley, 2014) has focused on how survey allocation and analysis methods affect abundance estimates and their precision. Changing the sampling design (e.g., random or stratified), changing the sampling-to-strata allocation, or defining new strata are ways to potentially improve survey precision (Smith & Hubley, 2014) and will be discussed more thoroughly in the third chapter of this thesis. The comparison between design-based and model-based index standardization methods can also affect estimates and their precision and is the focus of the second chapter.

1.3. Index Standardization Background

1.3.1. Abundance Indices

Management of marine fisheries throughout North America and Europe is often based on population status and productivity estimates from population models (i.e., stock assessment models; Maunder & Punt, 2013). Different types of assessment models are used in fisheries management (e.g., age-structured models, length-structured models, and age- and size-aggregated surplus production models) (National Oceanic and Atmospheric Administration, 2023). Although these models can integrate different information, a critical input is a time-series of survey abundance indices that are proportional to population abundance (Francis, 2011). These models help inform critical management decisions, as they are used to derive vital management reference points, such as target stock size (Fisheries and Oceans Canada, 2012). A surplus production model was created for NAFO SA2+Div.3K redfish but has not been formally accepted or applied directly for the stock assessment because of concerns about the input data and incomplete documentation for the rationale of the model formulation (Fisheries and Oceans Canada, 2020). These size-aggregated models also cannot adequately account for the episodic recruitment patterns that are common for redfish.

For species without a formal assessment model, index-based methods are commonly used. Indices are supposed to be indicative of the trends in abundance for a stock (Maunder et al., 2020). An example of a stock without an assessment model is NAFO 2J3KL Capelin, which is assessed based on acoustic survey abundance, a larval index, distribution from trawl surveys, biological characteristics, environmental parameters and forecast modelling (Fisheries and Oceans Canada, 2019). The stock is assessed based on the trends observed in all data sources. Whether a stock is evaluated with or without an assessment model, abundance indices are crucial and must be reliable; therefore, they must be accurate and precise. The precision of estimated indices is highly influential on the uncertainty in stock assessments and the reference points derived from the assessments (Cao et al., 2017). The importance of stock size indices in fisheries assessment is why there is substantial research to minimize variability in abundance index estimates (e.g., Maunder & Punt, 2004; Shelton et al., 2014; Walters, 2003). There are two common ways indices are derived: design- or model-based; model-assisted approaches are another less commonly used option.

1.3.2. Index Standardization: Design-based Estimates

Design-based survey index estimates derived from stratified random surveys are widely used among fisheries in the Northwest Atlantic. For NAFO SA2+Div.3K redfish, the indices have been derived from the design-based approach since 1977 and are still used in the latest assessment report, based on the 2015 assessment meeting (Fisheries and Oceans Canada, 2020). Design-based indices are stratum area-weighted averages based on the catches from the stratified random sampling design (Cadigan, 2011). The design-based approach estimates the stratum population average catch that would occur if all sites in the strata were sampled (Cadigan, 2011). In the design-based approach, the population average is a theoretically fixed population characteristic if all survey units could be sampled; the population average catch is not considered random. Of course, it is impossible to sample all sites in a survey to estimate the population average, but we can estimate this population quantity. The survey index is an area-weighted average of the stratum estimates of the population average catch.

An advantage of design-based indices is that they provide unbiased estimates with no assumptions about the underlying population (Thompson, 2012). Also, the survey catch is treated as a fixed quantity without measurement error, and randomness only comes from selecting the tow sites to sample (Cadigan, 2011). However, a disadvantage of design-based estimates is that they can have larger variance estimates (Smith, 1990) than model-based estimates. Also, design-based estimates are only for the strata that are sampled each year. Therefore, when there are substantial survey coverage gaps, the estimates may not be comparable from year to year. In SA2+Div.3K, there was inconsistent sampling in Division 2H before 2010, and Division 2G has not been sampled since 1999 (Fisheries and Oceans Canada, 2020), resulting in substantial survey coverage gaps. This means that the design-based indices for the stock primarily represent Divisions 2J and 3K; therefore, these indices may not reliably reflect trends for the entire redfish stock.

1.3.3. Index Standardization: Model-based Estimates

Fish species display spatial heterogeneity, which can be due to variability in habitat quality, human impacts, density-dependent changes in per capita productivity, or individual movement (Thorson et al., 2017). One historical approach to deal with the distribution variability is to use a simple general linear model (GLM) that includes location as a factor without a time-space interaction term (Maunder et al., 2020). However, this method can lead to bias in the abundance indices for different reasons, for example, when the spatial distribution changes over time (Maunder et al., 2020). Spatiotemporal models provide an alternative index standardization method and can explicitly estimate the spatial, temporal, and spatiotemporal effects (e.g., abundance) for the entire population across years (Thorson, 2019).

Thorson et al. (2015) found that given limited data, a spatiotemporal model (Geostatistical delta-GLMM) can be more statistically efficient and improve precision in estimates of abundance indices compared to a nonspatial model (Stratified delta-GLMM). Spatiotemporal models assume an inverse relationship exists between the degree of similarity (i.e., correlation) between catch rates and the distance between times and locations (Maunder et al., 2020). These models estimate the shape of the covariance function from a specified family and then incorporate smoothing for predictions that are close in space and time (Maunder et al., 2020). This smoothing can provide estimates in unsampled strata and improve estimates in under-sampled strata (Maunder et al., 2020). Spatiotemporal models can provide estimates for all sites in a survey domain and therefore provide estimates of population average catches for the entire survey area each year, even if there are unsampled strata. Spatiotemporal model-based abundance indices can be more comparable over years when there are substantial survey coverage gaps in some years. Breivik et al. (2021), used a spatiotemporal model to estimate abundance indices by length for North East Artic cod in Barents Sea. The study region had sizable areas with poor or no survey coverage, and they found the model could estimate the indices and be used to examine population density shifts.

The Vector Auto-regressive Spatiotemporal (VAST) model (Thorson, 2019) can estimate spatiotemporal effects and standardize abundance indices. The VAST model has been used to develop abundance indices for many different fisheries (e.g., Gertseva et al., 2019; Maunder et al., 2020; Thorson & Barnett, 2017). Spatiotemporal models can account for unbalanced data, including changes in sampling density and spatial extent over the years (Thorson et al., 2016), as is the case for Labrador shelf redfish. Furthermore, VAST indices can reduce variability in abundance indices compared to area-weighted GLM estimates (Maunder et al., 2020). Maunder et al. (2020) demonstrated this by standardizing abundance indices for the yellowfin tuna in the eastern Pacific Ocean using a VAST model and a GLM. They suggested that the area-weighted GLM gave higher weight to the poorly sampled strata which created more variability. They suggested that spatiotemporal models are helpful for index standardization when sampling intensity varies across a region.

1.4. Objectives

This study explores using a spatiotemporal model for index standardization for NAFO SA2+Div.3K redfish. In Chapter 2, I use data from the DFO multispecies surveys conducted from 1977 to 2020 to derive new model-based stock size indices for redfish in this region by filling in the survey coverage gaps using the VAST model. I also estimate the uncertainty for the VAST standardized biomass indices for the entire area and compare them with design-based estimates. This includes quantifying the uncertainty for estimates for un-surveyed strata. This research provides a first step for developing a reliable stock assessment time-series for the Labrador shelf redfish stock, a collapsed Canadian fishery with the potential of reopening. I additionally investigate juvenile distribution across SA2+Div.3K, which could be used to minimize juvenile bycatch and to assist in building a robust redfish management strategy to ensure the stock's long-term sustainability. In Chapter 3, I use the spatiotemporal model to test the efficacy of different survey designs to investigate the impact of dropping additional strata from RV surveys. This study provides the beginning steps for creating a more robust simulation study to test the effects of sampling design on spatiotemporal derived indices.

1.5. Figures

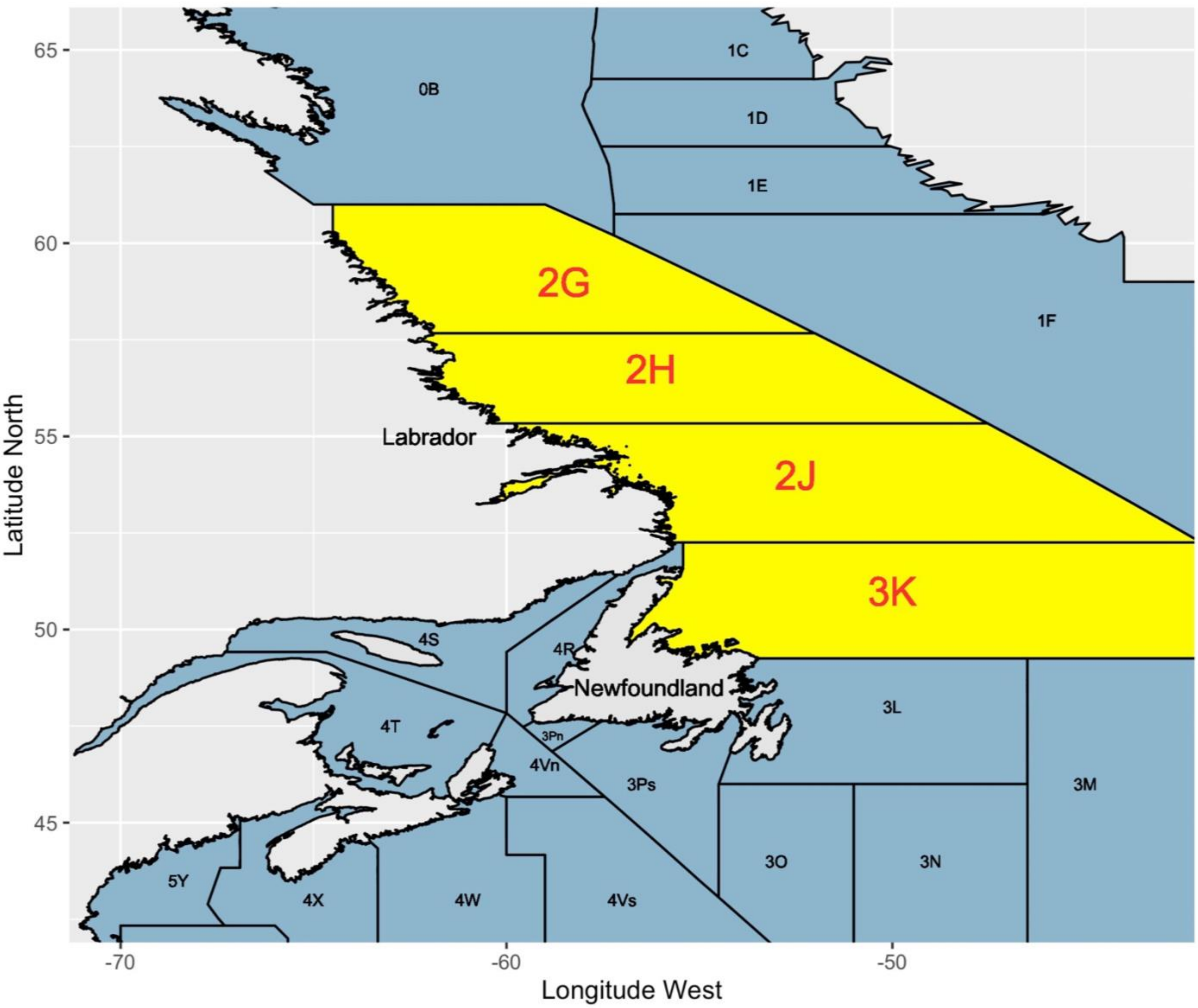


Figure 1.1. Map of the Northwest Atlantic Fishing Organization (NAFO) SA2+Div.3K.

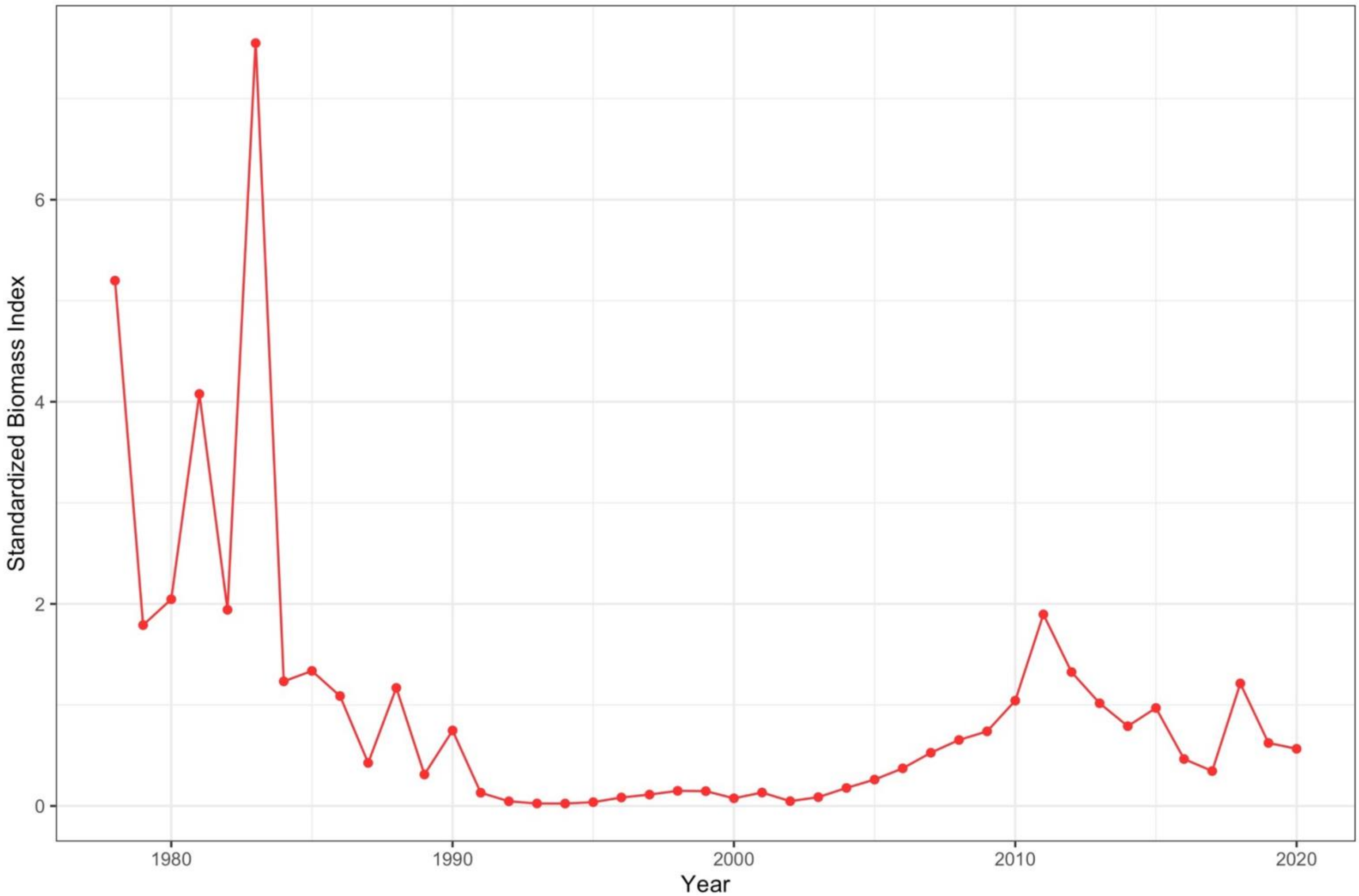


Figure 1.2. Redfish biomass indices for Divisions 2J3K from 1978 to 2020 based on design-based estimates.

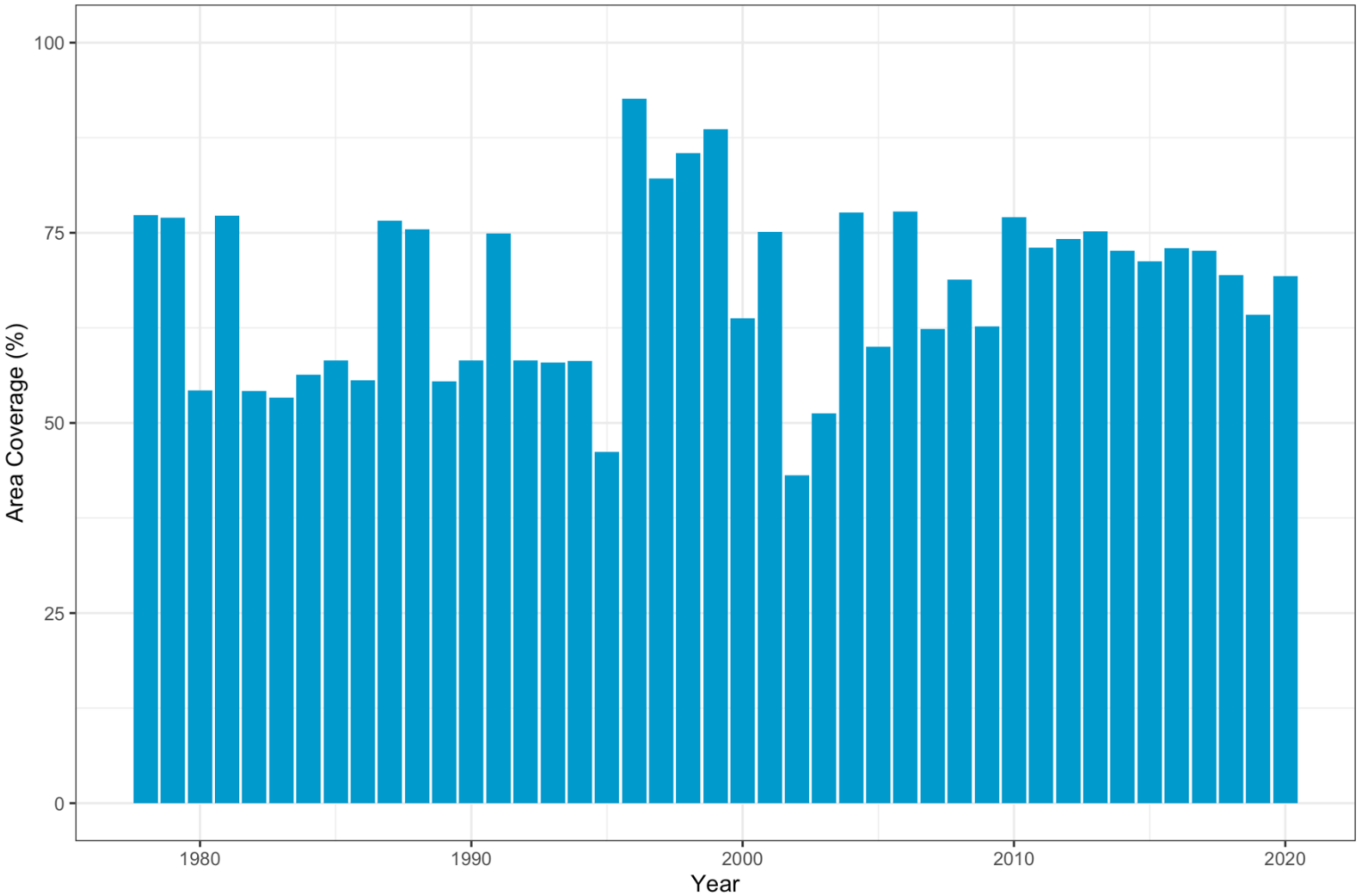


Figure 1.3. Percentage area coverage for the DFO groundfish trawl surveys conducted in NAFO SA2+Div.3K from 1978 to 2020. The area coverage was calculated based on the sum of the areas of sampled strata over the total area size.

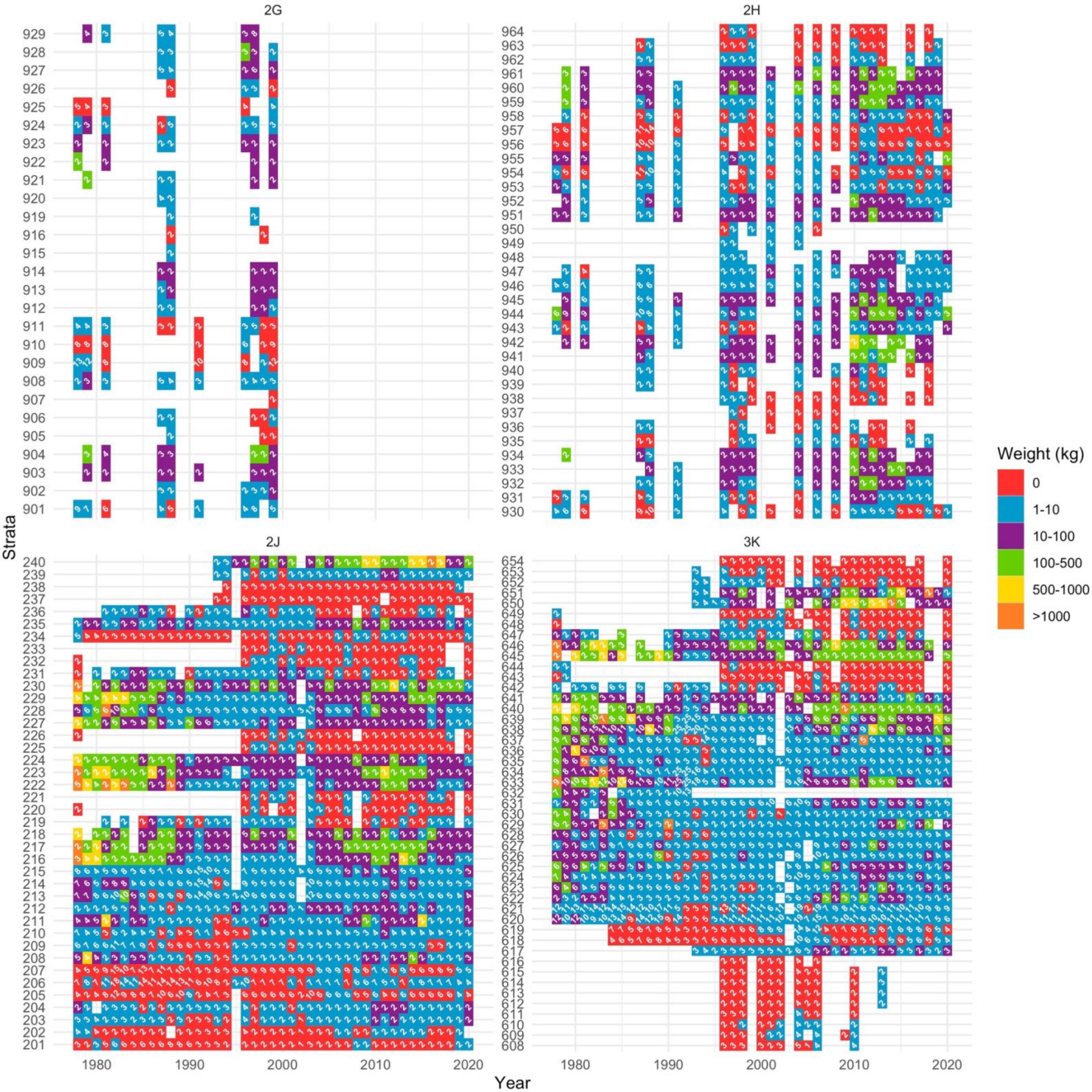
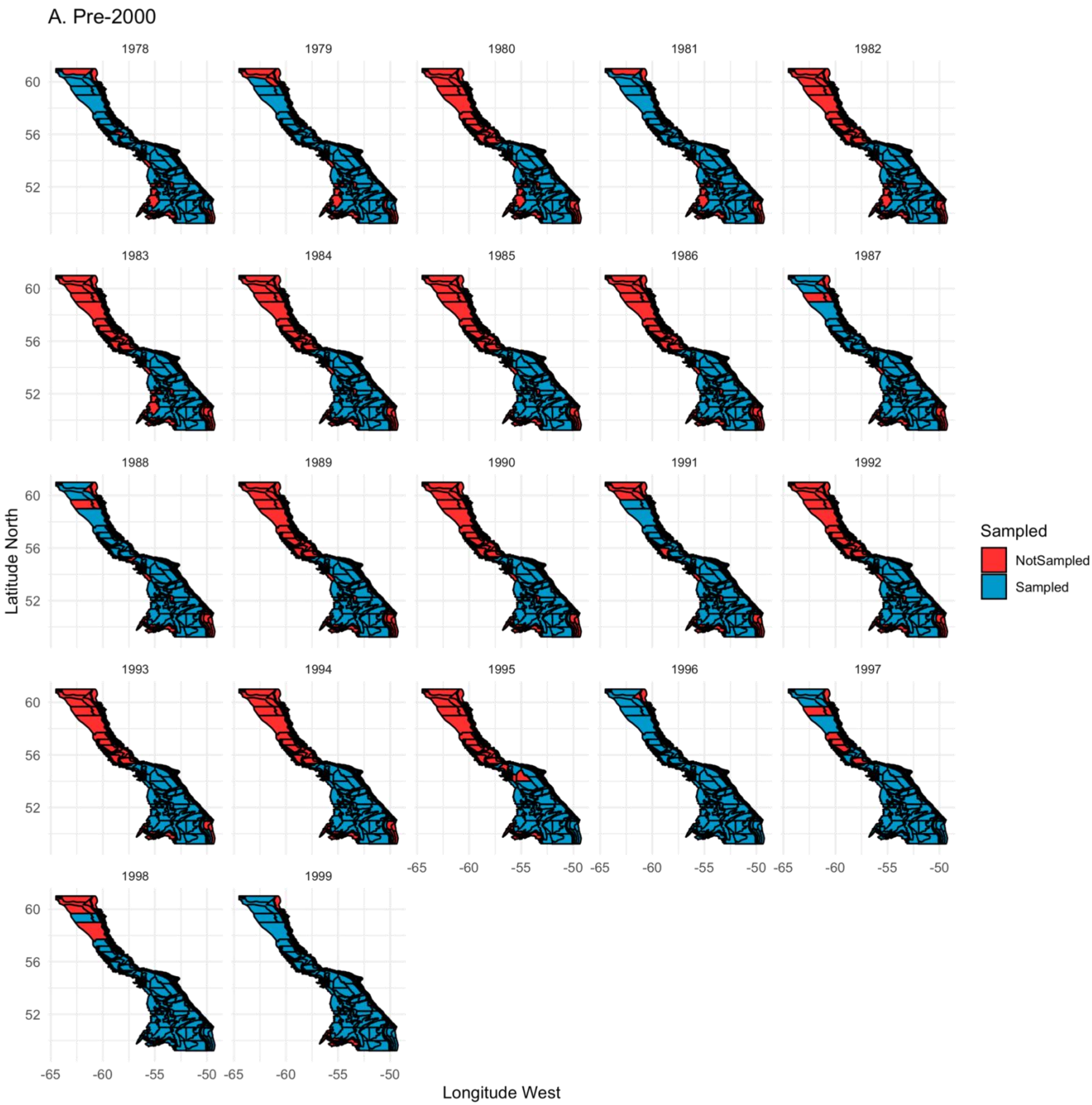


Figure 1.4. Strata sampled in NAFO SA2+Div.3K surveyed from 1978 to 2020. The colours indicate the average weight (kg) of redfish caught in the strata; a blank cell indicates no tows occurred. The number inside each tile is the number of tows that occurred.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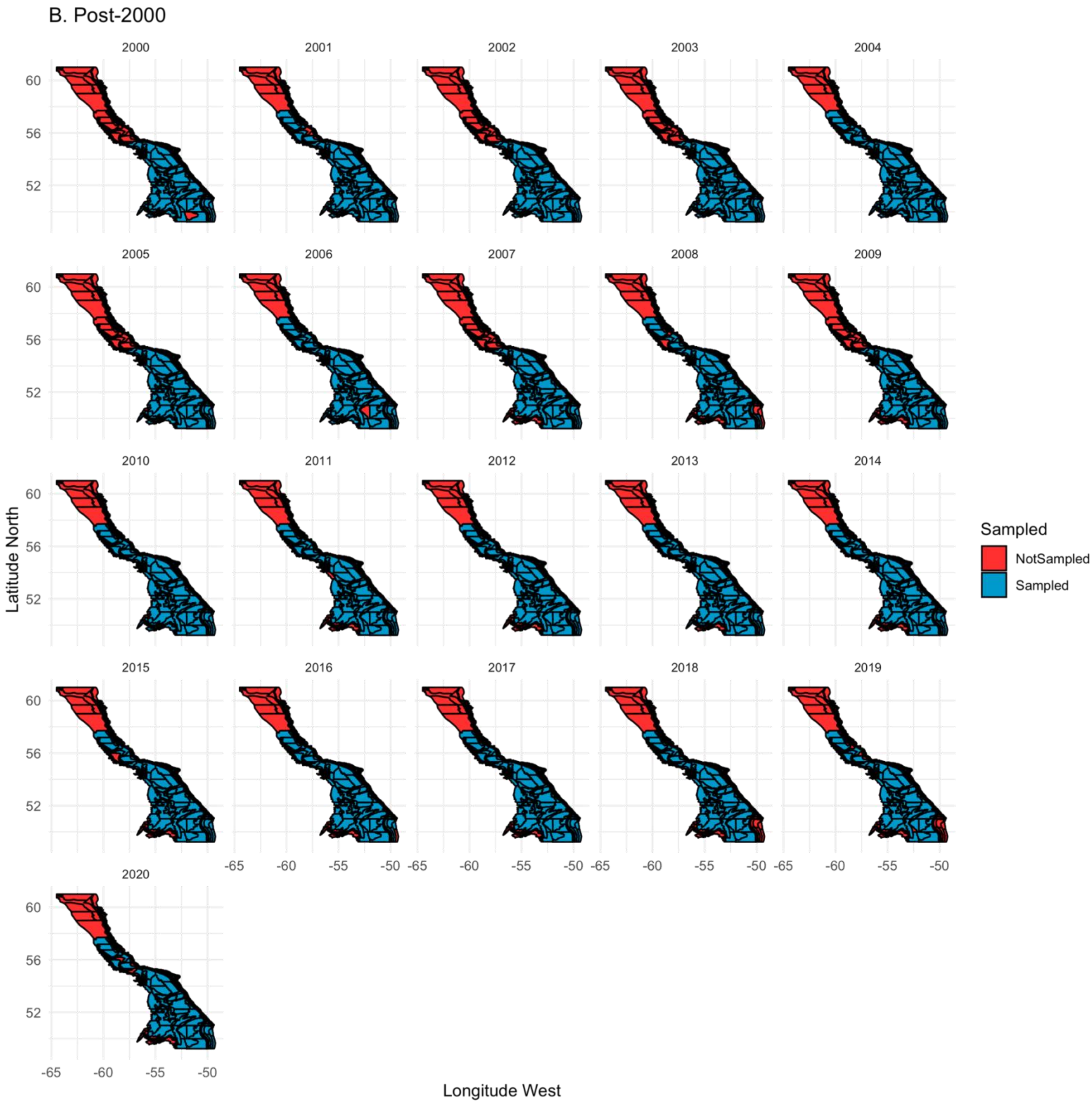

Figure 1.5. Map of the NAFO SA2+Div.3K strata from 1978 to 2020 (A. Pre-2000, B. Post-2000), where the blue regions indicate where at least two tows occurred that year and red regions indicate where no tow occurred in that strata.

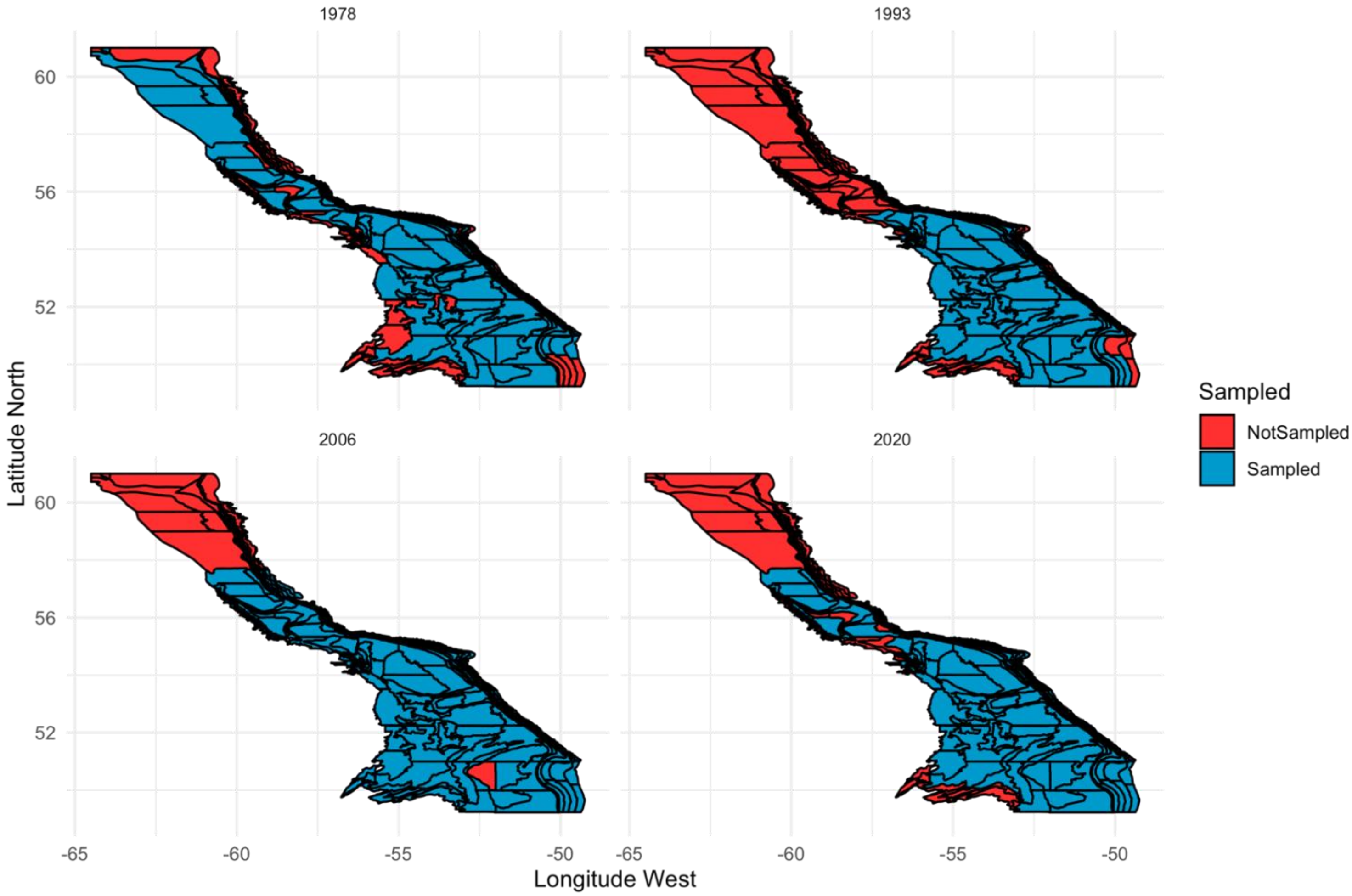

Figure 1.6. Map of the NAFO SA2+Div.3K strata, where the blue indicates where at least two tows occurred that year, and red indicates no tow occurred in that strata. Maps are the same as in Figure 1.5 but focus on four example years with varying spatial coverage for better visualization.

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Chapter 2: Index Standardization

2.1. Introduction

Redfish in NAFO SA2+Div.3K, located off the coast of Labrador and Northeastern Newfoundland, is currently under a fishing moratorium since 1997 (Fisheries and Oceans Canada, 2020). The highest catch was in 1959 with 187,000 t, but the fishery experienced a collapse by the mid-1990s; since the moratorium, the stock has experienced population growth (Fisheries and Oceans Canada, 2020).

Stock assessment models dictate crucial management decisions and rely on time-series of abundance indices. The precision of estimated indices can influence the uncertainty in stock assessment models and the reference points derived from them (e.g., Cao et al., 2017). Further, if there is no assessment model, management decisions (such as potentially when the fishery could re-open) are primarily influenced by abundance indices. This is the case for SA2+Div.3K redfish (Fisheries and Oceans Canada, 2020).

The indices for Labrador shelf redfish are derived by the design-based method, which is widely used for fisheries in the Northwest Atlantic. Design-based indices are area-weighted averages based on the catches from stratified random research surveys (Cadigan, 2011). However, a disadvantage of design-based indices is that they may not be comparable from year to year if the sampled strata change. DFO has conducted surveys on the Labrador shelf since 1977, but there are large survey coverage gaps. They have only consistently sampled Divisions 2J and 3K, and 2H since 2010, but they have not sampled 2G since 1999 (Fisheries and Oceans Canada, 2020).

Due to these large survey gaps, the design-based indices can only produce a complete time-series of abundance indices for Divisions 2J and 3K.

An alternate method for index standardization is a model-based approach. Spatiotemporal models can better account for unbalanced data regarding changes in sampling density or coverage (Thorson et al., 2016). These models estimate the correlation between catch and distance and can produce improved estimates in under-sampled areas (Maunder et al., 2020). The Vector Autoregression Spatiotemporal (VAST) model is one of these models that can estimate spatiotemporal effects and can be used to standardize abundance indices (Thorson, 2019).

In this chapter, I will describe the components of the VAST model and present the results of the model structures I compare and finally utilize. This chapter aims to derive new standardized biomass indices for the stock and quantify the uncertainty of the estimates. Further, I estimate density across the zone, including in under-sampled areas. Another issue for redfish is juvenile bycatch, primarily in shrimp fisheries on the Labrador shelf; therefore, I also aimed to examine the distribution of juvenile redfish using the best performing model.

2.2. Methods

2.2.1. Data

The data analyzed were supplied by Fisheries and Oceans Canada (DFO) from their multispecies stratified random bottom trawl surveys conducted annually in the fall from 1977 to 2020 in the NAFO SA2+Div.3K. The fall surveys typically occur from October to December but occasionally have started as early as July 30th or extended as late as Feb 1st. The tows ranged in depth between 90m and 1500m. The total number of tows was 13,577 (Paul Regular, DFO, Newfoundland, unpublish data). The data from 1977 (125 tows) was excluded from the analysis; therefore, the remaining number of tows in the analysis was 13,452. The 1977 data was excluded because it does not appear in any formal DFO assessment report and only took place in Division 2J, besides three tows in Division 3K.

In 1995, DFO switched the vessel and gear and other survey protocols (i.e., tow durations) they used for this survey from the MV Gadus Atlantica with the Engel 145 Otter trawl to the CCGS Teleost with the Campelen 1800 shrimp trawl. Comparative fishing was conducted in 1995 to develop conversion factors between the different trawl gears (Warren, 1996). The data collected prior to 1995 was converted by multiplying the conversion factor with the actual catch; this is, to convert Engel catches to values equivalent to what were estimated to occur had the Campelen survey protocols been used. I use this data, including the converted catches, for my research.

2.2.2. Model Components

Redfish catch biomass data from the DFO surveys were analyzed using a VAST (Vector Autoregressive Spatiotemporal) model available from GitHub (https://github.com/James-Thorson-NOAA/VAST). The VAST model was developed in the R statistical software (R Core Team, 2022) and based on Template Model Builder (Kristensen et al., 2016) package in R. The VAST model estimates: 1) density $d(s,t)$, over different locations, s, and years, t; and 2) the total yearly biomass for the entire region, $I(t)$. See Table 2.1 for a list of all defined variables in the model.

Survey catch biomass data are commonly analyzed using a conventional delta model, which estimates parameters for two independent generalized linear models (GLMs), separating encounter probability and catch rates of positive tows. The predictions from the two components can then be multiped together to estimate local density and, from that, local abundance (Thorson, 2017). Typically, a logit-link is used for the encounter probability, and a log-link is used for the positive catch rate. However, Thorson (2017) lists three theoretical problems with the conventional delta model:

(1) Difficulty interpreting coefficients. In the model, researchers can include covariates that affect the logit-encounter probability, $logit(p) = log(\frac{p}{1-p})$, which is the "log odds ratio" of the probability of encounter *(p)* over the probability of non-encounter *(1-p),* and/or the log-positive catch rate, log(r). For fixed or random effects that affect *logit(p)*, it is difficult to summarize the average effect of a covariate for *logit(p)* on population density as it depends on the values of all covariates and samples.

(2) Assumed independence among components. Encounter probability and positive catch rate are assumed to be statistically independent, where knowledge about encounter probability does not indicate anything about the distribution of positive catches. This independence is contrary to evidence that suggests otherwise; that is, a location with a greater chance of encounter likely has higher catch rates.

(3) Biologically implausible form when removing covariates. When identifying the effects that should be included in the model, the most parsimonious model may not make biological sense. That is, when removing covariates to find an appropriate degree of model complexity, the model may specify that a covariate only affects one of the two

components, encounter probability or catch rate. This only works if it makes biological sense for the covariate to affect only one of the components.

Because of these problems, I used a poison-link model, which addresses the problems of the conventional delta model by including dependency between the encounter probability and the positive catch rate. Using the poison-link model often improves model fit, decreases unexplained residual spatial variation, and provides biologically interpretable models (Thorson, 2017).

The poison-link delta model describes the probability distribution of survey tow biomass, *b* (Equation 2.1). The parameterization includes the encounter probability, *p(s,t)*, and the positive catch rate given the species was encountered, *r(s,t)* (both components are described below), where *s* is the tow location, and *t* is the year. It also includes the dispersion parameter, σ_b^2.

$$Pr(B=b) = \begin{cases} 1 - p(s,t) & if\ b = 0, \\ p(s,t) *\ Gamma\{B|r(s,t), \sigma_b{}^2\} & if\ b > 0. \end{cases} \tag{2.1}$$

The probability of encountering at least one redfish is

$$p(s,t) = 1 - \exp\left(-a_i * \exp\big(n(s,t)\big)\right). \tag{2.2}$$

In this equation *n(s,t) is* the first linear predictor (described below), and a_i is area swept (assuming that individuals are randomly distributed in the sampling area).

The catch rate given a positive encounter, $r(s,t)$, is described in Equation 2.3, including the area offset, the first linear predictor, $n(s,t)$, and the second linear predictor, $w(s,t)$.

$$r(s,t) = \frac{a_i * \exp(n(s,t))}{p(s,t)} * \exp(w(s,t)). \quad (2.3)$$

The two linear predictors in the model, which are the spatiotemporal parts, are $n(s,t)$ (Equation 2.4) and $w(s,t)$ (Equation 2.5). The first linear predictor models presence/absence, and the second predictor models estimated biomass given an encounter.

$$n(s,t) = G_n + B_n(t) + w_n(s) + \varepsilon_n(s,t). \quad (2.4)$$

$$w(s,t) = G_w + B_w(t) + w_w(s) + \varepsilon_w(s,t). \quad (2.5)$$

The components of the two linear predictors are defined the same but are indicated with different subscripts. I use the subscript i=*n or w* to indicate the respective linear predictor. Both predictors include an intercept (G_i), a random or fixed temporal intercept (B_i), a random spatial component $W_i(s)$ and a random spatiotemporal component $\varepsilon_i(s,t)$.

The linear predictors B_n, B_w, ε_s and ε_w are temporal processes. Different options in VAST can be used to specify the type of temporal process for both the intercepts (B_n and B_w) and the temporal variation in spatiotemporal vectors (ε_s and ε_w). The options are constant intercept (temporal component only), independent among years, random-walk, and first-order autoregressive (AR1) structures for either the temporal or spatiotemporal effects.

2.2.3. *Derived Quantities*

Density, *d(s,t)* (kg/km^2) for each location, *s*, and each year, *t*, is estimated by the product of the encounter probability and the positive catch rate, as shown in Equation 2.6.

$$d(s,t) = p(s,t) * r(s,t). \tag{2.6}$$

The total yearly biomass, *I(t)*, is estimated from the product of the density *d(s,t)* and the area associated with location *s, a(s)*. To estimate total biomass, the product is summed across all predictive locations, n_s.

$$I(t) = \sum_{s=1}^{n_s} a(s) * d(s,t). \tag{2.7}$$

The scale of VAST index estimates can be sensitive to modelling decisions, such as the choice of the distribution function and the number of knots (Thorson et al., 2021); therefore, I used standardized indices. The indices were standardized by dividing by the mean index value of the time-series to compare the relative trends with design-based indices that were standardized the same way.

The coefficient of variation was calculated for the index values by standardizing the annual standard deviation, *SD(t)*, by dividing by the mean index value of the time-series, $\bar{I}$ (Equation 2.8).

$$CV(t) = \frac{SD(t)}{\bar{I}}. \tag{2.8}$$

2.2.4. *Spatial Properties of the VAST Model*

The predictive locations of the model distributed across the study region are called “knots,” which are points with an associated area size. VAST uses the k-mean algorithm to determine the locations of the knots to minimize the total distance between the knots and the data or an extrapolation grid. The package R-INLA (Rue et al., 2009) creates a triangular mesh with a vertex of the triangle at each knot. I tested different numbers of knots for the model and chose 250 knots across the whole domain as a balance between computation speed and consistency in results. The results were relatively consistent even with a lower number of knots, but the indices trends became more consistent as the number of knots increased, as well as the AIC decreased; however, 250 knots was the maximum number that was computationally reasonable.

The Matern function was used to approximate the correlation matrices based on the distance between any locations (Lindgren et al., 2011). The approximation for the Matern correlation function has previously been used in spatiotemporal models (i.e., Thorson & Barnett, 2017). I used this function because the number of random effects in VAST is extensive; therefore, a sparse Matern precision matrix can dramatically improve estimation efficiency.

The association between the knots and the tows was set as either a piecewise constant or “fine-scale” bilinear interpolation. For the piecewise constant option, spatial variables at location s are fixed to the values at the nearest knot. When using bilinear interpolation, the association is done using the triangular mesh, where density is estimated in cells of an “extrapolation grid.” Using the fine-scale option is more computationally expensive.

Because fine-scale bilinear interpolation is computationally expensive, there was a trade-off between using it and including bias-correction for the log transformation of the random effects using epsilon-method in the model. Therefore, the two options of the model were: 1) a piecewise constant association and bias-corrected, 2) a bilinear interpolation association and non-bias-corrected. In the remainder of the thesis, I refer to these simply as the bias-corrected and non-bias-corrected models, respectively.

2.2.5. Model Fit

Various spatial and spatiotemporal structures were compared using their AIC scores to determine the best-fitting VAST model, as suggested by Thorson (2019). I tested different combinations of independent, random-walk and autoregressive (AR1) structures for both the temporal intercepts (B_n and B_w) and the spatiotemporal vectors (ε_s and ε_w). I used a Newton Optimizer with two extra steps and confirmed that the models converged (maximum gradient < 10^{-6}).

2.2.6. VAST Division Indices

The bias-corrected model was used to get the VAST survey biomass indices for a division, $I_d(t)$. Using Equation 2.9 (based on Equation 2.7), I calculated $I_d(t)$, where $d(k,t)$ is the density at the knot k, $a(k)$ is the area associated with the knot, and n_k, is the number of knots in the division. These index values were also standardized by the time-series mean.

$$I_d(t) = \sum_{k=1}^{n_k} a(k) * d(k,t). \tag{2.9}$$

The precision for the indices for individual divisions was not provided by the VAST package, which only provides the *SD* of the index values for the entire area of the model. To calculate the *SD* for the divisions, the covariance between knots and density would be needed; however, that information is not given as an output by the package.

2.2.7. VAST Strata Indices

The non-bias-corrected model was used for the strata estimates because, for the bias-corrected model, which used the piecewise constant association, I could only extract density at the knots. Not all strata had knots within their boundary; therefore, the bias-corrected model could not be used. I used the non-biased-corrected model, which had extrapolation cells within each stratum.

The stratum index values were also calculated similarly to the indices for the total zone and the divisions, using Equation 2.7. The density of an extrapolation cell, $d(s,t)$ and the arbitrary cell size, $a(s)$, set at 0.002, were used. The product of the two is then summed across all the cells within a stratum.

2.2.8. Design-based Estimates

The results of the VAST model were compared to design-based estimates. Therefore, all the design-based indices were standardized by the mean as well.

The VAST division indices were compared to design-based indices, $\hat{T}$, for the division (Equation 2.10), where the product of N_h (the number of sampling units in stratum h) and $\bar{y}_h$ (the average biomass caught in stratum h) are summed across all strata in the division.

$$\hat{T} = \sum_{h=1}^{H} N_h \, \bar{y}_h \, . \tag{2.10}$$

The unbiased estimator of the design-based variation of $\hat{T}$ is shown in Equation 2.11, where the unbiased estimate of the variance of a stratum, s_h^2, is defined in Equation 2.12.

$$\widehat{Var}(\hat{T}) = \sum_{h=1}^{H} N_h (N_h - n_h) \frac{s_h^2}{n_h} \, . \tag{2.11}$$

$$s_h^2 = (n_h - 1)^{-1} \sum_{h=1}^{n_h} (y_{hi} - \bar{y}_h)^2 . \tag{2.12}$$

The stratum total is just the product of N_h and $\bar{y}_h$(Equation 2.13).

$$\hat{T}_h = N_h \bar{y}_h . \tag{2.13}$$

The total NAFO SA2+Div.3K VAST indices were compared to the design-based indices for Divisions 2J3K. Due to the survey coverage gaps, design-based indices cannot be calculated for the entire region, and therefore the 2J3K indices are currently used to assess the stock. Due to limitations of the VAST package, CV could only be calculated for the total area indices, not subset areas, such as divisions or strata. A VAST model for only divisions 2J3K could be developed for a more direct comparison of the precision of the methods but would require a separate analysis, which was not within the scope of this thesis. Therefore, comparing the CV of the design 2J3K and the VAST NAFO SA2+Div.3K indices is not a comparison of the precision abilities of the different methods, as they include a different number of divisions; hence, there is an unknown effect of the quantity of data on the CV. The comparison is just to illustrate the difference between the derived VAST indices and the currently used design-based stock indices.

2.2.9. Juvenile Study

The same DFO survey data set, which included survey catch numbers-at-length, was used for the juvenile analysis. Juvenile catch biomass was estimated by applying a length-weight relationship (length-weight $W(l) = al^b$: a=0.01000 (0.00479 - 0.02087), b=3.07 (2.90 - 3.24), where l is the length) of individuals (Froese et al., 2014). Juveniles were defined as fish less than 20 cm, which is just within the more conservative estimates of redfish maturation size. The weights for all the size classes were estimated using a length-weight relationship, then aggregated together to get a total biomass estimate for juveniles (redfish <20 cm) per tow. In total, there were 10481 data points in the juvenile study.

The estimated juvenile catch biomass was analyzed using the same model components as the VAST model for the entire catch biomass. The AIC score was also used to determine the best-performing model for the juvenile population to estimate juvenile densities across the entire study region.

2.3. Results

2.3.1. Model Selection

Model selection was accomplished by assessing the AIC scores from the models with varying temporal and spatiotemporal intercepts. The comparison was first completed with fine-scale bilinear interpolation included in the model (Table 2.2). The best-performing model had a fixed temporal intercept and a lag-one autoregressive spatiotemporal intercept, referred to as the AR1 model (AIC = 63389.4). Models that included bilinear interpolation and bias-correction were computationally prohibitive; therefore, I re-ran four of the previous best-performing models without bilinear interpolation (using piecewise constant) but included bias-correction (Table 2.3). The model with the lowest AIC score remained the AR1 model (AIC = 66628.56). Based on a balance of consistency of the index trends, the decreasing AIC score, and computing time, 250 knots were selected for the model (Table 2.4).

2.3.2. Model Results

For brevity, only the relevant results of the AR1 model are presented in this Chapter, and supplementary figures are in Appendix A. All results are from the bias-correct version of the AR1 model.

The estimated biomass indices from the bias-corrected AR1 model (Figure 2.1) reached a low of 0.97 in 1993 and a high of 133.09 in 1978. In general, our model-based indices closely followed the trends of the 2J3K design-based indices. Both approaches estimate a considerable decrease in redfish from 1978 to 1990 and low abundance from 1990 to 2004. Stock abundance increased after 2004 but then declined during 2010-2015.

The CV was higher overall (higher SD values in proportion to the index values) for the 2J3K design-based indices than the VAST indices (Figure 2.2). The highest CV value (0.753) from the bias-corrected AR1 model was in 1978, and the highest for the design-based (3.642) was in 1983. The lowest CV for the design-based was 0.002 in 2002, and the lowest for the VAST was 0.010 in 1992.

The trends in the stock indices are also evident in the estimated spatial densities (Figure 2.3), including the drop and subsequent increases in redfish biomass. There was a greater proportion of higher-density areas in the 1980s compared to the 1990s and early 2000s. Regardless of the overall stock size in a year, the offshore areas always had a higher density than the inshore areas, except for a small region in the southeast with consistently low density. The highest density is typically in the mid and southern (2J or 3K) eastern region.

The uncertainty (SD) around the index value at each of the 250 knot locations ranged from 6.35×10^{-7} (in strata 619, inshore in Div. 3K) to 4.14 (in strata 639, mid-deep water in Div. 3K) (Figure 2.4). The uncertainty indicates higher variability in deep-water areas in the eastern regions of the NAFO zone. The highest values are typically in the more frequently sampled strata (Divisions 2J and 3K), especially in the southeast region. The uncertainty appears relatively uniform in most areas where little sampling occurred (2G), besides the deeper east section. The uncertainty does not appear to be highly linked to the sampling effort. Instead, it seems more related to the redfish biomass density level; in years with higher density (e.g., 1978), the standard deviation is higher overall than in years where density is lower (e.g., 1993; Figure 2.5). Figure 2.6, which compares the SD and CV of the index value to the density estimated across all the knots, illustrates the relation between SD and density. The SD usually increases as density increases. However, this is not the case for the CV; there is higher variation in the CV when density is low, but it remains reasonably constant as density increases; in other words, the density values increased more proportionally to the SD values.

2.3.3. Division Indices

The VAST indices for the three more sampled divisions (i.e., 3K, 2J and 2H) closely follow the design-based ones (Figure 2.7). For Division 2G, differences between the indices were larger for the two methods; for example, the biomass increased in the design index while the VAST index decreased from 1978 to 1979. Also, there was a spike in the design index for 1996, which is much less prominent in the VAST indices. However, the overall trend is difficult to compare for 2G because, for most years, a design-based index could not be calculated due to under-sampling.

2.3.4. Strata Indices

The NAFO SA2+Div.3K indices from two versions of the model (i.e., bias-corrected and non-biased-corrected) were quite similar with overlapping error bars (Figure 2.1); therefore, we concluded it was acceptable to use the non-bias-correct version to calculate strata indices.

Comparisons between the VAST and the design-based strata estimates are provided in Figure 2.8. I used the VAST model to fill in the unsampled strata, and the patterns in the VAST estimates aligned reasonably well with the design-based estimates. The prominent overall temporal trends are in both the design-based and VAST estimates, with higher estimates from both approaches around 1978-1985 and 2010-2015 than during the other years. However, there is both spatial and temporal smoothing in the VAST estimates that cause some differences. For example, the large gaps in the design-based estimates (especially prominent in strata >900) were estimated by VAST to have higher catches in the early years (1978-1990), even though little was caught in these years, because this was the consistent pattern in the other better-sampled strata.

For some illustrative strata (Figure 2.9), the trends in the VAST indices match the design-based indices well.

2.3.5. Juvenile Results

The VAST model with the lowest AIC score (AIC = 16247.61) for the juvenile redfish was a random-walk temporal intercept and an autoregressive spatiotemporal intercept (Table 2.5).

The density estimates (Figure 2.10) have similar patterns as the adults; density is higher in the eastern deeper water regions. Moreover, the small area in the southeast corner is a more prominent area of low density than its surrounding regions, compared to the adults. There are high-density areas in the eastern regions located in Division 2G, which overlaps with SFA4; however, higher density occurs in the southern divisions more than in Division 2G.

2.4. Discussion

This study 1) developed a Vector Autoregressive Spatiotemporal (VAST) model to interpolate survey biomass in unsampled survey strata, 2) developed new model-based biomass indices for the stock, and 3) quantified the uncertainty, including the predictions for unsampled strata. The model that performed the best had a first-order autoregressive (AR1) spatiotemporal structure. The top three performing models all had an AR1 spatiotemporal structure. A temporal correlation has been recommended for spatiotemporal variation when some areas have not been consistently sampled and for propagating “hot spots” from sampled areas to unsampled areas in adjacent years (Thorson, 2019). However, the greater complexity in the spatiotemporal components was more computationally demanding, and other aspects of the model, such as bias-correction and fine-scale were sacrificed.

The biological estimates (e.g., biomass indices and density patterns) derived from the AR1 VAST model follow generally known trends and biological patterns for this redfish stock. The biomass of NAFO SA2+Div.3K redfish decreased in the ’90s and the early ’00s and has shown slight increases in more recent years (Fisheries and Oceans Canada, 2020). This trend was evident in the overall VAST stock indices (Figure 2.1). Additionally, redfish prefer to inhabit deeper waters (Gascon, 2003). This preference is evident in the density estimates, where the deeper areas on the edge of the continental shelf typically have a higher density than the inshore areas (Figure 2.3). There is one small area of consistently lower biomass than surrounding areas in the southeast corner of the NAFO zone. This pattern is even more prominent in the juvenile density patterns (Figure 2.10). The strata in that area are also quite deep (with maximum depths ranging up to 1500m), which might be deeper than redfish prefer. Another consideration is that this area was only consistently sampled after 1995 and was primarily left unsampled when density was at its highest (in the ‘70s and ‘80s). A regular but more spaced-out sampling design is possibly more informative than more consistent sampling for only a specific period.

The uncertainty of the estimates at the knots appears to be influenced by several factors (Figure 2.4). Our initial expectation was that the regions with less consistent sampling would have higher uncertainty than regularly sampled regions. However, some frequently sampled areas have higher uncertainty than the under-sampled regions. One factor that affects the SDs is biomass density; when this density is low, the SDs will tend to be lower than when densities are high.

This is because there is less variation in catch when density is low, as it is likely only small catches can occur; when density is higher, there is potentially greater variation in catch (Figure 2.6). This effect is potentially amplified with a patchy or aggregated distribution, where in overall higher-density areas, a cluster could be sampled or missed, making the catch more variables and resulting in higher uncertainty. Consequently, the SD is overall higher in years with greater biomass. Sampling designs that at least sample all the areas every few years might be more beneficial to estimate density for the entire stock area than consistently sampling one area and never sampling another. Chapter 3 will examine how different sampling designs could influence the VAST model and how they will change the uncertainty.

In the scope of this thesis, the only comparison between design-based CVs and VAST CVs is between the design-based 2J3K indices and the VAST SA2+Div.3K indices (Figure 2.2). This was because the design-based indices could not be calculated for the total area due to survey gaps, and the CV could not be calculated at a division level for VAST because of package limitations. The indices currently used to assess the stock (and were used in the attempts of an assessment model) are the 2J3K design-based indices. For management purposes, the VAST-derived indices for the stock provide greater precision than the 2K3K design-based indices. However, as the indices are based on a different number of divisions (therefore different amounts of data), it is not a complete or fair comparison to conclude that the model is more or less precise than the design-based method. Further research is needed to compare the precision between the model and the design-based approaches, potentially looking at the precision at a division level, only Divisions 2J3K, or comparing only the sampled strata.

Although the model-based indices have advantages (such as filling in under-sampled areas), there are also potential biases introduced by the model. Extrapolating the spatial and temporal correlations to primarily unsampled areas assumes that these effects function to the spatial scale they are extrapolated to. For example, it assumes these trends and correlations continue over the distance between Division 2G and the other Divisions. If this assumption is not valid, it could lead to a positive or negative bias depending on whether the abundance of redfish in the sampled region is higher or lower than in the unsampled region. This is an important assumption, as the distance between the data and the data gaps is quite extensive. The effect of these substantial data gaps is unknown. This study compared the model estimates to design-based estimates to investigate model bias, as design-based indices are unbiased. However, as there is not enough data to produce design-based estimates for many years in 2G and 2H (and the strata within them), this study could not determine if there is any indication of bias in these regions. Therefore, these results should be taken skeptically until further studies check for model bias. Simulation studies for spatiotemporal models have been implemented before to check for model biases (e.g., Cao et al., 2020; Thorson & Haltuch, 2019). Future work should look at developing a simulation study to investigate whether the VAST indices for Labrador shelf redfish are biased and to examine their accuracy.

Other future work should look at different configurations of knots, potentially placing one in each stratum, to better understand how the strata sampling design affects the uncertainty of the filled-in data. VAST allocated knots proportionally to the density of available data; therefore, lesser sampled regions receive fewer knots (Maunder et al., 2020). Another limitation of the model is that redfish is a species complex; however, separating the species caused concerns with previous assessment models for the stock (Fisheries and Oceans Canada, 2020). The pre-1995 survey data is also converted, which may cause biases if the conversion is incorrect. This may be more of a problem for the juvenile estimates as there is a larger difference in the juvenile catch than in other size classes between the two different trawl gears (Power & Orr, 2001). Another consideration is that six data points appear to be duplicate data points in the data set, which went unnoticed until the analysis was completed. However, as those points represented <0.001% of the data in the analysis, they likely had a negligible effect on the results.

This study could be the potential starting point in building a spatial management strategy for the stock. Many users (DFO and industry) could use the intuitive distribution maps for management purposes, such as examining the distribution of bycatch species (e.g., juvenile redfish overall with the shrimp fisheries). There has been substantial bycatch in SFA4 that overlaps with Division 2G (Courtney D'Aoust, 2021). The VAST model estimated the density in the relatively unsampled Division 2G by using the temporal and spatial correlation from data across the entire NAFO region. Like the adults, a higher density of juvenile redfish appears in the deeper water areas (Figure 2.10) in all areas of NAFO SA2+Div.3K, including Division 2G.

Interestingly, the model estimated higher density in the more southern areas than in the northern areas, where substantial bycatch was observed in 2021. Again, there is an assumption that the spatial and temporal trends observed in the more sampled regions apply to the large unsampled area between Division 2G and the other Divisions. If this assumption is incorrect, the estimated distribution of juvenile redfish may be biased in the north and potentially elsewhere. Therefore, more current data in Division 2G could help inform the juvenile distribution in the region, either from survey data or the addition of fishery-dependent data. Another possible reason could be related to the fishing effort; if the effort was more concentrated in high-density areas in SFA4, it could cause higher bycatch. Potentially, these juvenile density maps could help inform where fishing efforts are made to avoid high juvenile density areas to minimize juvenile bycatch.

Furthermore, VAST indices could potentially provide more precise indices for stock management. As there is no assessment model, these indices could help inform management decisions, such as when the fishery could reopen and acceptable catch levels. Also, the indices could be used in the development of a stock assessment model. Indices of relative abundance are widely considered the most critical input into stock assessment models (Francis, 2011). Spatiotemporal indices were compared to nominal indices (ratio of the total catch to total effort) in a stock assessment model for yellowfin tuna in the eastern Pacific Ocean (Xu et al., 2019). It was found that the spatiotemporal indices increased the log-likelihood, suggesting those indices were more consistent with the other data in the model, as well as reducing residual patterns (Xu et al., 2019). Additionally, spatiotemporal indices were used in the stock assessment model to assess northern shrimp in the Gulf of Maine; they were found to improve the overall fit of the stock assessment model and model diagnostics compared to design-based indices (Cao et al., 2017).

Overall, the spatiotemporal model estimated density patterns across the region to fill in the survey sampling gaps and derived new biomass indices. The distribution maps generated will be useful to guide direct and shrimp bycatch fisheries. However, it is unknown if there are any significant model biases. Simulation testing would be needed to determine further whether there are any model biases in either the total population or the juvenile model.

2.5. Tables

Table 2.1. List of variable symbols used in the equations.

Symbol	*Descriptions*	*Dimensions*
	Index	
s	Spatial location	
t	Year	
b	Biomass per survey tow	
h	Stratum index	
	Constants	
a_i	Area swept	0.2
$a(s)$	VAST cell size area	0.002
V	Matern smoothness	1
	GLM	
$n(s,t)$	First linear predictor (p1)	s,t
$w(s,t)$	Second linear predictor (p2)	s,t
	Fixed Effects	
G_n	Global intercept for p1	
G_w	Global intercept for p2	
	Random Effects	
$B_n(t)$	Temporal variation for p1	t
$B_w(t)$	Temporal variation for p1	t
$W_n(s)$	Spatial variation for p1	s
$W_w(s)$	Spatial variation for p2	s
$\varepsilon_n(s,t)$	Spatiotemporal variation for p1	s,t
$\varepsilon_w(s,t)$	Spatiotemporal variation for p2	s,t
	Derived Quantities	
$p(s,t)$	Encounter probability	s,t
$r(s,t)$	Positive catch rate	s,t
$d(s,t)$	Local predictor biomass density	s,t
$I(t)$	Predictor total biomass	t
	Strata and Division Estimates	
y	Biomass caught in tow	
$\bar{y}$	Average biomass caught	
s_h^2	Stratum variance	
$\hat{T}$	Index estimate	
n	Number of sampling units sampled	
N	Total number of sampling units	
$\bar{d}$	Average density	

Table 2.2. An AIC comparison for different temporal and spatiotemporal model structures with bilinear interpolation. Only converged models (maximum gradient $<10^{-6}$) are shown.

Temporal Intercept	*Spatiotemporal Intercept*	*AIC*	*Δ AIC*
Fixed Effect	Fixed effect	63925.6	536.2
Fixed Effect	Independent Among Years	63925.6	536.2
Fixed Effect	Random Walk	63685.74	296.34
Fixed Effect	Autoregressive	63389.4	0
Independent among years	Fixed effect	64013.05	623.65
Independent among years	Independent Among Years	64013.05	623.65
Independent among years	Random Walk	63741.61	352.21
Independent among years	Autoregressive	63468.28	78.88
Random Walk	Fixed effect	63918.73	529.33
Random Walk	Independent Among Years	63918.73	529.33
Random Walk	Random Walk	63708.97	319.57
Random Walk	Autoregressive	63409.88	20.48
Constant Intercept	Fixed effect	64301.61	912.27
Constant Intercept	Independent Among Years	64301.61	912.27
Constant Intercept	Random Walk	63771.55	382.15
Constant Intercept	Autoregressive	63586.7	197.3

Table 2.3. An AIC comparison of models without bilinear interpolation (piecewise constant). The chosen models were four of the best-performing models from the AIC comparison with bilinear interpolation.

Temporal Intercept	*Spatiotemporal Intercept*	*AIC*	*Δ AIC*
Fixed Effect	Random Walk	66899.41	270.85
Fixed Effect	Autoregressive	66628.56	0
Independent among years	Autoregressive	66678.41	49.85
Random Walk	Autoregressive	66630.74	2.18

Table 2.4. AICs for models with different numbers of knots. Models were bias-corrected but did not use bilinear interpolation.

# of Knots	*AIC*	**Δ AIC**
50	70826.44	4197.88
100	69066.59	2438.03
150	67753.01	1124.45
200	67075.65	447.09
250	66628.56	0

Table 2.5. Juvenile Model Selection. Only converged models (maximum gradient <10^{-6}) are shown.

Temporal Intercept	***Spatiotemporal Intercept***	***AIC***	***Δ AIC***
Fixed Effect	Fixed effect	16881.24	633.63
Independent among years	Independent Among Years	16905.76	658.15
Random Walk	Independent Among Years	16820.54	572.93
Random Walk	Autoregressive	16247.61	0

2.6. Figures

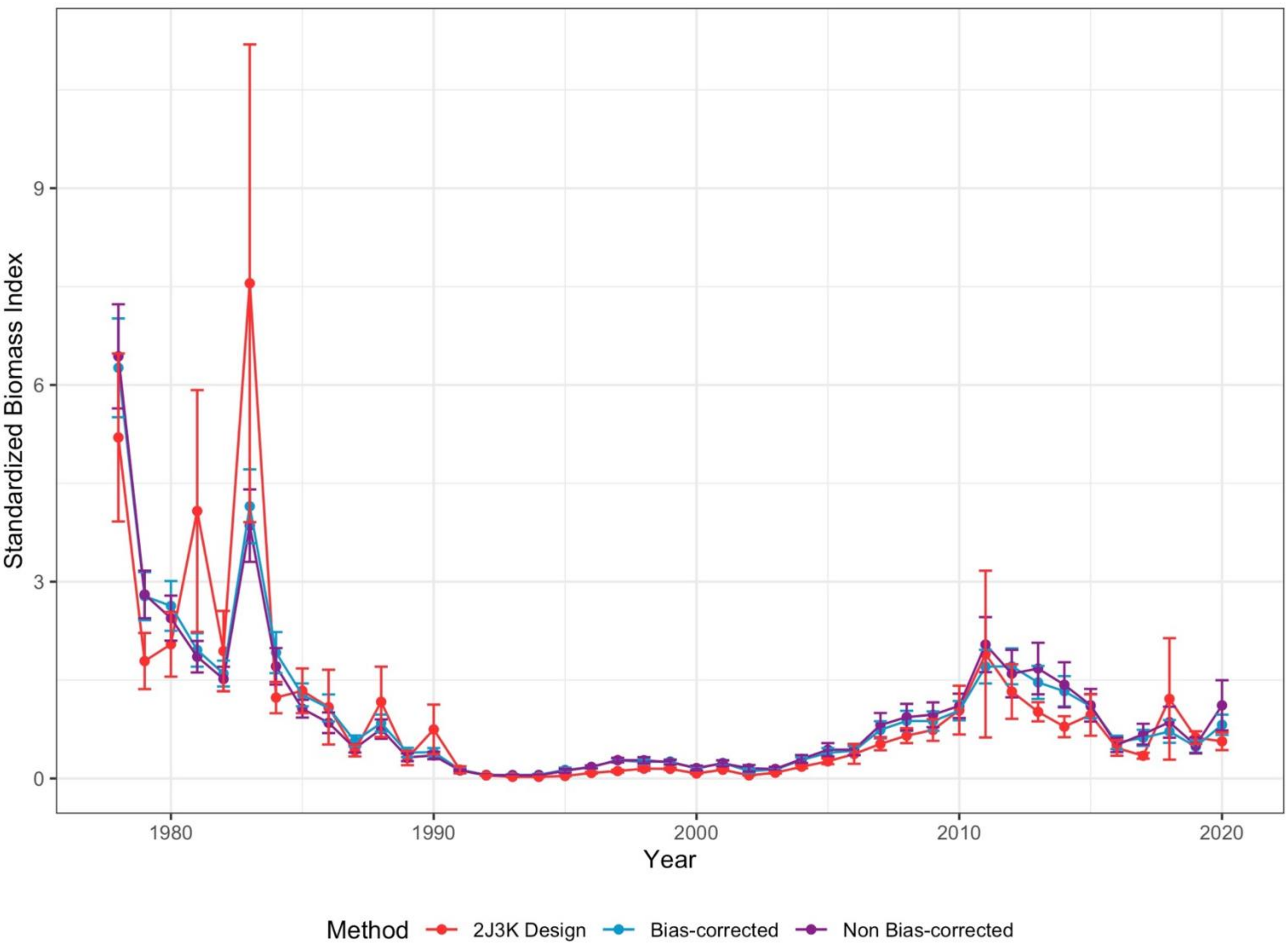


Figure 2.1. Estimated biomass indices (bias-corrected and non-bias corrected) derived from the AR1 VAST for the entire NAFO SA2+Div.3K and the design-based estimates for divisions 2J3K from 1978 to 2020. The error bars show ± 1 CV, and the colour indicates the method to derive the indices.

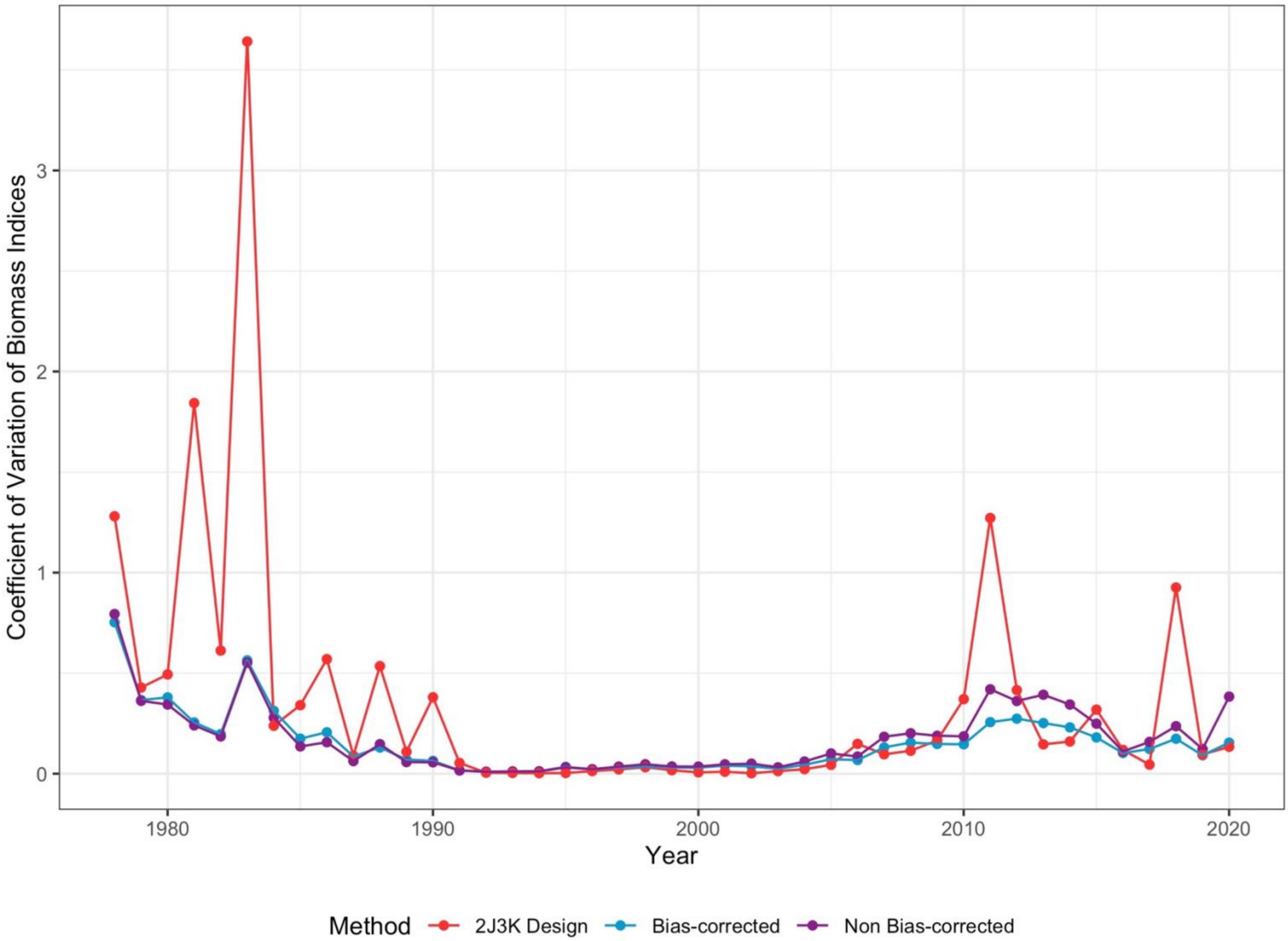


Figure 2.2. The estimated coefficient of variation (CV) derived from the AR1 VAST models for NAFO SA2+Div.3K and the design-based estimates for 2J3K from 1978 to 2020. The colour indicates the method to derive the indices.

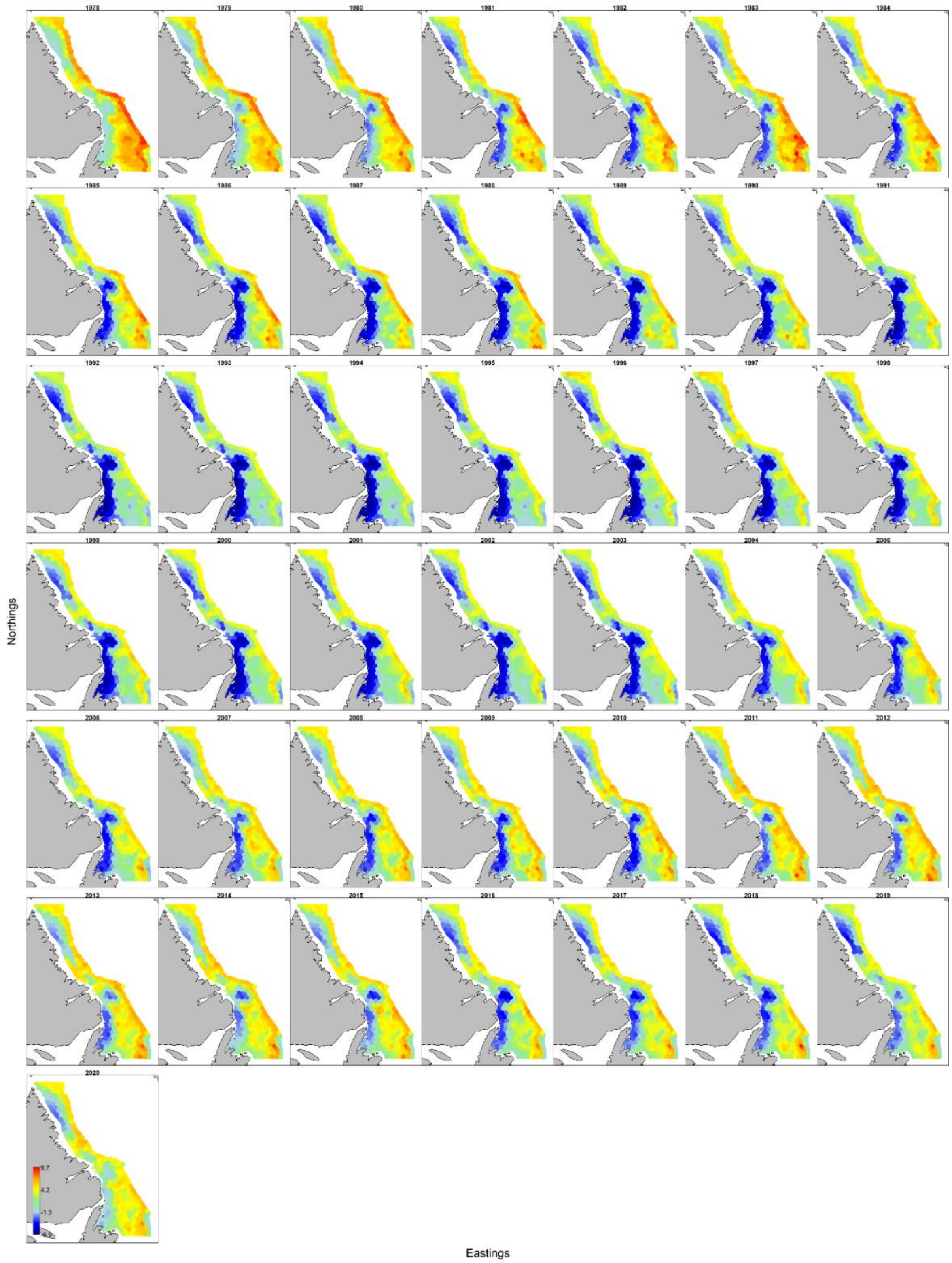
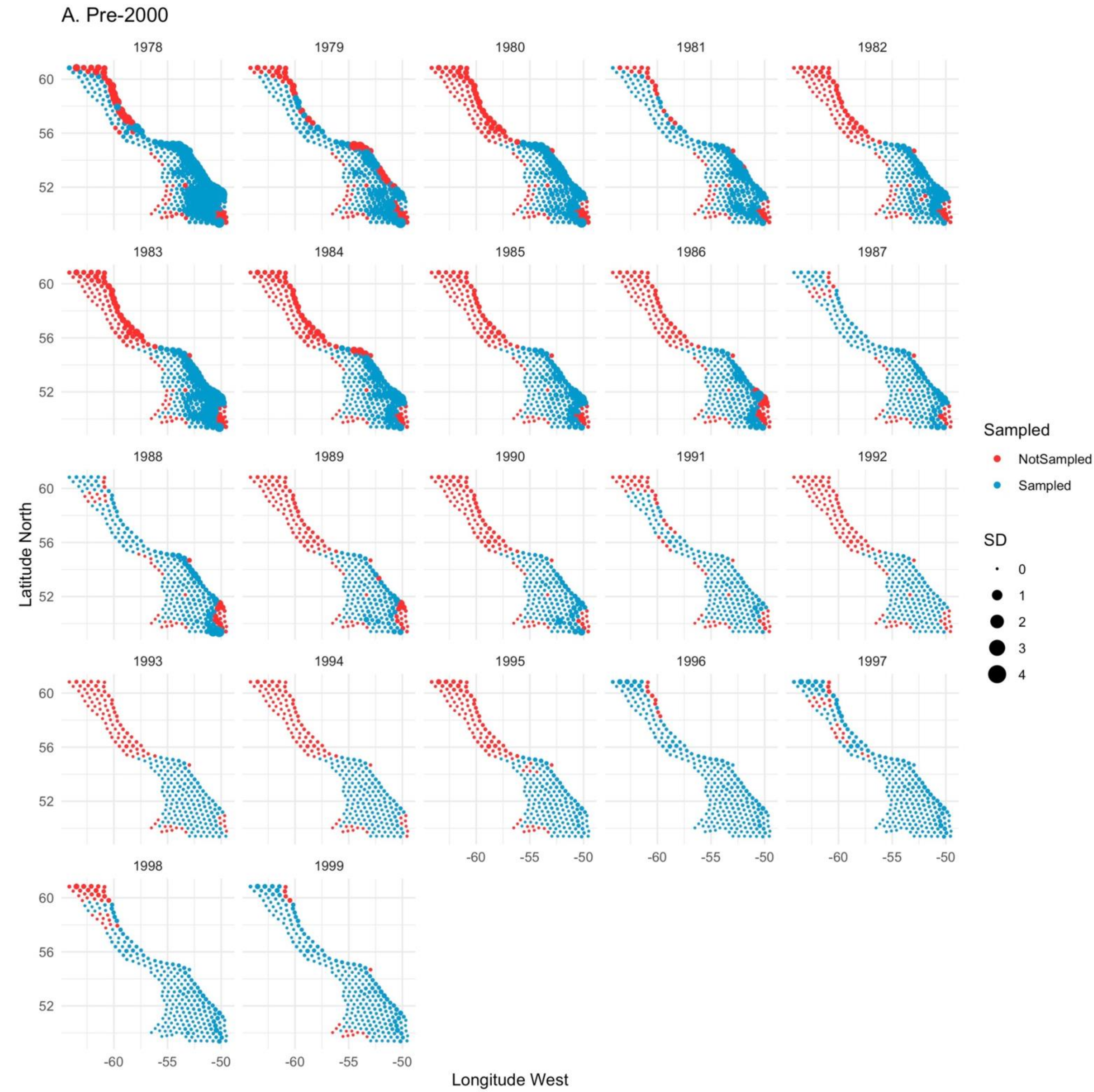


Figure 2.3. The natural log density distribution (kg/25Km^2) for NAFO SA2+Div.3K redfish from 1978 to 2020 that was estimated from the bias-corrected AR1 VAST model.


A. Pre-2000
1978
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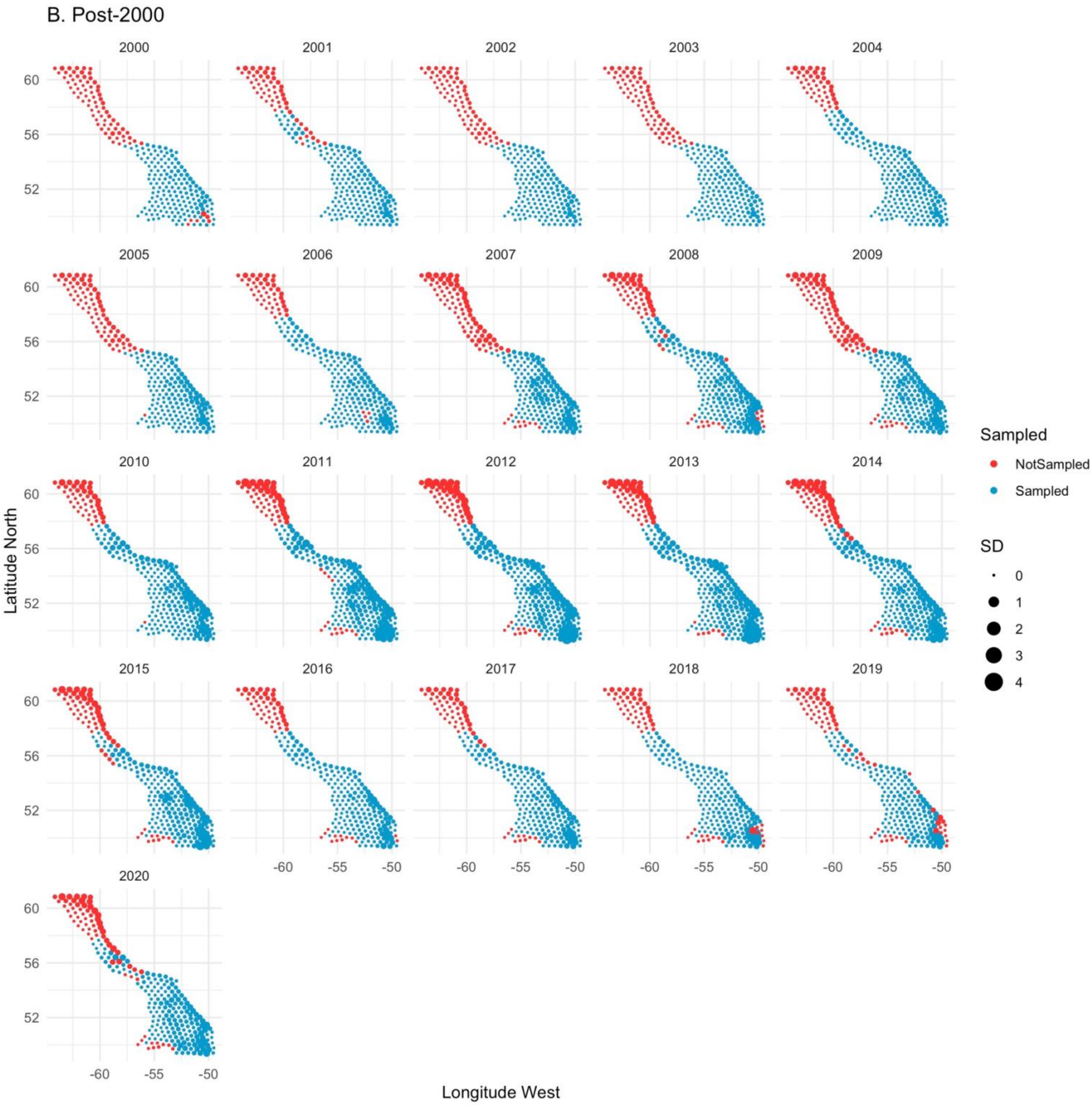

Figure 2.4. Map of the estimated standard deviation (SD) for the estimated index value at the 250 knots in the model spread cross NAFO SA2+Div.3K for 1978 to 2020 (A. Pre-2000, B: Post-2000) from the VAST model. The dot size indicates the SD values, and the colour indicates whether the knot was in a sampled (blue) or un-sampled (red) strata.

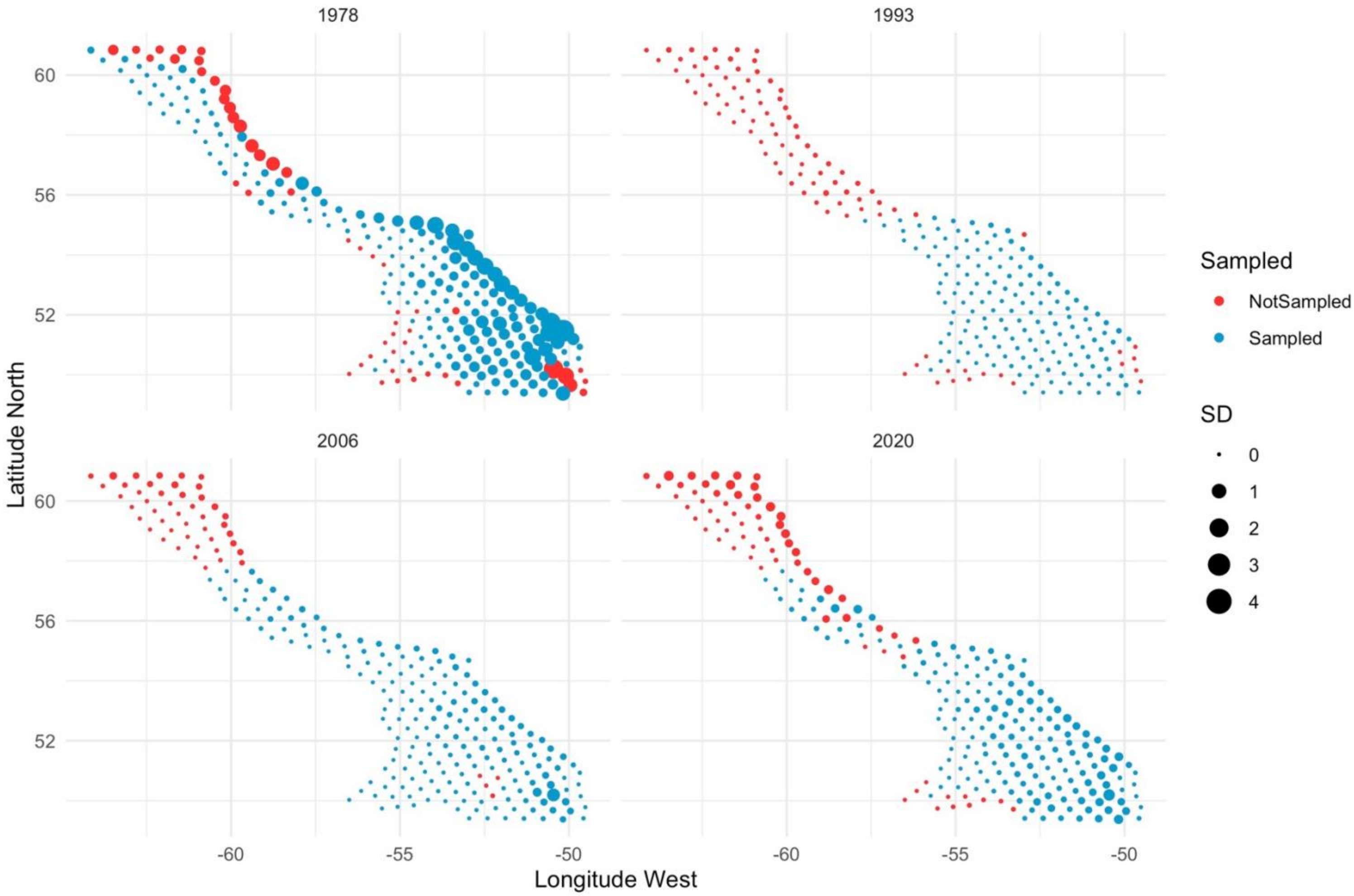

Figure 2.5. Map of the estimated standard deviation (SD) for the estimated index value at the 250 knots in the model spread cross NAFO SA2+Div.3K for four example years from the VAST model. The dot size indicates the SD values, and the colour indicates whether the knot was in a sampled (blue) or un-sampled (red) strata.

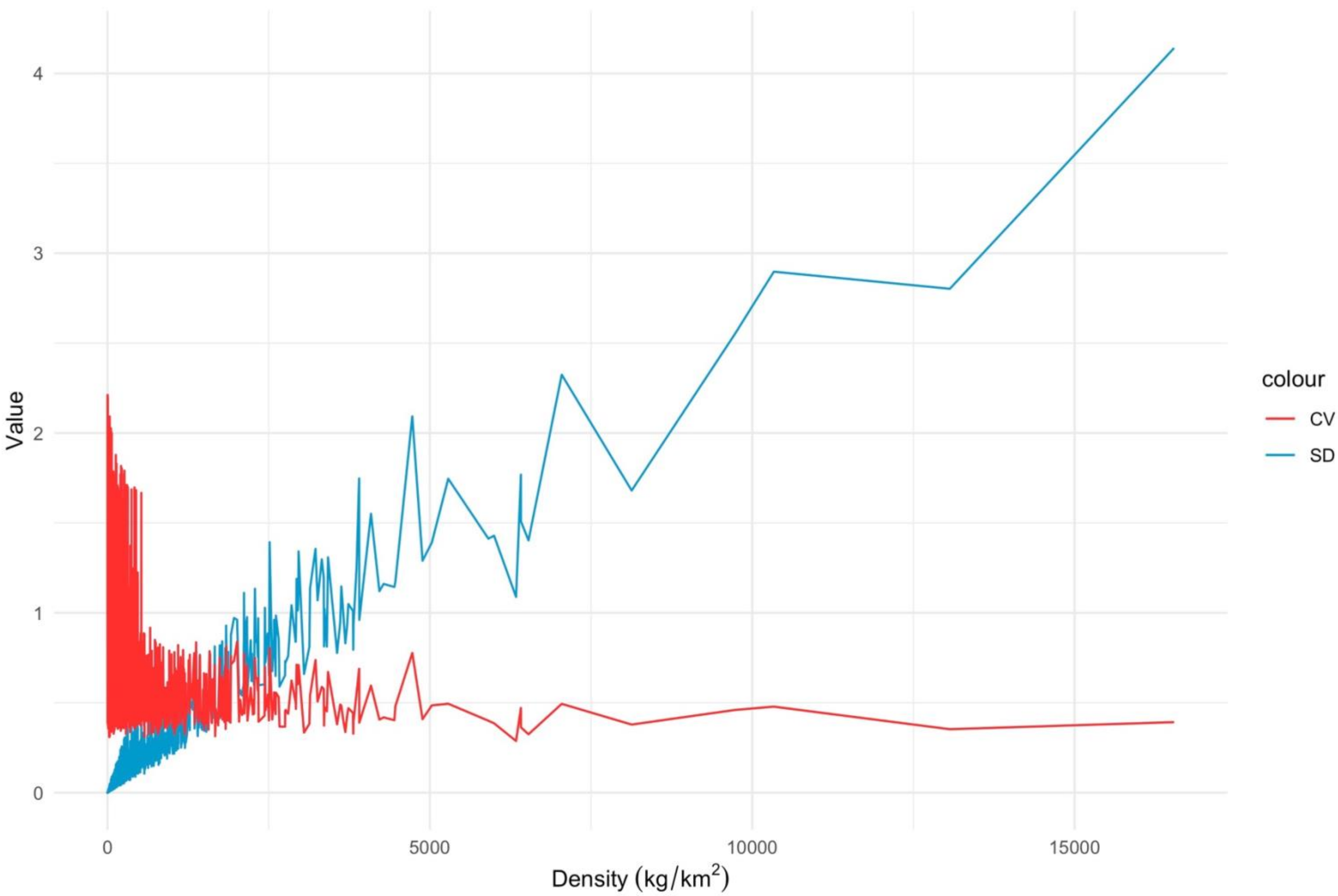

Figure 2.6. The SD (blue) and CV (red) for the index estimate at each knot vs. the density at the knot. For all 250 knots used in the VAST model for NAOF SA2+ Div.3K across the 1978-2020 time-series.

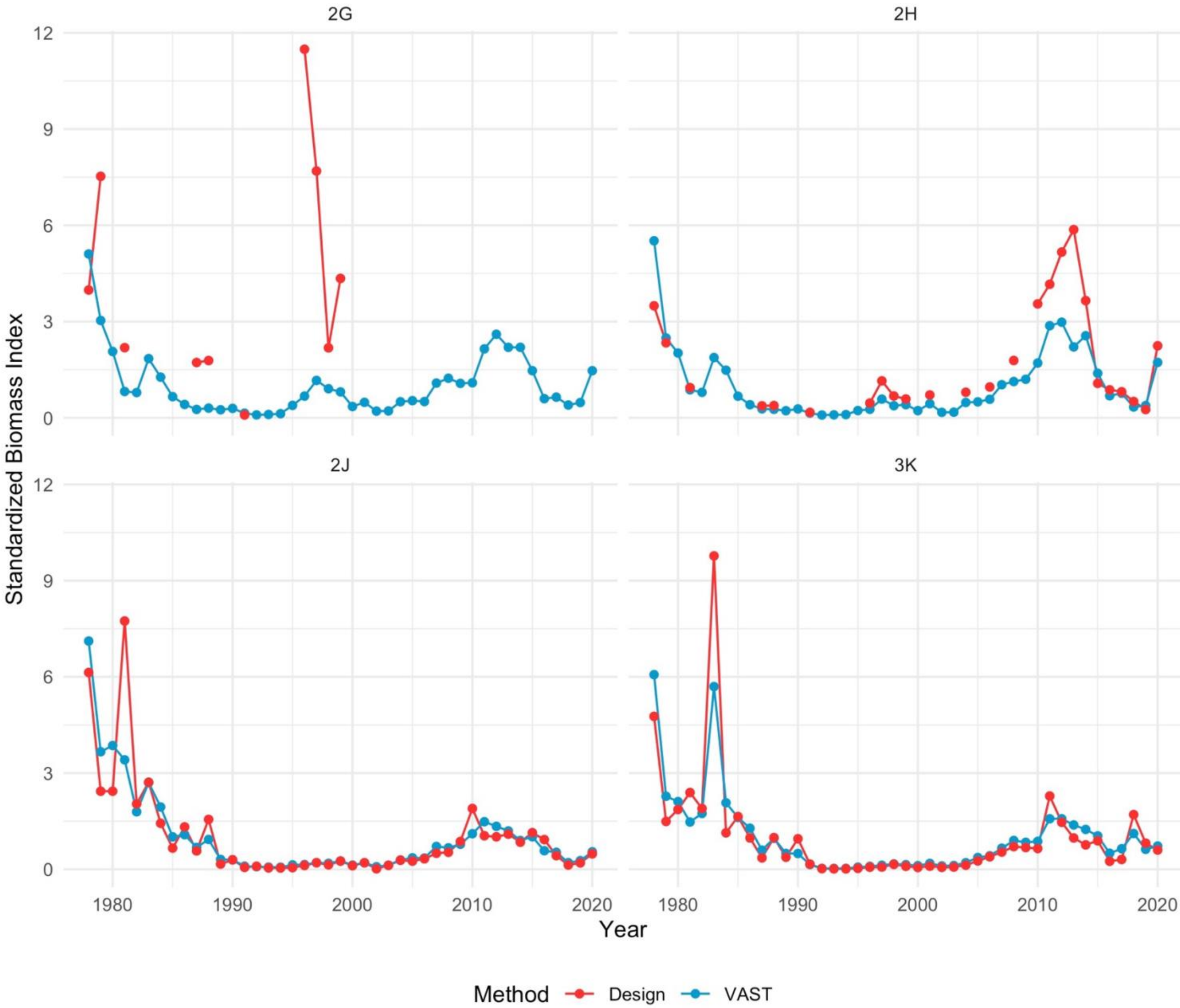

Figure 2.7. Time-series from 1978 to 2020 comparing design-based (red) and VAST-based (blue) estimated standardized biomass indices for the four divisions within NAFO SA2+Div.3K.

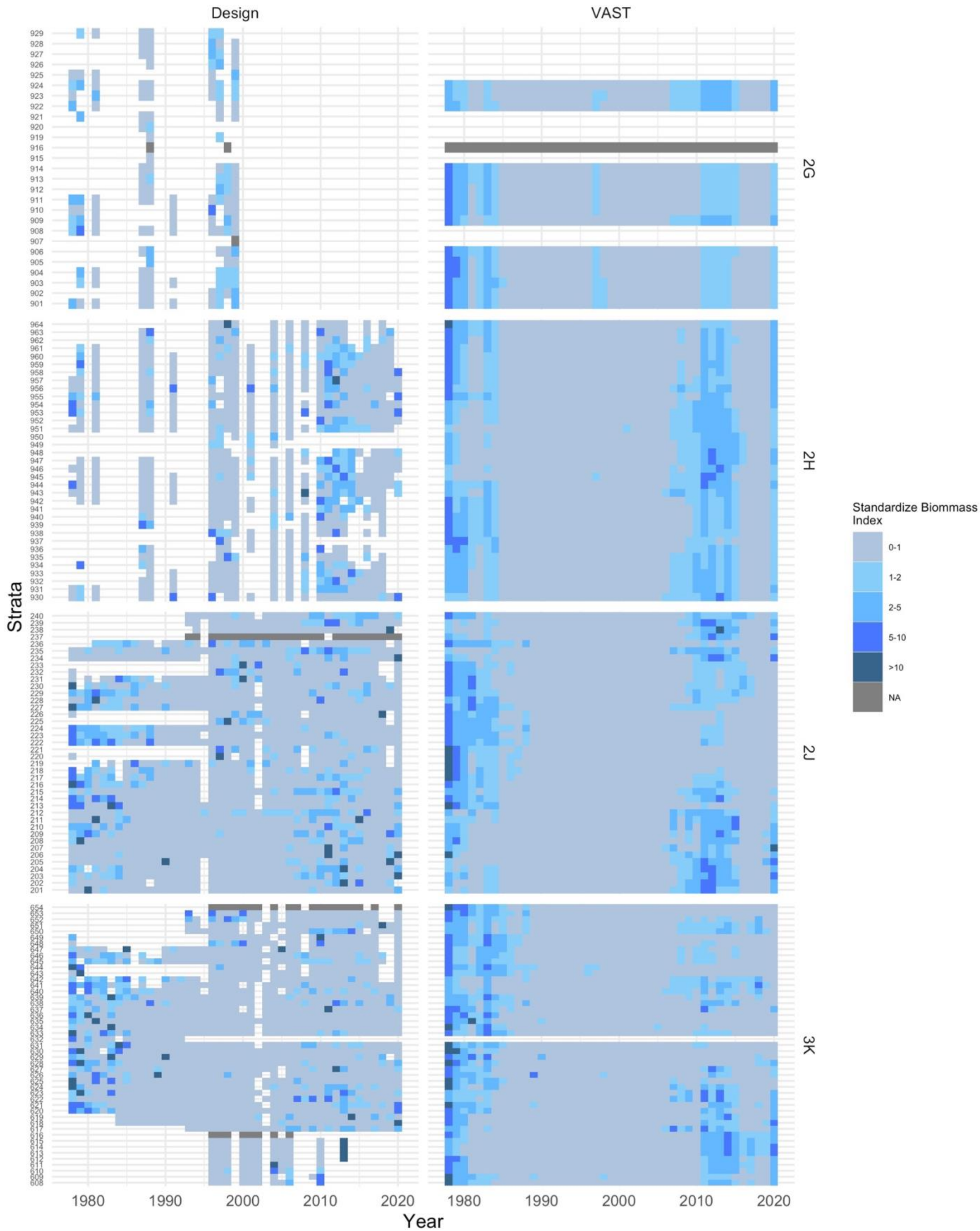

Figure 2.8. Comparison of the standardized index value for each stratum for the AR1 VAST model and design-based estimates for redfish in NAFO SA2+Div.3K from 1978 to 2020. The colour indicates the binned index value.

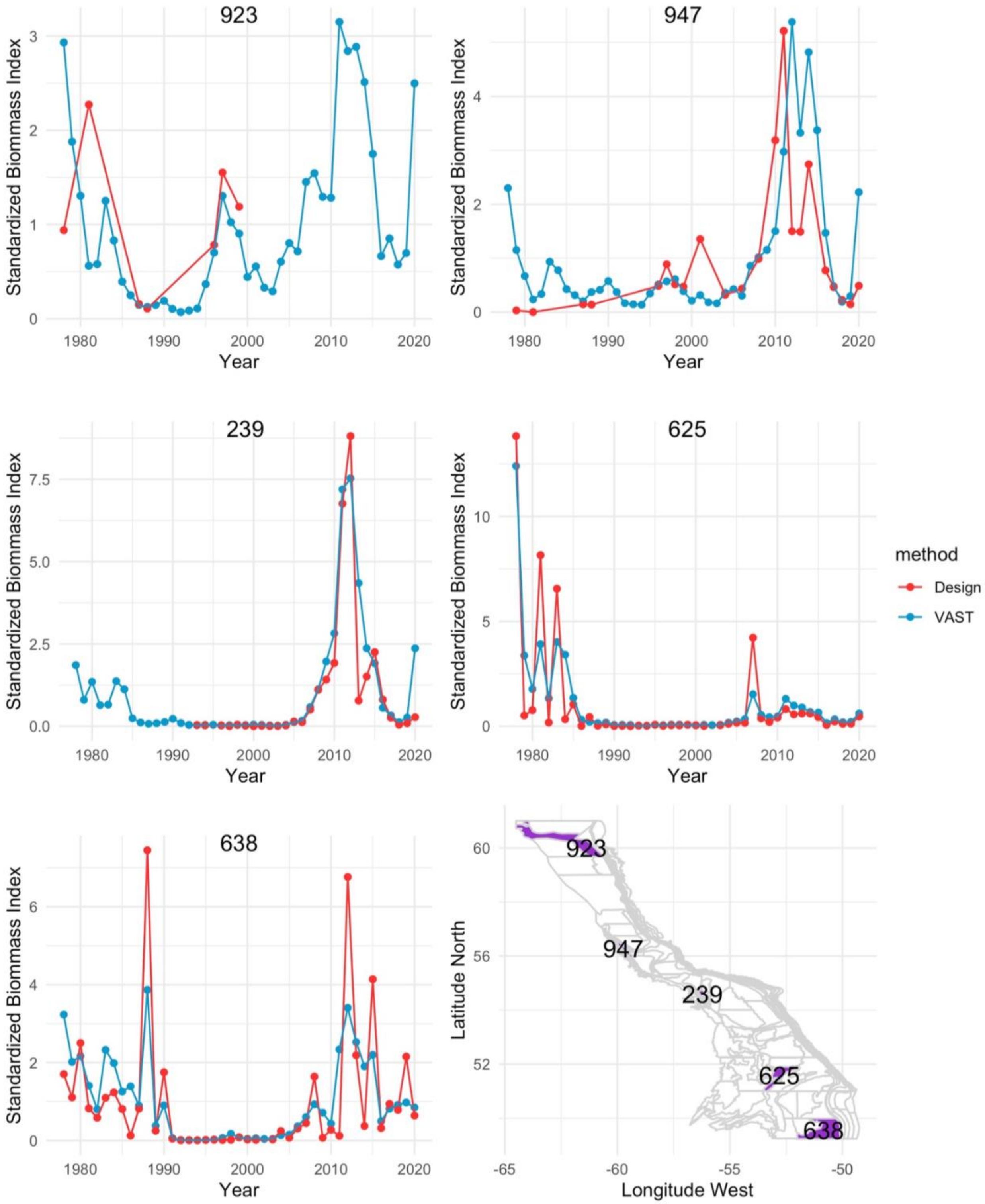

Figure 2.9. Time-series from 1978 to 2020 comparing the standardized index values from VAST (blue) and design (red) for five example strata within NAFO SA2+Div.3K. The map in the bottom right indicates the location of the five selected strata in purple.

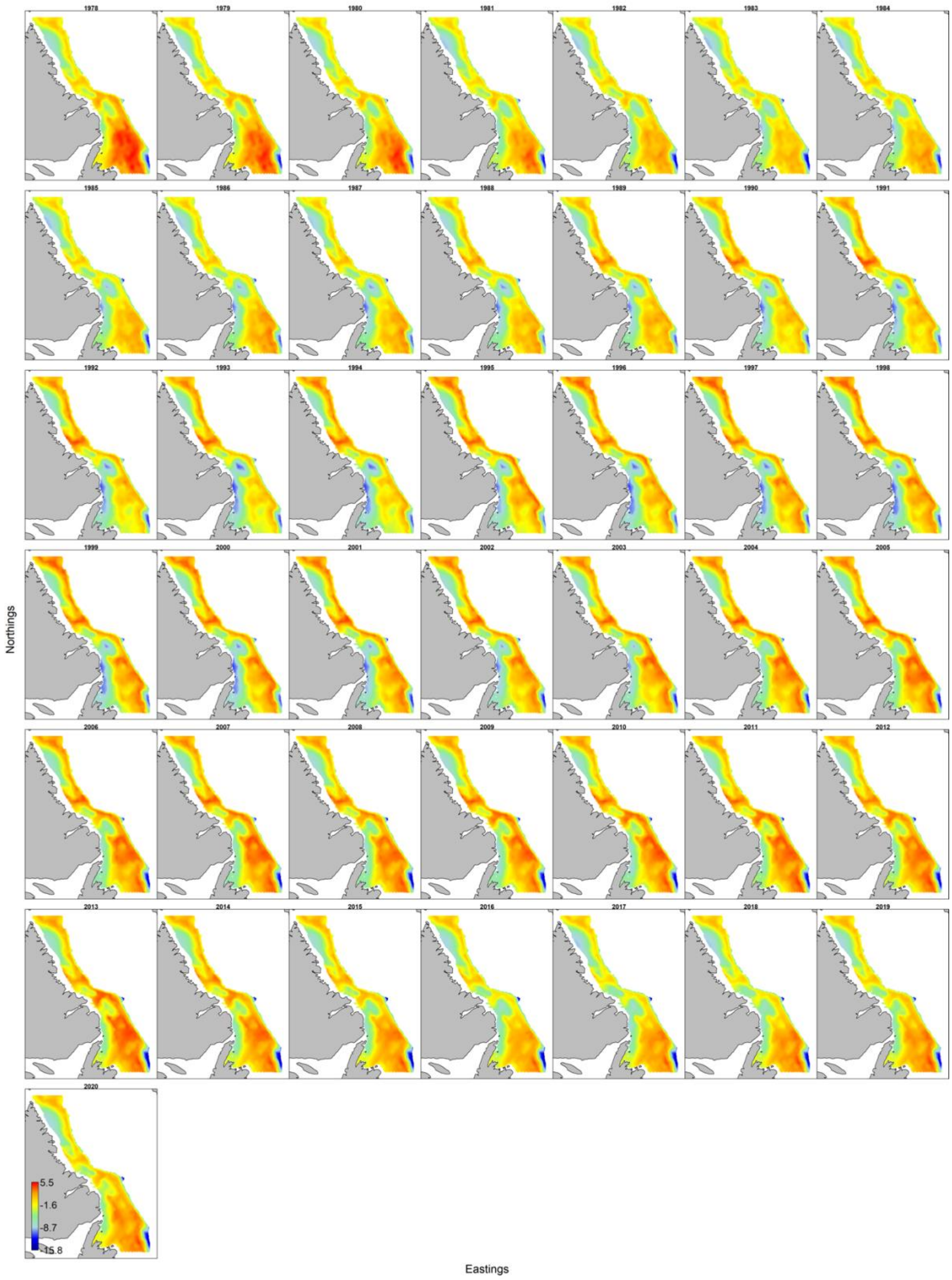

Figure 2.10. The natural log density distribution (kg/25Km^2) for juvenile (< 20cm) redfish in NAFO SA2+Div.3K from 1978 to 2020 that was estimated from the VAST model.

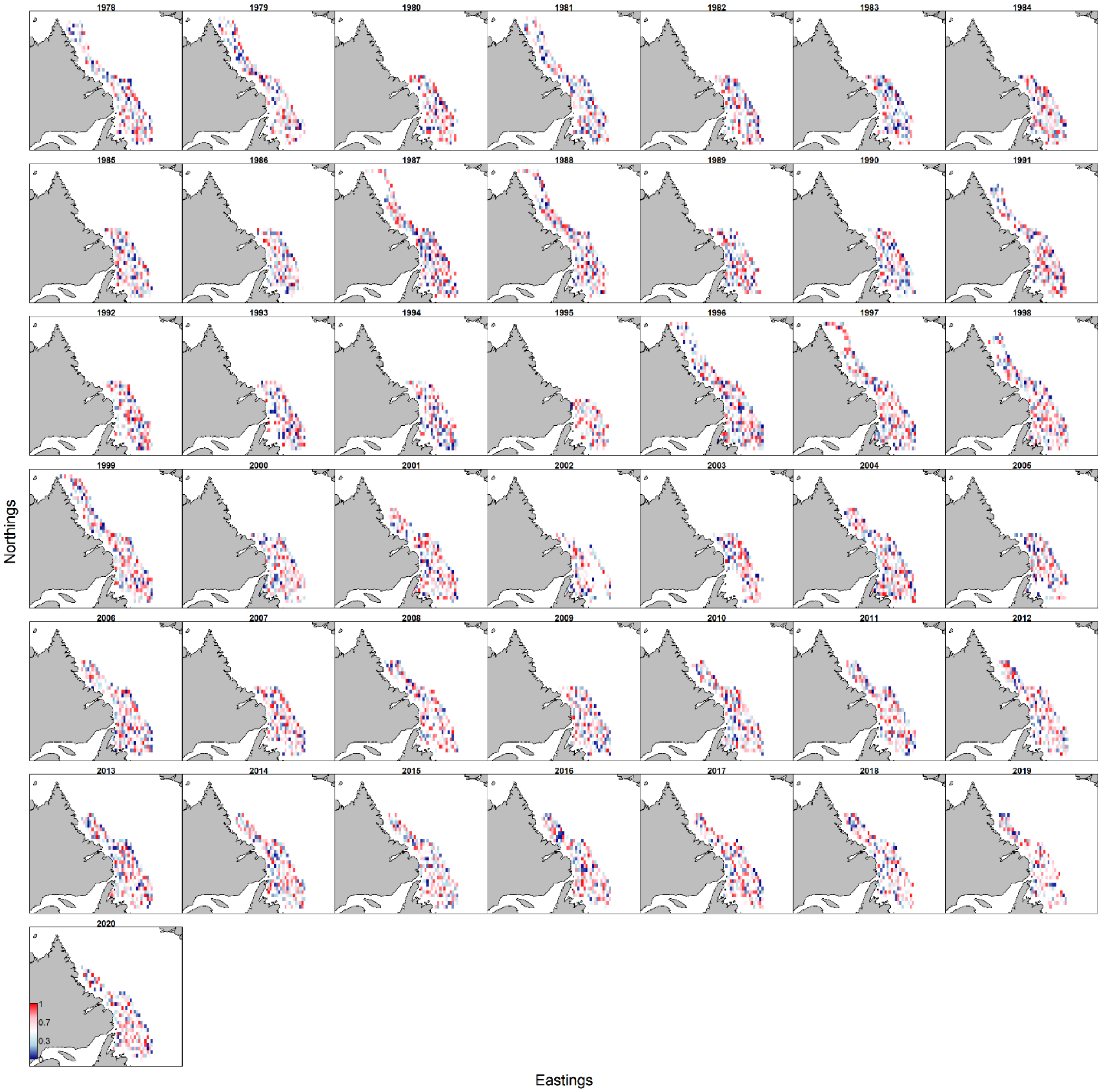

Figure 2.11. A map of the quantile residuals from the VAST model for NAFO SA2+Div.3K redfish.

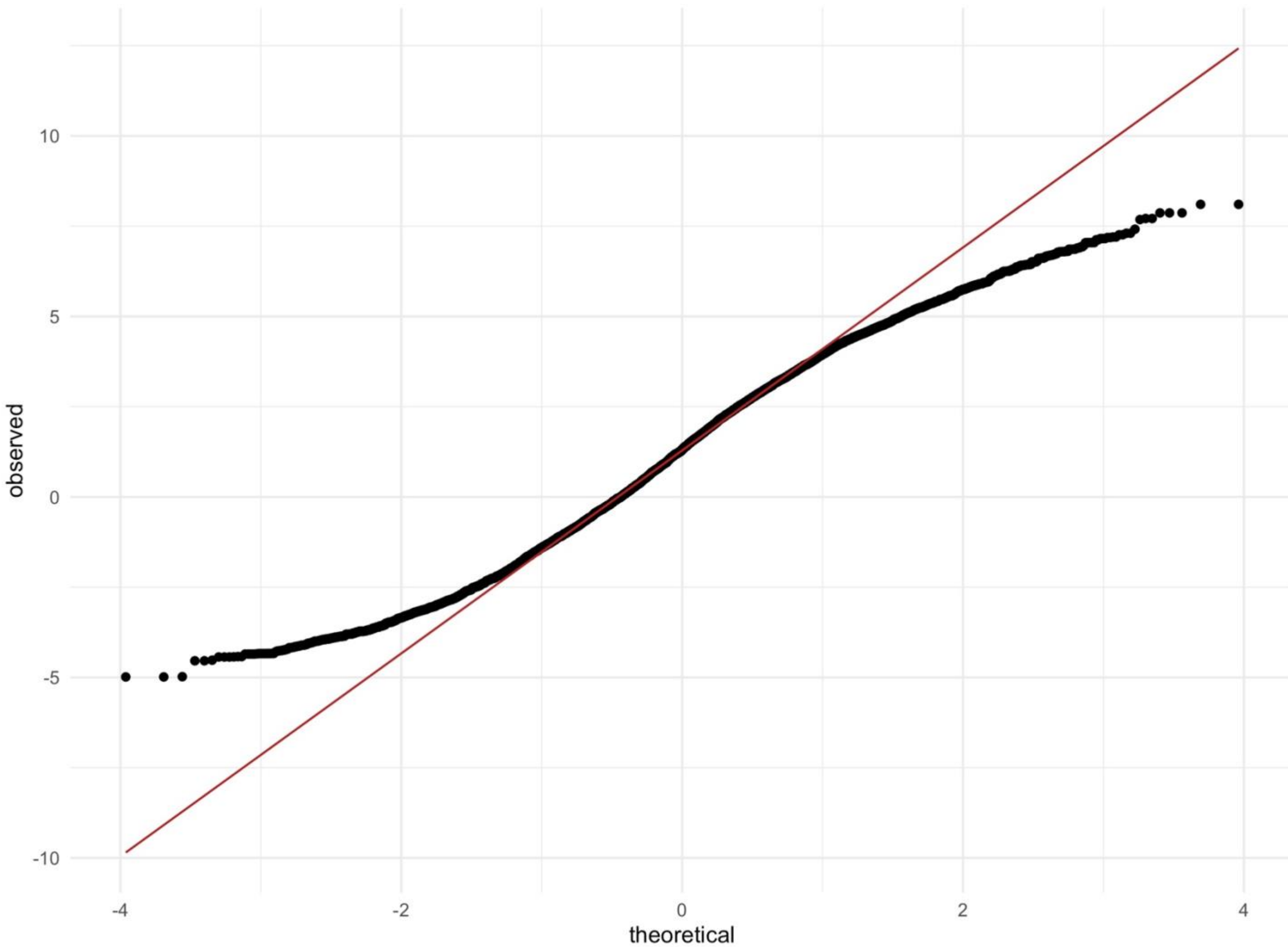

Figure 2.12. A quantile-quantile plot for the log(residuals) from the VAST model for NAFO SA2+Div.3K redfish.

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Chapter 3: Survey Simulation Study

3.1. Introduction

In this Chapter, I use a simulation study for NAFO SA2+Div.3K redfish to examine the impact of changes in survey design and set allocations on estimated abundance indices derived from a spatiotemporal model.

3.1.1. Survey Design and Allocation

Fisheries surveys are typically limited by financial and logistical factors (Maunder et al., 2020), thus restricting the number of samples and overall coverage, as illustrated in Chapter 1. These restrictions may greatly affect the applicability of design-based indices and affect the precision of model-based indices. Therefore, survey considerations (e.g., sample design and allocation) are essential to reliably capture changes in population dynamics and abundance.

The most common fisheries survey sampling design is a stratified random, with strata based on geographical areas (Kimura & Somerton, 2006) and depth for many stocks in the Northwest Atlantic (e.g., Fisheries and Oceans Canada, 2020; Gavaris & Smith, 1987; Treble, 2022). Simple random sampling (SRS) is generally not the best way to sample aggregated populations; when sample sizes are small, samples may not be evenly distributed throughout the survey domain using a SRS design, possibly causing over or under-representation of the population (Kimura & Somerton, 2006). A stratified random sampling (StRS) design is typically preferred over SRS because sampling is designed to be spread-out over-all strata in the survey domain and allows allocation to vary between strata to improve the precision of abundance estimates

(Gavaris & Smith, 1987). These authors examined the survey stratification and allocation of StRS by comparing the design-based variance to that from SRS for Atlantic cod on the East Scotian Shelf. They found that there were only mediocre improvements in the precision of estimates using a stratified design and altering allocation compared to SRS; therefore, they recommended designs not to have many strata and to use proportional allocation, where the stratum sample size is proportional to the size of the stratum. However, some prior knowledge of strata variance needs to be known to optimize stratum sample sizes for StRS (Kimura & Somerton, 2006).

There are obviously many potential choices of good designs, which should be examined carefully. There is considerable research examining fishery-independent survey optimization, often using simulation studies used to evaluate designs centred around specific objective (e.g., Lieu et al., 2009; Xu et al., 2015; Yu et al., 2012. Yu et al. (2012) compared the efficiency of common designs (i.e., SRS and StRS) to three "adaptive" survey designs, which depend on previous observations in sampling. They compared these designs in a simulation study of yellow perch in Lake Erie using five different metrics to compare the performance, i.e., bias, variance of the mean, mean squared error, relative efficiency, and coefficient of variation. They found that adaptive two-phase sampling outperformed SRS and StRS and had greater precision due to more effective sample-to-strata allocation. Xu et al. (2015) used a simulation study to evaluate the survey for multiple species, looking at the abundance indices for 11 species (including finfish and invertebrates), abundance indices for fish groups, and three species diversity indices. Surveys often target multiple species, and an optimized study design should consider all major target species. with the survey in NAFO SA2+Div.3K is a multiple species survey; however, for the scope of this thesis, I will focus on the effect of the survey design on redfish VAST-derived biomass indices.

I investigate the survey design using a simulation study and a population based on Northwest Atlantic Fisheries SA2+Div.3K redfish. I will examine the impact of the design on biomass indices derived from a spatiotemporal model. The surveys in SA2+Div.3K are multispecies surveys conducted by Fisheries and Oceans Canada (DFO). They use a stratified random sampling design, which allocates at least two samples per sampled strata and assigns the other samples in proportion to the strata sample size. For the scope of this study, I will allocate two samples per stratum; this follows the condition of a minimum of two samples per stratum but deviates from their design of allocating more samples based on stratum size.

3.1.2. Survey Design Performance Metrics

Typically, it is essential to have some metric to test the performance of a sampling design in terms of precision and accuracy (Liu et al., 2009). Precision is the degree to which further measurements would produce a similar result (Taylor, 1997), and accuracy is how close a value is to the actual value. Different metrics can be used to evaluate precision, such as relative standard error, variance, or the coefficient of variation (e.g., Liu et al., 2009; Wang et al., 2009; Yu et al., 2012). Bias is a metric for accuracy; further, mean squared error can assess both bias and precision (e.g., Ducharme-Barth et al., 2022; Yu et al., 2012). Other performance measures have been used in survey design studies, such as coverage or efficiency (e.g., Ducharme-Barth et al., 2022; Yu et al., 2012).

Several ways to improve precision include changing sampling designs (i.e., SRS or StRS), defining new strata, or different sampling allocations in strata (Smith & Hubley, 2014). Further, these survey changes can affect the precision of stock assessment model outputs. Smith and Hubley (2014) examined how past changes to the sea scallop survey design impacted the precision in the scallop stock assessment model. They found that the changes in the survey that reduced the uncertainty of indices resulted in reduced uncertainty in reference point limits estimated by the stock assessment models. However, most of this research on study design has been done with design-based indices (e.g., Gavaris & Smith, 1987; Smith & Hubley, 2014). Using model-based index standardization has also been examined as a method to improve the precision of abundance indices (e.g., Cao et al., 2017; Thorson et al., 2015). The second Chapter of this thesis explored the comparison between design-based and model-based indices more in-depth.

Checking for bias is also vital for comparing survey designs. Suppose a survey systematically leaves out a specific area type (e.g., shallow or deep water); in that case, it may over or under-sample aggregations, potentially resulting in similar biases as fisheries-dependent data. A simulation study by Ducharme-Barth et al. (2022) used a spatiotemporal delta-GLMM to derive abundance indices and examined model error and bias when using data from various fisheries sampling patterns. They showed that preferential sampling based on the underlying biomass resulted in similar abundance indices to random sampling, with the preferential ones being less biased. Furthermore, they found that the expansion or contraction of sampling resulted in poorly estimated abundance trends, and the indices became quite variable when the sampling effort was constrained to a specific area.

DFO changed research vessels in 2022, and because of possible limitations of the new vessels, depths over 1000 m may no longer be reached or therefore sampled. Shallow water strata may also be removed from the survey designs because of time constraints on the surveys (Personal communication with Dr. Paul Regular). Hence, I next want to examine how different survey allocations and changes in survey coverage may influence SA2+3K redfish indices estimated via spatiotemporal models. Using simulation studies, I investigate the potential consequences of decreasing survey coverage on model-based estimates. Simulation studies are commonly used to look for biases in model-based abundance indices (e.g., Cao et al., 2020; Thorson & Haltuch, 2019) and to examine different survey configurations (e.g., Ducharme-Barth et al., 2022; Liu et al., 2009; Wang et al., 2009; Yu et al., 2012). Simulation studies are a tool to help compare study designs, as it is often impossible to physically conduct numerous sampling designs. They can test for biases by comparing the estimated indices to known "true" estimates. They can also be used to compare estimated precision from different allocation designs. For example, Ducharme-Barth et al. (2022) used simulation techniques to examine how different spatial sampling patterns may bias model-based estimates of abundance.

3.1.3. Application to NAFO SA2+Div.3K Redfish

As demonstrated in the first chapter of this thesis, there are substantial coverage gaps in the surveys in NAFO SA2+Div.3K. Currently, the survey primarily allocates effort towards the southern three divisions (i.e., 3K, 2J and 2H), leaving Division 2G un-surveyed since 1999 (Fisheries and Oceans Canada, 2020). There have also been discussions about the surveys dropping the deep-water strata in the zone. In the second chapter, I derived biomass indices from a spatiotemporal model (VAST model) for SA2+Div3K redfish. I want to examine the effects of survey allocation and investigate if dropping deep-water strata will cause substantial changes to the precision in the model-based estimates and determine if dropping the extra strata will cause biases for this stock.

3.2. Methods

3.2.1. Simulated Data Set

Catch biomass was simulated at specified tow locations using the Vector Autoregressive Spatiotemporal (VAST) model developed in the second Chapter. I described the structure of the model in Chapter 2. The locations for the simulated tows were based on all the observed tow sites (specific latitude/longitude combinations) from across the 43 survey years (1978-2020). There were originally 13413 different tow sites across the 43 years. Catch biomass was simulated at all 13413 locations every year; this resulted in a total of 576766 tow data points across the entire study period (Figure 3.1).

3.2.2. Survey Configurations

All data for the survey configurations were selected subsets from the simulated data set. Three sampling design scenarios were used to test survey configurations: 1) randomly selected strata, 2) consistent reduction of deep-water strata, and 3) sampling all strata.

The first scenario of random selecting strata was done because, due to survey logistics (e.g., vessel issues or weather), strata could potentially be missed at random. Further, as there are currently large consistent gaps, I wanted to compare how the same sampling effort, if spread out more throughout SA2+Div.3K, might potentially influence the precision of indices.

For randomly selected strata (reducing effort), different percentages of strata coverage were tested (i.e., 25, 50 and 75% coverage). These scenarios will be referred to as RS25%, RS50% and RS75%, respectively. Random strata were chosen at the appropriate coverage percent level from all the strata that had ever been sampled. The sampled strata were allowed to vary from year to year, but the same number of strata were selected each year. There were 149 sampled strata in the NAFO zone; therefore, 37, 74 and 112 strata were randomly selected yearly for 25, 50 and 75% strata coverage, respectively. Two randomly selected tow locations were chosen in each sampled stratum for all coverage percentages. Two locations were selected per strata to follow the DFO typical sampling design allocating at least two tows per strata. However, unlike the DFO survey designs, additional tows were not designated proportionately to the strata size, as I did not have a set number of tows to allocate; I based it on the number of strata I wanted to sample instead. Thus, it resulted in a total of 2 sets × 37 strata × 43 years = 3182 tow data points for RS25%, 6364 for RS50% and 9632 for RS75%. Hence, the sampling designs I investigate (i.e., only two sets per stratum) differ substantially from those used by DFO.

Ten different simulated surveys (combinations of random strata and random tow locations) were selected for each percentage level scenario. Ten surveys were used because they represented a balance between the consistency of the results and the computation scope of the project. Although a simulation sample size of 10 is a very low number, the results of the ten different surveys did not show much variation in the trend of the indices; this is illustrated in the results from the ten simulated surveys from 25% strata sampled scenario (Figure 3.2); with the other scenarios even more consistent.

For the second scenario, consistently dropping deep-water strata (DDWS), the strata were dropped based on the maximum tow depth set in the survey data. All strata with a maximum tow depth greater than 700 m were considered "deep water." This depth was used as the cut-off because it represented a reasonable balance between deep and non-deep strata in the data set. Additionally, deep strata (>700 m) were not sampled for Division 2H in 2014 and 2015 (Fisheries and Oceans Canada, 2020), so it seemed to be a realistic cut-off. I did not have information on the maximum depth of the new vessels until after the study was completed. Strata 918 (located in Division 2G) had no data, so it was not categorized either way. Therefore 51 strata were considered deep water >700 m, and 98 strata were not (Figure 3.3). All the strata <700 m were sampled yearly, and similar to the random strata sampling scenario, two random tow locations were selected for each of the strata selected for sampling. There was a total of 8428 data points across the entire study period. Also, like the random design, ten runs were completed with different randomly selected tow locations within the selected strata.

Additionally, ten simulated surveys were done where all 149 strata were sampled yearly. Two tow locations within each stratum were randomly selected, allowing the locations to vary annually. There was a total of 12814 data points for these surveys for the all-strata-sampled (AS) scenarios.

3.2.3. Comparison

The indices developed from the various sampling designs were compared to the yearly average population tow biomass (based on usually 13413 values each year) of the simulated data set. I use bias (B) and the average coefficient of variation (CV) as the performance comparison criteria of the different study designs. A list of the notation used to calculate the performance metrics is found in Table 3.1

The AR1 VAST model (see Chapter 2) was applied to each simulated survey dataset to estimate the biomass indices *I(t)* for each year *t*. The *I(t)* of the i^{th} survey was calculated based on equation 2.7 in Chapter 2 and was standardized by dividing by the mean index value of the respective time-series. Then, the average yearly index values of a sampling design scenario were calculated from the ten (N) surveys within each scenario (i.e., RS25%, RS50%, RS75%, DDWS, AS; Equation 3.1).

$$\bar{I}(t) = \frac{\sum_{i=1}^{N} I_i(t)}{N}, \tag{3.1}$$

where $I_i(t)$ is the standardized index for the i^{th} survey. The bias (B) was calculated by taking the absolute difference between the average index value (i.e., Equation 3.1) of each scenario and the standardized average tow biomass of the respective year ($\bar{y}(t)$) (Equation 3.2).

$$B(t) = |\,\bar{y}(t) - \bar{I}(t)|. \tag{3.2}$$

The average annual CV (Equation 3.3) of the index values from each scenario's ten (N) surveys was calculated as,

$$\overline{CV}(t) = \frac{\sum_{i=1}^{N} CV_i(t)}{N} . \tag{3.3}$$

To get an overall B and CV value for each scenario, the *B(t)* and $\overline{CV}(t)$ were averaged over the T number of years of the time-series to get $\bar{B}$ and $\overline{\overline{CV}}$ (Equation 3.4 and 3.5, respectively).

$$\bar{B} = \frac{\sum_{i=1}^{T} B(t)}{T} . \tag{3.4}$$

$$\overline{\overline{CV}} = \frac{\sum_{i=1}^{T} \overline{CV}(t)}{T}. \tag{3.5}$$

3.3. Results

The average index estimates for the different scenarios are all quite comparable (Figure 3.4). All the scenarios produce similar trends, with higher abundance at the start in 1978, then a decrease in abundance in the '90s and early 2000s, followed by increases in the later 2000s. The trends also aligned with the results from the standardized population (i.e., 13 413 locations each year) average tow biomass, which I considered to be the "true" values.

The highest bias (B) was 0.935 for the RS50% scenario in 1983 (Figure 3.5). Four of the five design scenarios (all but the DDWS scenario) had their highest B in 1983. The DDWS scenario had its highest B value of 0.622 in 1981. Overall, the average bias was the highest (0.167) for the

DDWS scenario, and the lowest average (0.117) was for the AS scenario (Table 3.1). The lowest B value of 0.0005 was with AS in 1992. The bias increased as the percentage coverage decreased.

The CV decreased as sampling coverage increased (Table 3.2) (Figure 3.6). The highest $\overline{CV}$ value (least precision) of 1.165 was for the RS25% scenario in 1978. All five coverage scenarios had their respective highest $\overline{CV}$ in 1978. The lowest $\overline{CV}$ value (highest precision) of 0.006 was for the AS scenario in 1992. The RS25% scenario had the highest $\overline{\overline{CV}}$ (0.186) and the AS scenario had the lowest $\overline{\overline{CV}}$ (0.102). The $\overline{\overline{CV}}$ (0.157) from the DDWS scenario resulted in levels between the RS25% and RS25% coverage scenarios.

3.4. Discussion

This study explored the consequences of reducing sampling effort and dropping strata in the NAFO SA2+Div.3K survey, which already has substantial coverage gaps. Specifically, I investigated how changes in coverage affected redfish biomass indices standardized by a VAST model. The different survey designs were tested in a simulation study and compared by their precision and bias for the derived biomass indices.

I found that neither dropping extra strata randomly nor systematically dropping deep water strata resulted in substantial changes in the model-based index trends. The bias between all study designs was quite comparable, with the DDWS scenario only being slightly larger. This result is likely because the different areas had similar temporal trends. These trends in the dataset are similar between the deep-water strata and the non-deep-water strata (Figure 3.7). Therefore, even when a portion of the area is removed, the VAST model still estimates that same trend. Also, the cut-off depth of 700 m is more extreme than the maximum depth of 1000 m of the new research vessels, so there would likely be even less effect if at a 1000 m cut-off. However, the reason removing deep water areas likely has a more minor effect than expected is because the spatial distribution appears to be relatively static for redfish.

The results might change if there were distribution shifts in the population, where the temporal trends were not so similar between the various geographical areas. Hence, if sizable changes in their distribution are observed, the effects of dropping strata should be re-evaluated. These distribution shifts have been reported elsewhere due to fishing pressure and climate change, causing changes such as localized density reduction or changes in depth or location preferences (Currie et al., 2019). If there are distribution changes, adaptive sampling techniques potentially provide a better way to capture species distribution as they consider past observations in the sampling. With the advantages of being more flexible and more efficient at picking up aggregations (Liu et al., 2011), it could be a better design if distribution changes occur. However, this technique would not be applicable for this redfish stock, as the survey is multispecies and therefore needs to consider the other target species.

I caution against extending these conclusions to other groundfish species caught in the same survey; this study only considers how changes to the survey might affect redfish biomass indices, and other species may have different results. Other groundfish species potentially share some similar characteristics to redfish (e.g., habitat preference). However, redfish are ovoviviparous, which may limit their mixing more than other species (Cadigan et al., 2022), and therefore maybe they have a more static distribution than other species.

I found that the precision of indices decreased with decreases in coverage, as expected. Systematically dropping an area appeared to affect precision more than randomly dropping strata. The DDWS scenario had more data points than the RS50% scenario; however, it resulted in lower precision. The results indicate that if a substantial area is left out of the survey, it may affect the precision to a greater extent than randomly dropping more samples. It could be more beneficial for the current NAFO SA2+Div.3K survey if the same number of tows were collected but spread out more randomly than how they currently systemically leave out Division 2G. Rather than dropping strata to save time, I recommend reducing the number of samples allocated to strata. However, I recognize that there may be other logistical reasons why some strata cannot be effectively sampled (e.g., depth, rough bottom).

One assumption of this study is that the simulated data represents the true redfish distribution; however, the simulation data was developed from a potentially biased model. Further, the model smooths its estimates; therefore, the simulated data set developed from the model is smoothed over, which is contrary to the aggregations that are sometimes observed for redfish. Consequently, the simulated data may not represent actual redfish sampling that may be patchier. If actual sampling followed the tested scenarios, there could be more variation in the catch, possibly resulting in more biased and less precise estimates.

Additionally, for the tested scenarios in the study, two samples were selected from each stratum; this differs substantially from the stratified sampling scheme conducted by the DFO, which allocates based on strata size. As VAST does not aggregate the data based on strata, the same way that the design-based method does, having two samples per strata would not necessarily have substantial effects on the VAST model (besides the overall reduction of samples that this causes). If looking at smaller scales, such as the strata themselves, this could potentially have a larger effect on the VAST estimates, as the reduction in data would be more noticeable. This study did not compare to design-based estimates, as the aim of this study was to look at the effects on the model estimates. However, this could be a good direction for future work.

Another minor consideration, similar to Chapter 2, was that there were six duplicate data points from the original data set in the simulated data set (a total of 576766 data points). This is why there are greater than 13413 tows x 43 years = 576759 data points. The points were not noticed until after the analysis but were not multiplied across the other years as they contained the same latitude and longitude combinations. However, as this represented a neglectable percentage of the data and I conducted multiple simulations, these duplicated points would have likely had negligible effects on the results.

The VAST model is very computationally expensive, and it was not in this project's timeline to do a more rigorous simulation study. Future work should develop a more comprehensive analysis, potentially looking at different survey designs such as more systematic designs, simple random sampling, or adaptive sampling, as well as more simulated surveys per scenario. Specifically for Labrador Shelf redfish, a simulation study with sampling similar to the surveys missing Division 2G2H should be conducted, as well as the additive effects of missing 2H2G and deep water should be evaluated.

More computationally feasible spatiotemporal models are also needed. This problem is greatly compounded if the model-based index standardization is extended to include size, which is needed for state-of-the-art stock assessment models. Furthermore, this study just looked at changing the sampling coverage, focusing on allocating sampling effort in space. There is limited literature that focuses on allocating effort over time (Wang et al., 2009). A future study could also look at changing sampling intervals, such as sampling strata at different time intervals, for example, every two years. Additionally, other studies have compared other performance criteria, such as coverage or efficiency or different precision metrics (Ducharme-Barth et al., 2022; Yu et al., 2012), that could be analyzed in a future study.

In conclusion, this study found minimal effects in biasing the index values developed for redfish from a VAST model when the coverage for surveys in NAFO SA2+Div.3K was reduced. The precision decreased as sampling decreased, but not substantially. Random sampling with greater area coverage appeared to have higher precision than more concentrated sampling. This study illustrated that the VAST model was reasonably robust to the potential changes to the sampling design in SA2+Div.3K. This study adds to the research in Chapter 2, illustrating the potential use of the VAST model in the management of Labrador shelf redfish. Further, the VAST model should be examined for other fisheries where financial or logistical considerations limit the sampling effort. However, this study is only a beginning step for a more comprehensive analysis of survey designs and their effects on VAST abundance indices.

3.5. Tables

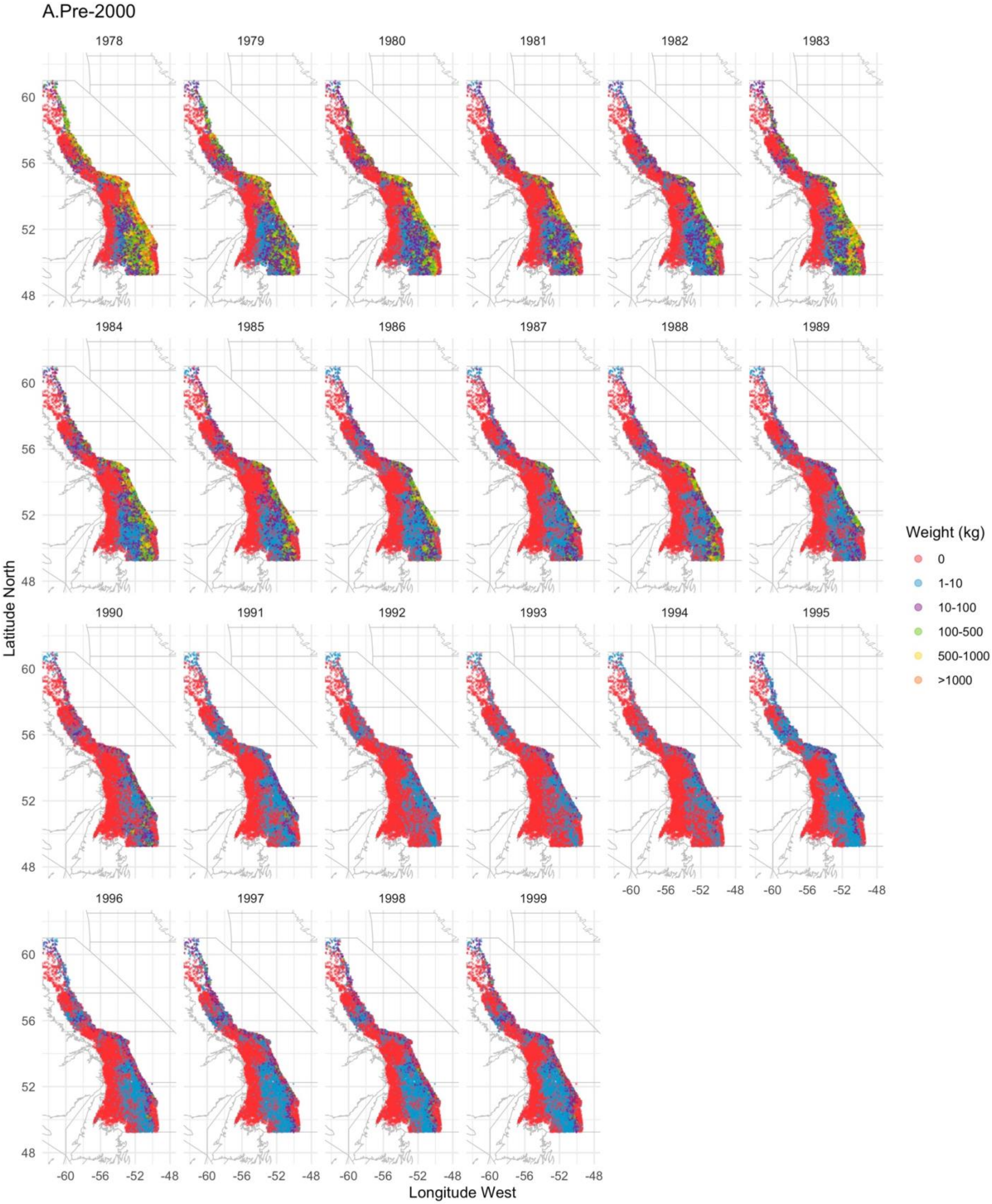
Table 3.1. List of the notation used in the equations.

Symbol	*Descriptions*	*Dimensions*
Indices Calculation		
i	Survey	
t	Year	
$I_i(t)$	Annual index	t
$\bar{I}(t)$	Averaged annual index	t
$\bar{y}(t)$	Average annual biomass	t
$CV_i(t)$	Annual coefficient of variation	
N	Number of surveys per scenario	10
Comparison Metrics		
$B(t)$	Annual bias	t
$\bar{B}$	Averaged B(t)	
$\overline{CV}(t)$	Average annual CV	t
$\overline{\overline{CV}}$	Averaged $\overline{CV}(t)$	

Table 3.2. The bias (B) and the mean coefficient of variation ($\overline{\text{CV}}$) results for each survey design scenario averaged over the time-series (1978-2020).

	Survey Design				
	25%	50%	75%	100%	Dropping deep water
$\bar{\boldsymbol{B}}$	0.142	0.136	0.124	0.117	0.167
$\overline{\overline{\boldsymbol{CV}}}$	0.186	0.137	0.115	0.102	0.157

3.6. Figures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Longitude West
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-52
-48
Weight (kg)
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1-10
10-100
100-500
500-1000
>1000

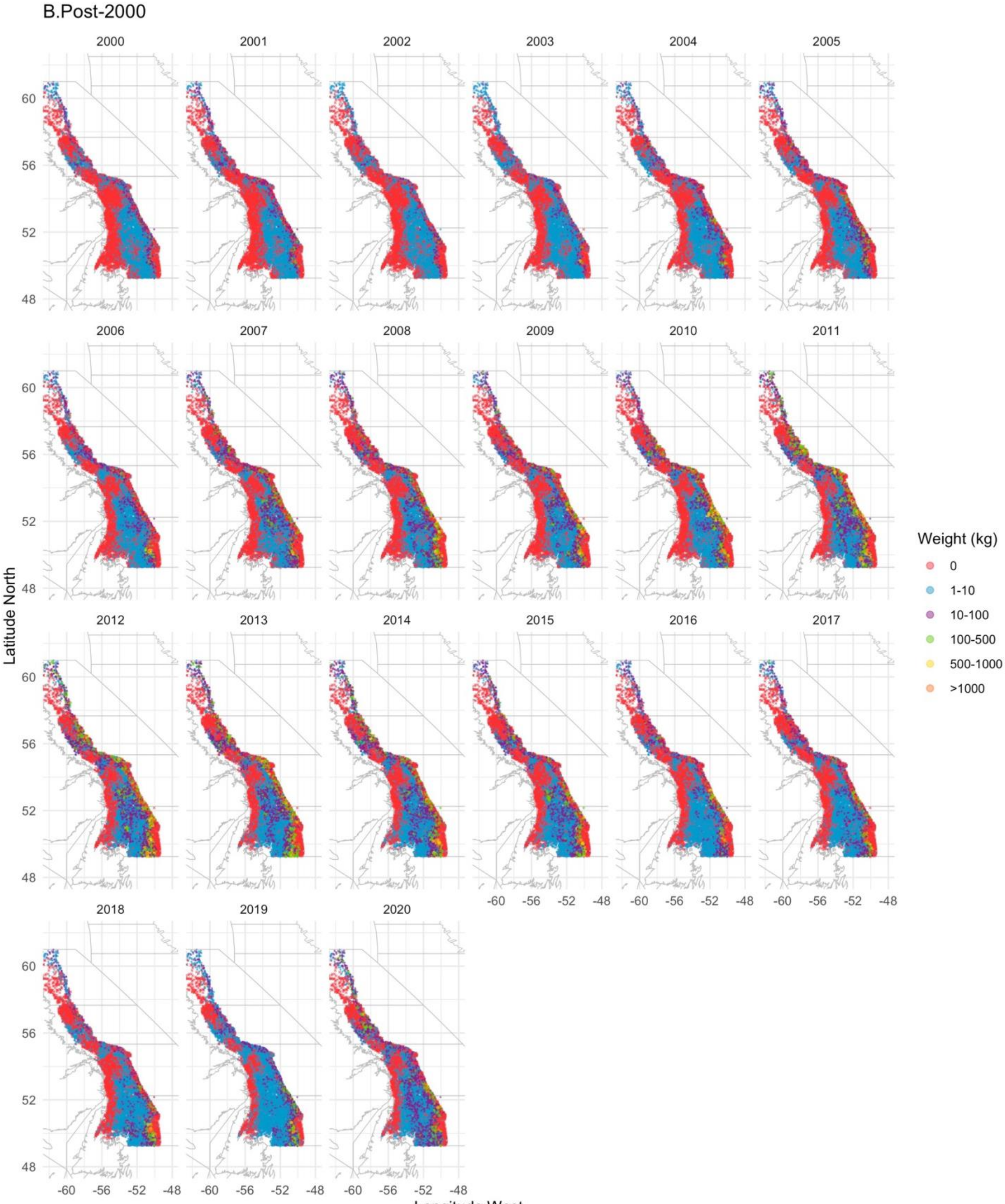

Figure 3.1. Maps of the simulated data points, with the colour indicating the simulated tow weight. Each year is a separate map in the time-series of 1978-1999 (A) and 2000-2020 (B).

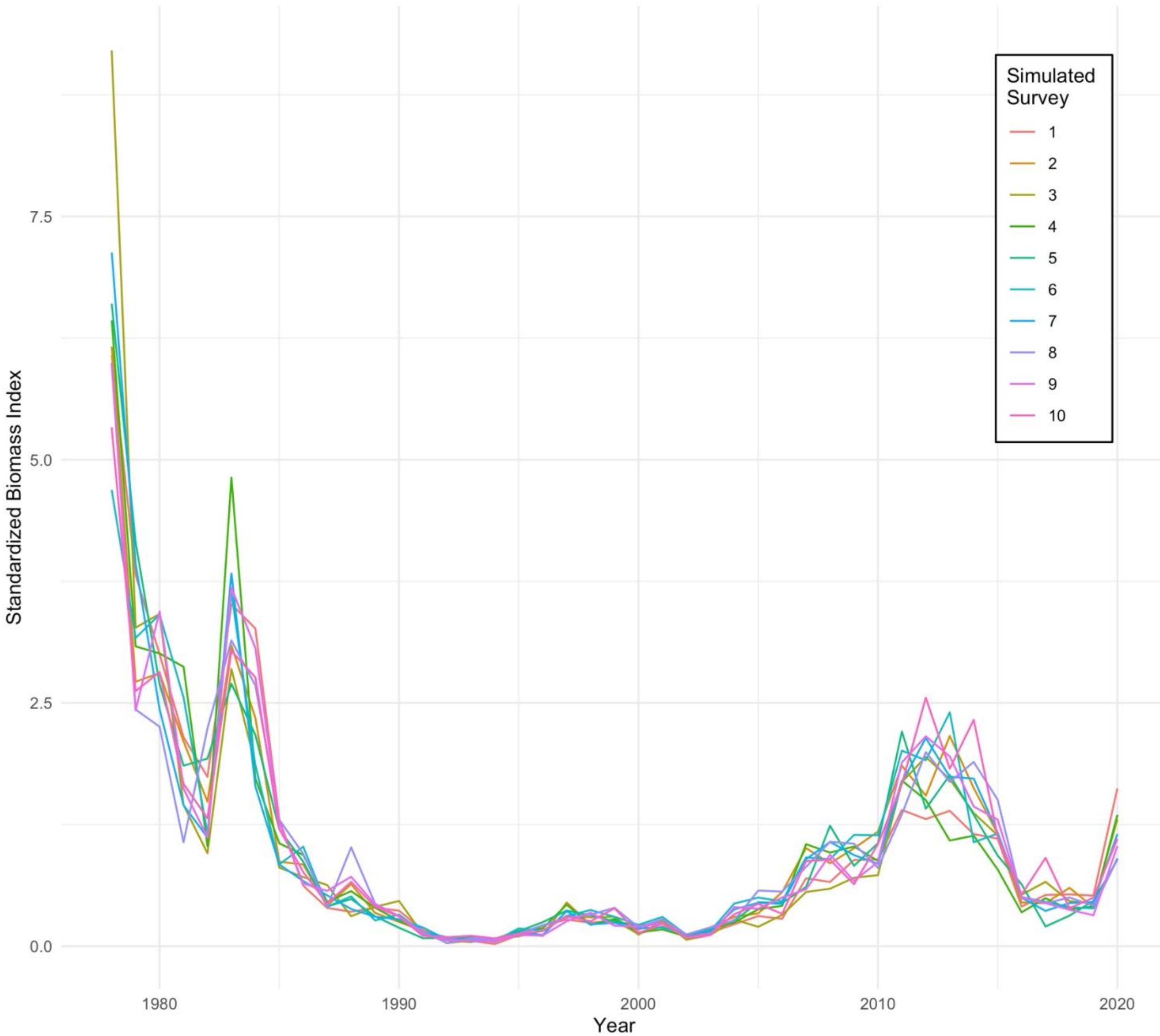

Figure 3.2. A time-series (1978-2020) of the standardized index values from the ten different simulated surveys where 25% of the strata were sampled (RS25% scenario). The colour represents the results from each of the various surveys.

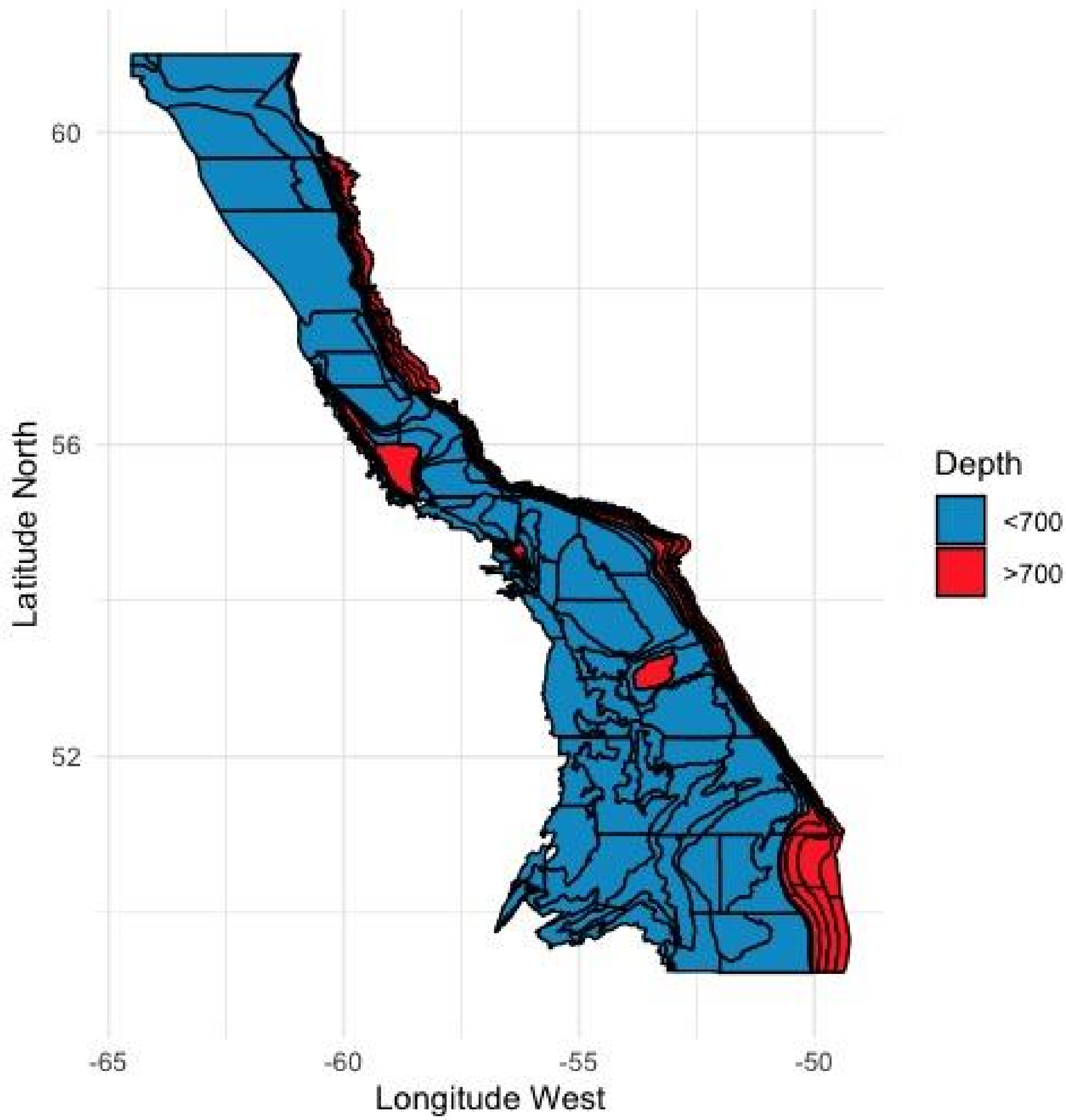

Figure 3.3. A map showing the strata that had set tow depths >700 m (red) and <700 m (blue).

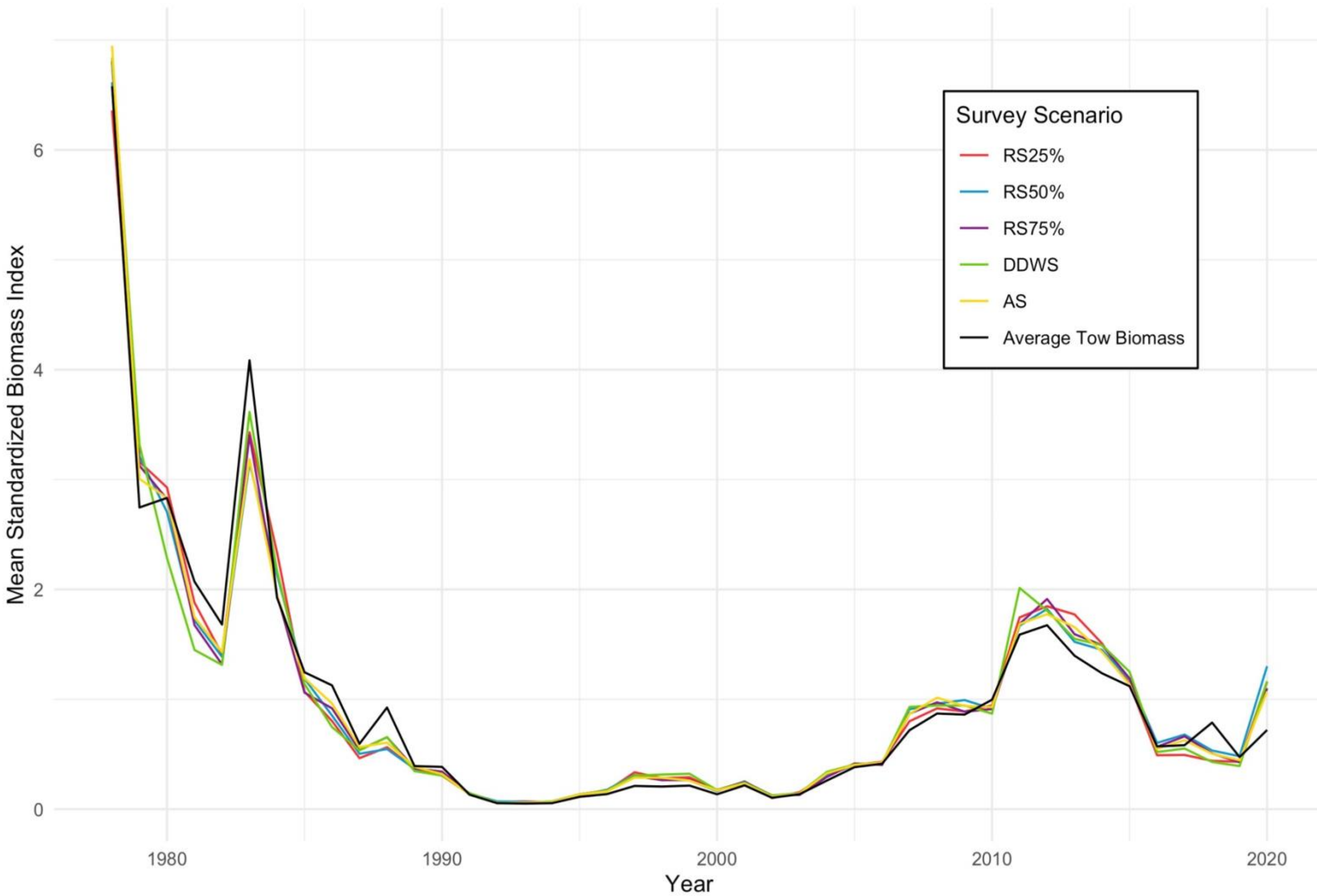

Figure 3.4. The mean standardized estimated biomass indices from each survey scenario from the simulated survey data for NAFO SA2+Div.3K redfish. The colour indicates the different coverage scenarios, with n =10 surveys each.

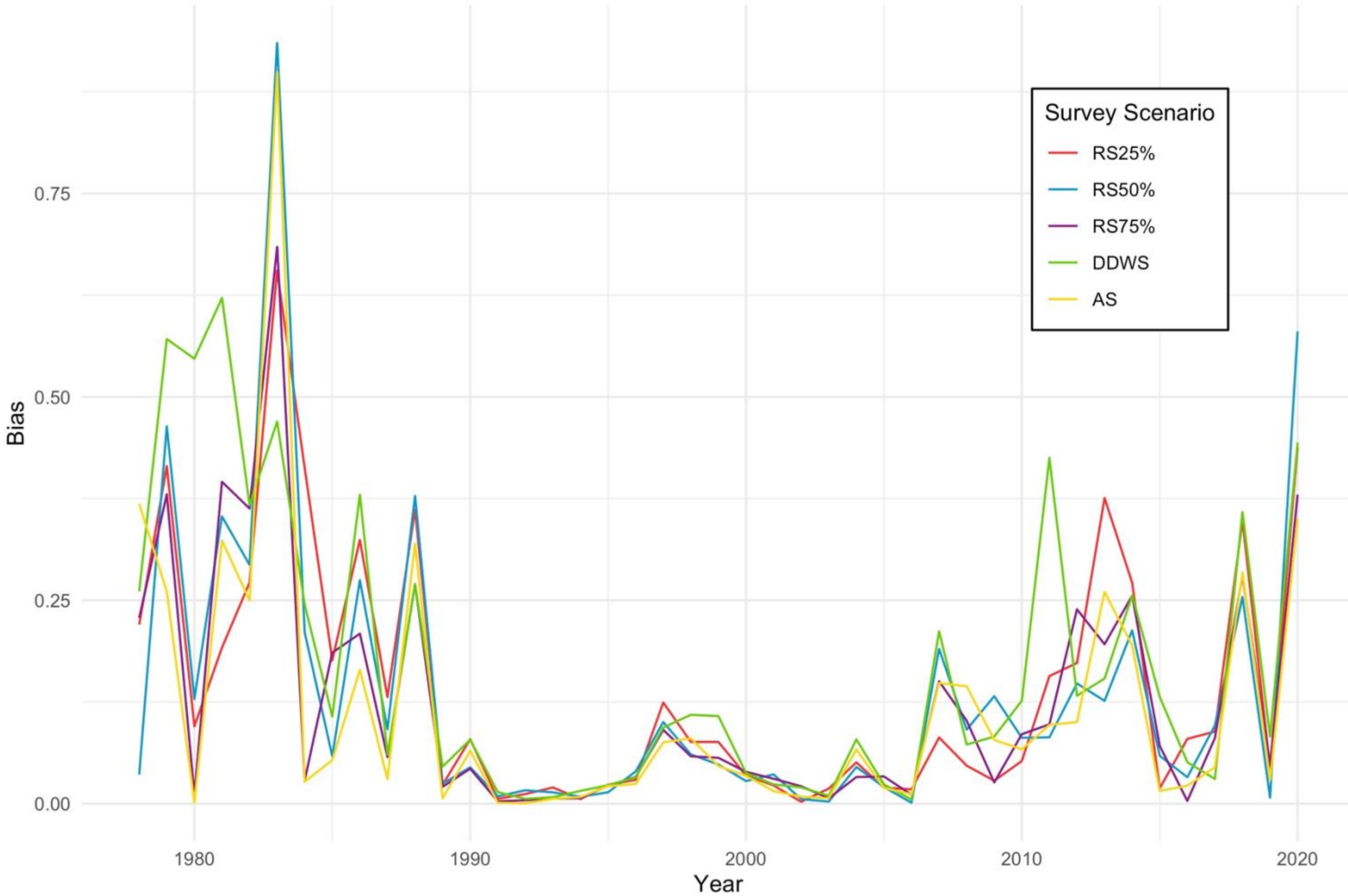

Figure 3.5. The annual bias of the index estimates from the various survey scenarios compared to the yearly average simulated tow biomass. The colour indicates the different coverage scenarios, with n=10 surveys for each

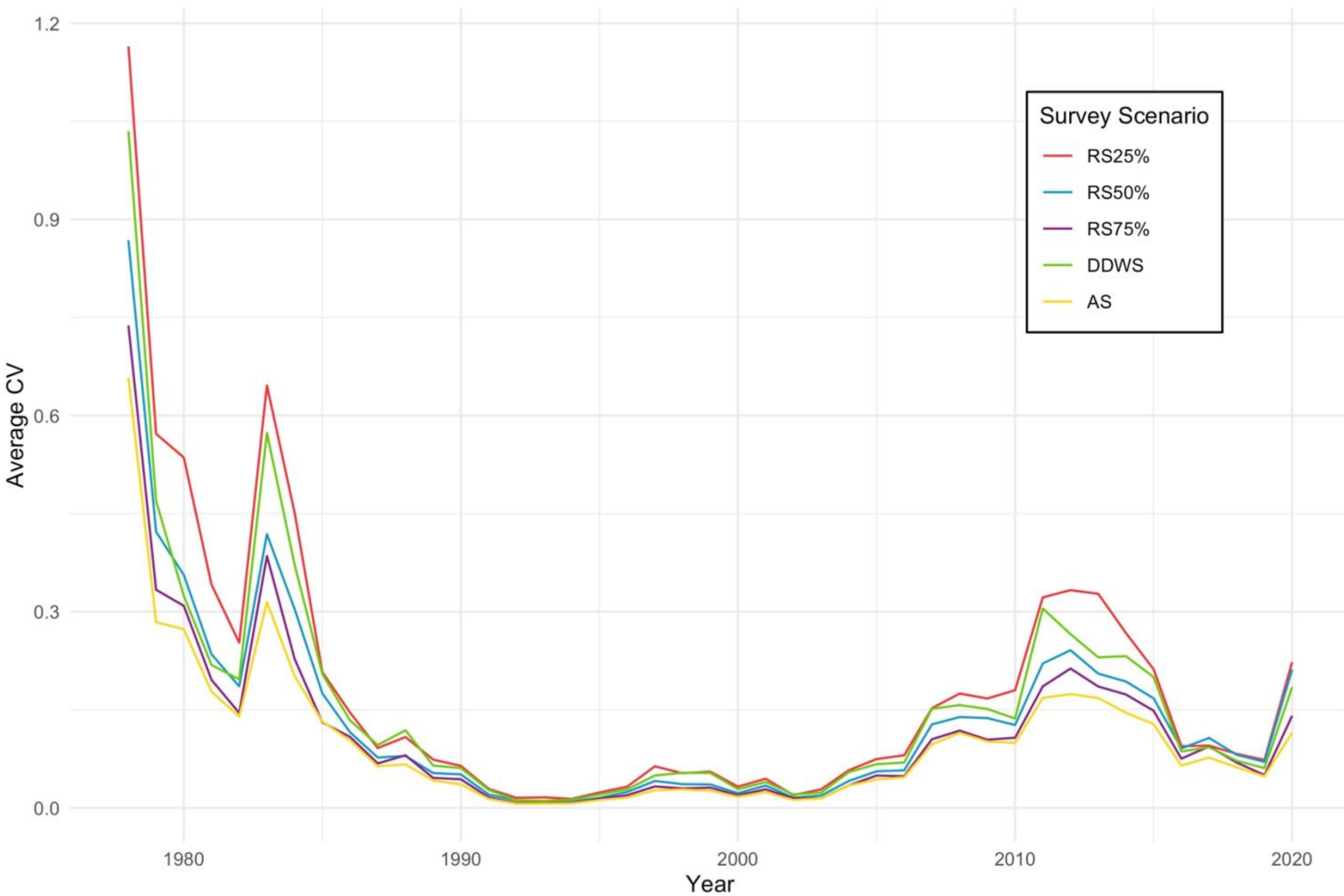

Figure 3.6. The annual average CV of the estimated biomass indices from the various survey scenarios from simulated survey data for NAFO SA2+Div.3K redfish. The colour indicates the different coverage scenarios, with n =10 surveys for each.

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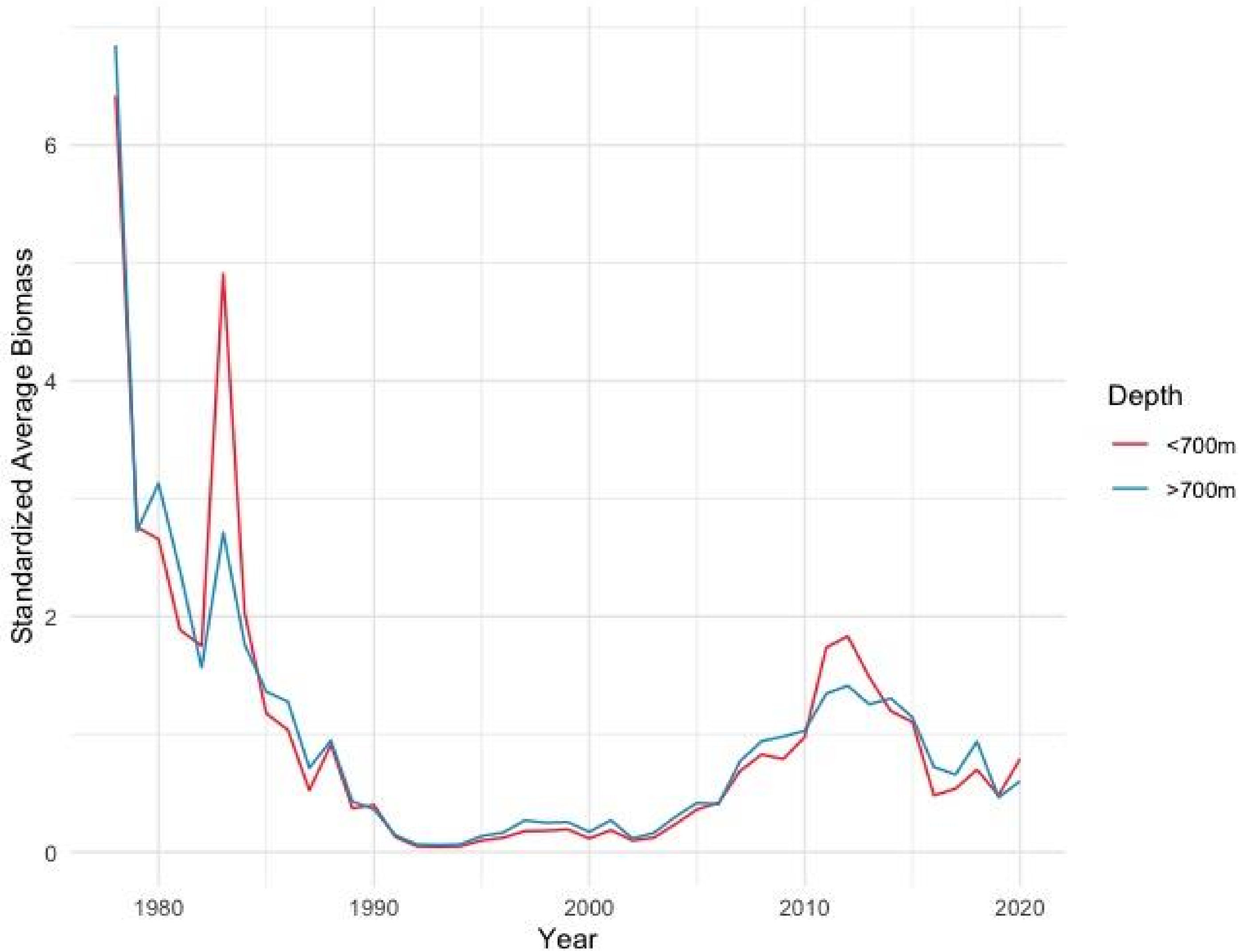

Figure 3.7. The average biomass/year in the simulated data set for deep-water (>700 m) and not deep-water (<700 m). The colour indicates the area type.

3.7. Bibliography

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Chapter 4: Summary and Conclusions

4.1. Summary and conclusions

The research of this thesis investigated spatiotemporal modelling for Labrador shelf (NAFO SA2+Div.3K) redfish, a once collapsed stock that is recovering. The second chapter of the thesis explored using a spatiotemporal model to develop new indices for stock biomass. The third chapter described the results of a simulation study to investigate the effects of survey design on the biomass indices derived from the VAST spatiotemporal model.

In the first chapter, I described the biological characteristic of redfish and how they present challenges for fisheries management. I then described the Fisheries and Oceans Canada (DFO) survey conducted in NAFO SA2+Div.3K and the currently used design-based method for index standardization. I detailed how the DFO surveys were conducted in the fall of 1978- 2020 and had substantial survey coverage gaps, especially in Division 2G in the northernmost area. Therefore, due to the substantial coverage gaps, traditional design-based indices cannot be derived for the total stock. Therefore, the second chapter aimed to use a Vector Autoregressive Spatiotemporal (VAST) model to derive new redfish biomass indices by filling in the survey gaps and quantify the uncertainty of the filled-in data.

I tested different spatial and spatiotemporal structures of the VAST model and found that the best-fitting model had a fixed temporal intercept and a lag-one autoregressive spatiotemporal intercept. I used this model to fill in the survey coverage gaps, generate distribution maps across the entire stock region, and derive new indices for the stock. The model-based indices basically followed the same trends as the currently used 2J3K design-based indices. Also, the model filled in major data gaps and provided indices in all four divisions, which the design-based methods could not. However, one substantial assumption was made, that the spatial and temporal patterns picked up in the sampled areas apply to the lesser sampled areas. This assumption could potentially influence the uncertainly and cause bias. A simulation study should be conducted to validate all the model results, especially those within the more data-limited regions. Breivik et al. (2021), used a latent spatiotemporal Gaussian model, similar to the VAST model, for North East Artic cod in the Barents Sea. The study region had large areas without survey coverage. They showed the model estimated length-based abundance indices and indicated population density shifts; they also validated the results in a simulation study.

Additionally, regarding precision, the CVs for the VAST indices were smaller than the CVs for the design-based indices. However, this comparison was between the entire NAFO SA2+Div.3K VAST indices to 2J3K design indices; therefore, caution should be used when comparing the levels of precision. A more direct comparison should be conducted in future research, potentially only including the sampled divisions or strata.

The juvenile results show the distribution across the entire sample region, including the area that overlaps with Shrimp Fishing Area 4. The distribution maps provide easy to interpret distributions for juvenile redfish and could potentially help inform where fishing efforts should occur to avoid high levels of juvenile redfish bycatch. Further, the intuitive distribution maps potentially provide the basis for a first step in developing a spatial management strategy for the stock. Again, the same assumptions apply to the juvenile model that apply to the entire population model. Most pertinent for the juvenile results is the second assumption about the model working with the high degree of data limitations because the region of most interest is the area that is most data limited. Similarly, a simulation study must be done to validate the juvenile model results.

Future research could also explore the addition of covariates into the model. The VAST model can incorporate covariates, such as temperature or depth. Adding temperature could help explore if redfish distribution remains static with changing temperatures and, therefore, could help inform the level of survey effort needed to capture the distribution. Using depth as a covariate could aid in spatial management by providing more information on stock distribution. This could be especially important in relation to juvenile bycatch and shrimp fishing effort. Further, adding other data sources could be explored, such as fishery-dependent data, which could cover some of the data limitations of the surveys. Gonzalez et al. (2021), combined both survey and commercial data to estimate the spatiotemporal distribution of cod in the North Sea. They found they needed to account for both vessel and gear effects, but their modelling approach was more robust to spatial-biased sampling and could fill in data gaps (specially for different sizes of cod).

Overall, the results from the second chapter show that the VAST model is a promising avenue for future research and then possible future adoption into NAFO SA2+Div.3K redfish stock assessment and management. This research is the first step in developing a spatial management plan for the stock. The indices could help inform management decisions such as reopening the stock and the indices could potentially be used in an assessment model. The distribution maps could help inform fishing efforts to minimize bycatch. Further, the results suggest that the VAST model can provide information to fill in data gaps and, therefore, should be a method examined for other stocks with survey limitations.

The third chapter was a simulation study examining the consequences of reducing sampling effort for the DFO surveys, specifically looking at the effects on the VAST-derived biomass indices regarding bias and precision. The DFO survey in the region already has substantial survey gaps, and there is the potential for sampling effort to be reduced further. I simulated a data set from the VAST model developed in Chapter 2. I then randomly selected data based on different sampling design scenarios, which were various percentage levels (i.e., 25, 50, 75, and 100%) of randomly sampled strata and a scenario of dropping the deep-water strata (>700 m). I found that neither reducing the sampling effort randomly nor dropping the deep-water strata caused substantial changes in the trends of the indices. However, I found that systematically dropping the deep-water strata caused a slightly higher bias than in the other scenarios. Reducing the sampling effort increased the CV, lowering the precision of the indices, with the least sampling effort (25%) having the highest CV. Dropping deep-water strata had the next highest CV, higher than the 50% random sampling scenario, which had fewer data points in total. The bias and CV results indicate that systematically dropping strata has more of an effect than reducing strata randomly. However, the extent of the effect was not large, potentially due to the overall redfish biomass trends throughout the region being quite similar.

A major assumption made in the research was that the simulated data accurately represents redfish distribution. However, as the data set was based on the unvalidated results of the VAST model, that assumption may be incorrect. Most notable is that the VAST model smooths estimates; therefore, the actual distribution of redfish may be patchier than that of the simulated data set, causing more variation in catch, potentially causing biased and less precise results.

The results from the chapter three study illustrated that the VAST model can still be used for index standardization even when the sampling data is further reduced. The model showed limited effects in terms of bias or precision with changes to the sampling design. This study provides a basis for developing a more robust simulation study looking at more scenarios to explore the effects of the sampling design on spatiotemporal derived indices.

Ultimately, the results from both chapters indicate that VAST could be a tool used to help the management of Labrador Shelf redfish. However, there were major assumptions made in the research, and substantial future research needs to be conducted before the model results could be used for stock assessment or fisheries management. Priority research steps should include a simulation study to examine if there is model bias, a study for a more direct precision comparison between the index standardization methods, and a more robust simulation study for the effects of the sampling design. If the results from future studies follow the promising results of this research, then the adoption of a VAST model should be considered in the management of the stock.

4.2. Bibliography

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Appendix A. Supplementary Figures

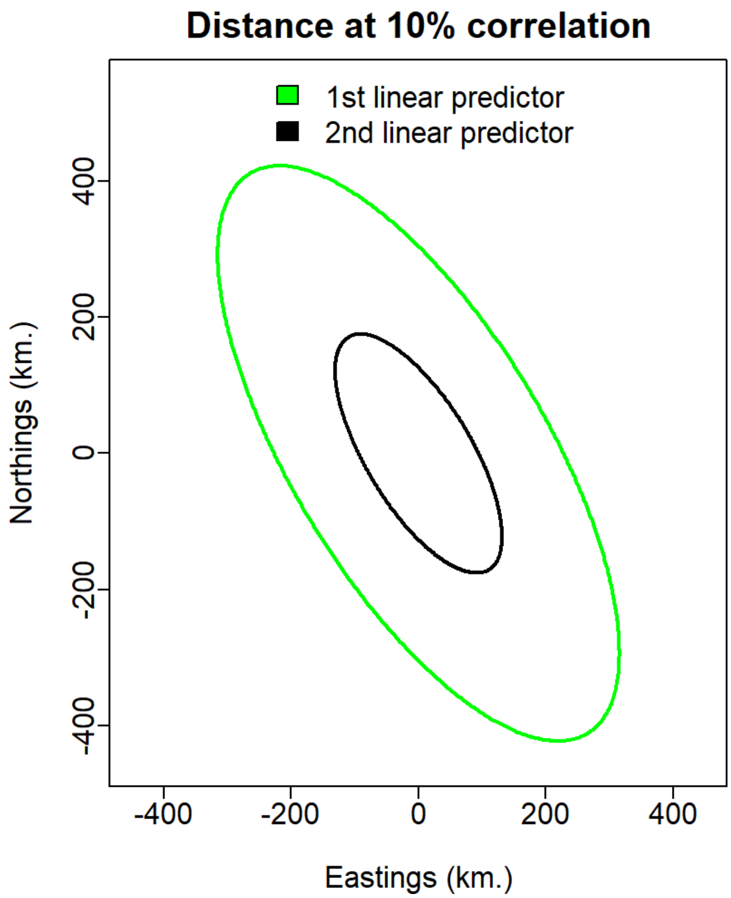

Figure A.1. Estimated Anisotropy from the VAST model for NAFO SA2+Div.3K redfish.

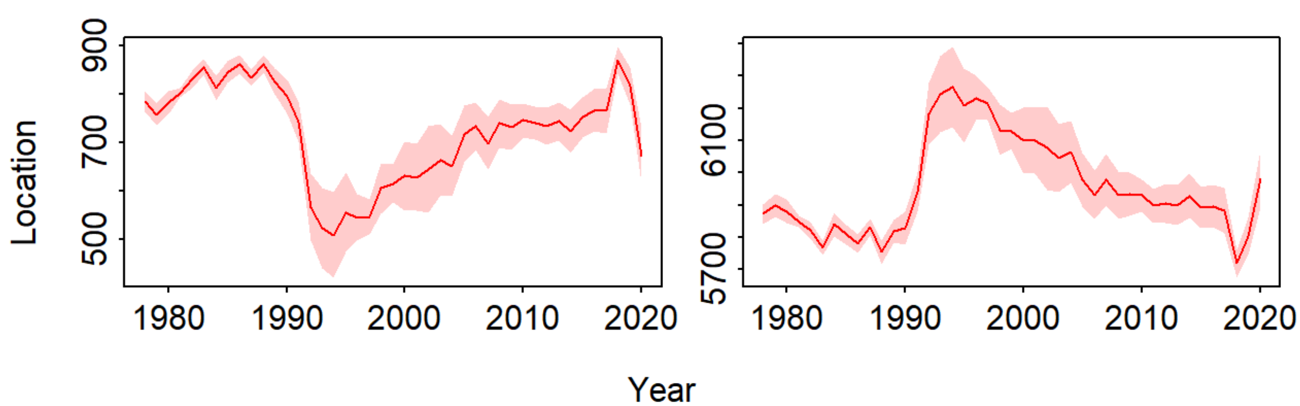

Figure A.2. The time-series (1978-2020) of the center of gravity estimated from the VAST model for NAFO SA2+Div.3K redfish.

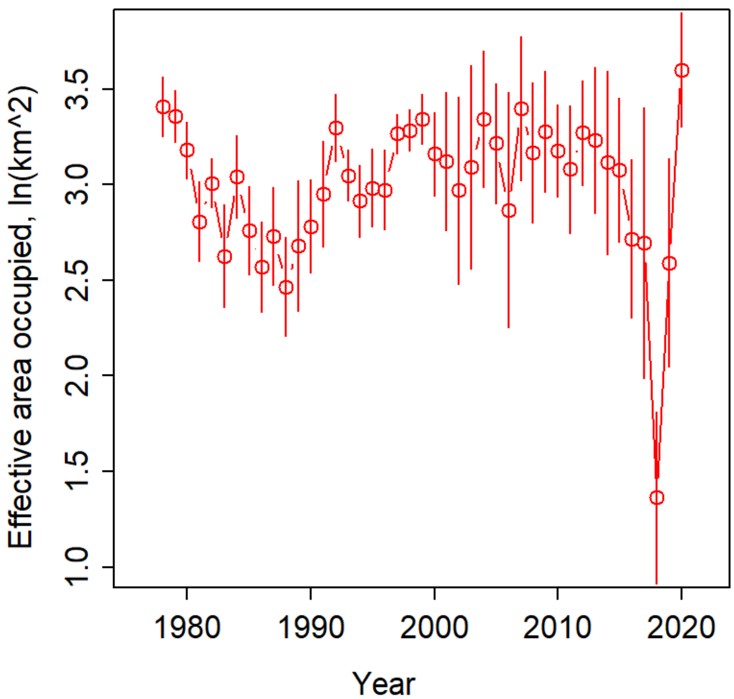

Figure A.3. The time-series (1978-2020) of the estimated effective area from the VAST model for NAFO SA2+Div.3K redfish.

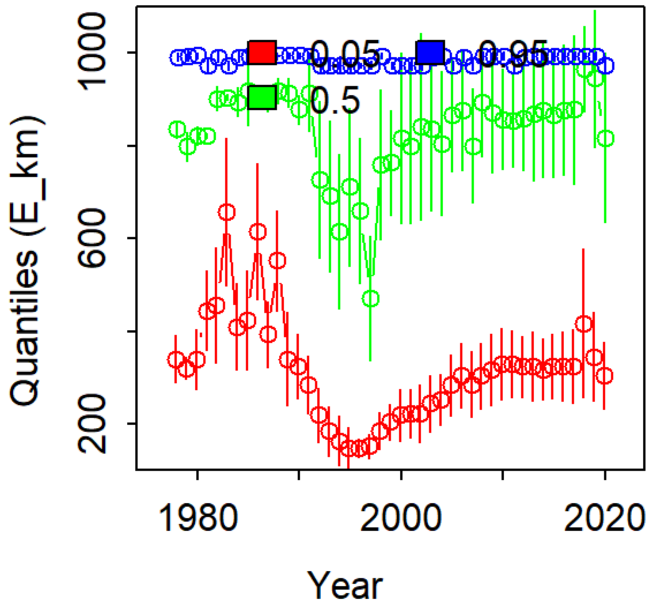

Figure A.4. The time-series (1978-2020) of the estimated range edge east from the VAST model for NAFO SA2+Div.3K redfish. The colours indicate the different quantiles.

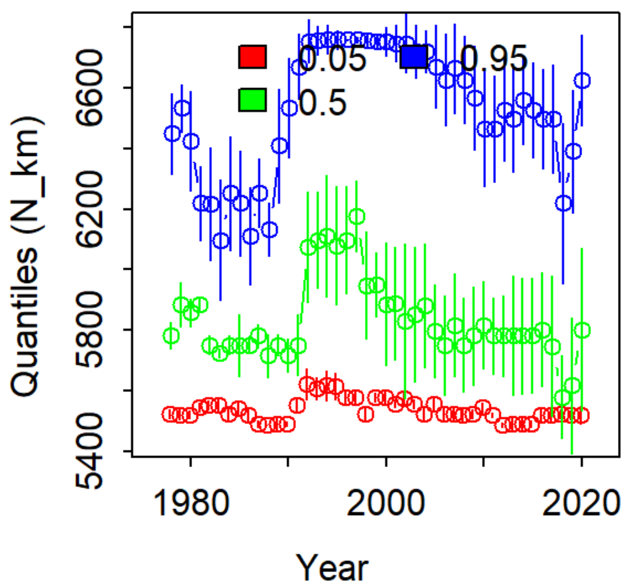

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Figure A.5. The time-series (1978-2020) of the estimated range edge north from the VAST model for NAFO SA2+Div.3K redfish. The colours indicate the different quantiles.