Exploring Preference Heterogeneity in Agent-Based Models: An Application in BC's Recreational Rainbow Trout Fishery

by

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Abstract

The inclusion of heterogeneous angler preferences could improve recreational fisheries management, yet to date exploration of the influence preference heterogeneity has on spatial patterns of angler effort has received little attention. To address this gap in the literature I developed an agent-based model (ABM) with agent behaviour grounded in a discrete choice experiment (DCE). I applied the agent-based model to the recreational Rainbow Trout fishery in the Omineca Wildlife Management Region, BC, and compared spatial patterns of angler effort and related fishing mortality for four models with varying specifications of preference heterogeneity. My results suggested that accounting for greater preference heterogeneity leads to a concentration of modelled angler effort on a preferred subset of lakes closer to major population centres, both for the population and for sub-groups of anglers. Further, my results indicated that changes in fishing mortality were not correlated with greater preference heterogeneity. Rather than varying as a result of shifting patterns of angler effort, fishing mortality varied due to the changing composition of anglers at each lake site. The modelling approach developed could be used to inform management efforts in the Omineca region, providing insight into the composition and spatial distribution of anglers, in turn furthering efforts to develop group specific fishing experiences.

Keywords: Recreational Fishing; Preference Heterogeneity; Agent-based Models; Rainbow Trout; British Columbia.

To the challenges that test us and the friends and family that help us through.

And to Kathryn, for your continued support, patience, and humour. I promise I'll be more fun now.

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List of Acronyms

DCE	Discrete Choice Experiment
RUT	Random Utility Theory
RUM	Random Utility Model
MNL	Multinomial Logit Model
LCM	Latent Class Model
ABM	Agent-based Modelling
OFAT	One-factor-at-a-time
RT	Rainbow Trout *(Oncorhynchus mykiss)*
FFSBC	Freshwater Fisheries Society of British Columbia
PG	City of Prince George, British Columbia

Glossary of Terms

Recreational Specialization	A theory used to describe and account for variation in recreationalist behaviour, and place it along a continuum from novice to specialist in terms of the user's level of participation, and preferences for equipment, skill/difficulty, technique, catch, and regulations (Bryan, 1977). Occasional or novice anglers are thought to be less concerned with technique or equipment, and more concerned with catching more fish, while specialist anglers are less concerned with regulations or catching numerous fish, and more so with catching large fish through techniques and gear that require advanced skill and experience (Bryan, 1977).
Catch-Orientation	An angler's tendency to respond positively or negatively toward "catching something, retaining fish (as opposed to releasing), catching large fish (size), and catching large amounts of fish (numbers)" (Anderson, Ditton, & Hunt, 2007, pg 182). It is assumed that the angling population is comprised of multiple subgroups that can be differentiated according to their catch-orientation (Anderson et al., 2007).
Catch	The number of fish caught by an angler.
Catchability	The proportion of the fish stock removed per unit of effort (Post et al., 2002).
Effort	A measure of angler participation in the fishery defined as the amount of fishing gear (e.g. boats, fishing rods) applied to a fishery over a given time period (FAO, 2017). In my research, gear is equal for all anglers, and angler effort is measured as days fished per year per lake.

Glossary of Mathematical Notation

Angler Sub-Model	
g	An Individual (i.e. Angler)
G	Total number of anglers
U	Total Utility
V	Observed Utility
ε	Unobserved Utility (Error Term)
i	An alternative (i.e. lake)
j	Set of alternatives (i.e. lakes within a region)
J	Total number of alternatives in set j
β	Coefficient for an attribute
X	Attribute of an alternative
K	Total number of attributes describing an alternative
P	Probability of choosing an alternative
Y	Membership likelihood function
γ	Vector of class-specific coefficients in latent membership likelihood function
Z	Vector of latent perceptions, latent attitudes, and sociodemographic variables in the latent membership likelihood function
ζ	Error term in latent membership likelihood function
s	Angler class
S	Total number of angler classes
W	Probability of class membership

Rainbow Trout Sub-Model	
N	Total population of a fish stock
n	Population of fish in an age class
t	Current time period
T	Total time periods
c	Age class
A	Mortality
R	Recruitment
ST	Number of fish stocked in a lake

Methods	
C	Catch
$\mathrm{N}/Area$	Density of Rainbow Trout in a lake (Fish/ha)
E	Effort (5.4 hrs)
q	Catchability
D	Days fished annually
SL	Selectability
G	Total number of anglers on a lake
L	Length of Rainbow Trout (in)
L_{∞}	Theoretical maximum length of Rainbow Trout (in)
WT	Weight of Rainbow Trout
EGG	Total number of eggs produced in a lake
egg	Total number of eggs produced by an age class
Enc	Encounters
$Area$	Lake area (ha)
$Expl$	Area exploitable by an angler during a day of fishing

Analysis	
Z	Instantaneous Mortality (assuming no natural mortality)
F	Instantaneous Fishing Mortality Rate
λ	Simpson Diversity Index

Chapter 1.

Introduction

1.1. Angler Preferences and Recreational Fisheries

Angler behaviour is an integral part of recreational fisheries and has important implications for fisheries management. Recreational fisheries are characterized by complex interactions among anglers and between anglers and fish stocks (Ward et al., 2016). Changes in the abundance or structure of fish stocks influence angler behaviour, which in turn influences fish stocks (Ward et al., 2016). Thus, anglers are not separate but a part of recreational fisheries, and should be explicitly integrated into fisheries management (Schlüter et al., 2017). Failure to understand and incorporate the social components of recreational fisheries into management plans may lead to overexploitation and even collapse of fish stocks (Post, 2013).

Recreational fisheries are spatially structured systems composed of multiple fishing sites (e.g. oceans, lakes, rivers, streams) embedded in a landscape that are linked by the site choices of anglers (Hunt, Arlinghaus, Lester, & Kushneriuk, 2011; Post, Persson, Parkinson, & van Kooten, 2008). When determining where to fish, anglers evaluate multiple sites, making comparisons and trade-offs between the characteristics of the sites (e.g. fish abundance, available facilities, etc.). Changes to the characteristics of one site influence the abundance and structure of fish stocks at others, as anglers alter their behaviour (e.g. site choice, or gear) in response (Post et al., 2008). Thus, though spatially isolated, fishing sites embedded in a landscape are connected by the site choices of highly mobile anglers (Carpenter & Brock, 2004).

An angler's choice of fishing site is driven by their knowledge, expectations, and preferences (Gao & Hailu, 2010). Preference is commonly understood as a choice of one option over another. However, through the application of a utility-theoretic framework, where an individual's decisions are understood to be premised on the maximization of the utility (i.e. satisfaction, well-being) they derive from an option (Fishburn, 1968), preferences can be conceived of as the relative importance an individual places on the perceived characteristics of an option such as a lake (Hensher, Rose, & Greene, 2005). This approach allows researchers to capture trade-offs between characteristics and among lakes, and identify those characteristics of a fishing site that are important to anglers.

Choice models follow a utility-theoretic approach and are commonly used to understand angler preferences. By examining anglers' choice of an alternative (e.g. a lake) from a set of possible alternatives (e.g. lakes within a region) that are described by a bundle of characteristics, or attributes (e.g. travel distance, fishing quality), researchers attempt to predict and explain angler preferences (Dabrowska, Hunt, & Haider, 2017). Researchers use responses about hypothetical or intended behaviours (i.e. a stated preference) to estimate models of angler preferences and choice behaviour. Stated preference choice models are effective in exploring hypothetical or future scenario, or where data is unavailable or hard to collect, and understanding how anglers may respond to environmental or regulatory changes at a lake site (Hunt, 2005).

1.2. Angler Preference Heterogeneity

There are ongoing efforts to improve the representation of angler behaviour and preferences in recreational fisheries research. Early studies that attempted to simulate the behaviour of anglers conceptualized the recreational fishing system as a "predator-prey" relationship, limiting the attributes of a fishing experience to those that were catch-related (e.g. fish abundance, catch rate, catch size) (e.g. Beard, Cox, & Carpenter, 2003; Post, Mushens, Paul, & Sullivan, 2003). However, researchers of "human dimensions" in recreational fishing argue that the predator-prey model overly simplifies human behaviour and may lead to unrealistic representations of recreational fisheries systems (Paulrud & Laitila, 2004). Human dimensions research highlights the importance of a broader perspective on angler behaviour; one that recognizes catch and non-catch related attributes of the fishing experience (Hunt, 2005). From a review of published research, Hunt (2005) proposed six attributes that influenced angler site choice: the cost of an experience, fishing quality, environmental quality, facility development, crowding, and regulations.

Human dimensions research also established that preferences vary among anglers, and that the so-called "average angler" does not exist (Aas & Ditton, 1998; Shafer, 1969). Instead, angler preferences are diverse, or heterogeneous, and anglers differ in their preferences for catch-based (Arlinghaus, Beardmore, Riepe, Meyerhoff, & Pagel, 2014; Connelly, Knuth, & Brown, 2001), and non-catch based attributes of a fishing experience (Aas & Ditton, 1998; Knoche & Lupi, 2016; Wilde & Ditton, 1991). Failure to account for the heterogeneity of angler preferences may exacerbate the initial issue(s) management efforts were trying to address (Johnston, Arlinghaus, & Dieckmann, 2010, 2013; Shafer, 1969). As such, accounting for preference heterogeneity has become a critical avenue of research in fisheries management (Fenichel, Abbott, & Huang, 2013; Post, 2013; Ward et al., 2016).

Heterogeneity of angler preferences can arise from inter-angler, intra-angler, or unobserved variation among anglers (Dabrowska et al., 2017). Inter-angler heterogeneity captures the variation of preferences among anglers that do not differ between fishing trips. Variation can result from sociodemographic differences, the angler's origin (home), catch-orientation (preferences for the number and size of the fish caught or harvested (Anderson et al., 2007)), and specialization (preferences for equipment, skill/difficulty, technique, catch, and regulations (Bryan, 1977)), among others.[1] Intra-angler heterogeneity captures the differences in contextual factors that vary between fishing trips, such as trip duration or the fish species targeted. Finally, while both inter- and intra-angler heterogeneity can be observed by the researcher, unobserved heterogeneity results from unobserved perceptions and attitudes of the angler (Swait, 1994). As such, unobserved preference heterogeneity cannot be identified prior to observing angler choice behaviour but must be accounted for through statistical measures based on the properties of the estimated choice model (Dabrowska et al., 2017).

Accounting for inter-, intra-, and unobserved sources of heterogeneity has uncovered notable variation in angler preferences. Studies that included inter-angler heterogeneity have found that angler preferences for catch, the size of fish caught, fish species, and regulations varied by their origin, catch-orientation, and angler specialization. Where preferences of resident and non-resident anglers were considered (i.e. angler origin), non-residents were less sensitive to changes in expected catch (Criddle, Herrmann, Lee, & Hamel, 2003), but placed higher monetary value on the expected catch and the size of the fish caught (Lew & Larson, 2014). Studies examining

[1] See the Glossary for a full definition of key terms.

angler catch-orientation captured preference variation for fish species, fish size, and the number of fish harvested as opposed to caught and released (Carlin, Schroeder, & Fulton, 2012; Hutt, Hunt, Schlechte, & Buckmeier, 2013). Research accounting for angler specialization has led to contrasting results, with some studies finding that increased specialization correlated with angler acceptance of increased regulation (Ditton & Oh, 2006; Dorow, Beardmore, Haider, & Arlinghaus, 2009; Hyman, DiCenzo, & Murphy, 2017), while others found that more specialized anglers were most resistant to increased regulation and least responsive to the status of the fish stock (Beardmore, Haider, Hunt, & Arlinghaus, 2013; Dorow, Beardmore, Haider, & Arlinghaus, 2010). Researchers who account for intra-angler heterogeneity have found that an anglers' willingness-to-pay and the satisfaction from catch and fish size vary across fish species (Beardmore et al., 2015; Haab, Hicks, Schnier, & Whitehead, 2012). Further, studies that allowed for heterogeneity in trip duration found that anglers expressed different preferences for single and multiple day trips (Hunt, Boots, & Boxall, 2007; Lupi, Hoehn, & Christie, 2003). Finally, accounting for unobserved heterogeneity has uncovered variation in preferences for the timing and frequency of trips throughout a season, the monetary value placed on a fishing trip, and the monetary value placed on the quality of a fishing season (Provencher, Baerenklau, & Bishop, 2002; Provencher & Bishop, 2004). It is clear from past studies that accounting for inter-, intra-, and unobserved heterogeneity uncovers distinct preferences among anglers and reemphasizes the importance of accounting for this heterogeneity in models that mean to inform management decisions.

How to represent heterogeneity and which sources to include in a model may have considerable influence on model outcomes (Campbell, Vedel, Thorsen, & Jacobsen, 2014). For example, when contrasted with choice models that did not account for sources of heterogeneity, accounting for sociodemographic influences led to increased angler preferences for the size of fish caught (Carlin et al., 2012). When sociodemographic influences were coupled with catch-orientation, anglers derived more utility from participation and placed a higher value on the number of fish caught (Carlin et al., 2012). Similarly, when unobserved heterogeneity was accounted for, groups of anglers were found to attach different values to a fishing trip and to the number of trips taken in a season, and varied their responsiveness to changes in the quality of the fishing experience relative to a homogenous angling population (Provencher et al., 2002;

Provencher & Bishop, 2004). Accounting for heterogeneity uncovers variation in preferences between anglers, and results in preferences that are notably different from choice models that ignore heterogeneity.

Thus, including additional sources of heterogeneity in models of angler behaviour may better reflect the preference heterogeneity in the underlying angling population. I refer to this as increasing the preference heterogeneity specified in the model. However, increasing preference heterogeneity is not synonymous with increasing model accuracy. Every variable included in a model contains a degree of uncertainty (Oreskes, 2003). Uncertainty arises from questions of how to conceptualize the system being modelled, to know which variables and relationships are important, and how to parameterize those variables and relationships (Oreskes, 2003). While including additional sources of heterogeneity may better reflect preference heterogeneity and enhance behavioural realism (Hunt, Haider, & Bottan, 2005), it also increases the overall uncertainty present in the model (Oreskes, 2003). Thus, in a model with many variables, even if it appears to replicate system processes and outcomes, the additional complexity may limit understanding of the system and obscure the relative influence of each variable (Oreskes, 2003). However, rather than judging the value of a model with regard to its accuracy, models should be evaluated in terms of their ability to provide useful insights into the research problem being investigated (Box, 1979).

1.3. Preference Heterogeneity and Spatial Patterns of Effort

Recreational fisheries are characterized by dynamic interactions and feedbacks between anglers and fish stocks (Ward et al., 2016). In fisheries management, there is a need to understand how angler preference heterogeneity influences angler-fish interactions (Arlinghaus, Cooke, & Potts, 2013). In non-spatial simulations (single fishing site), the composition of the angling population, defined by varying preferences for catch and non-catch related attributes of the fishing experience, led to different socially optimal fisheries regulations (Johnston et al., 2010). When three homogeneous representations of the angler population were compared to one containing a mix of all three angler types, the fisheries regulations (maximum number of fishing licenses and size restrictions) that delivered the greatest overall welfare differed (Johnston et al., 2010). Different assumptions regarding the heterogeneity of anglers, and their preferences, may lead to different recommendations for fisheries regulations, and failure to account for heterogeneity may lead to stock overexploitation or collapse (Johnston et al., 2010).

While insightful, simulations limited to a single fishing site ignore the spatial dimension inherent in angler decision-making. Travel distance has been found to have a considerable influence on patterns of angler behaviour and related impacts to the fishery (Post & Parkinson, 2012; Post et al., 2008). Previous research has shown that angling effort is concentrated on lakes closer to population centres, and declines as travel distance (or travel cost) increases (Abbott & Fenichel, 2013; Hunt et al., 2011; Post et al., 2008). This pattern of angler effort impacts the effectiveness of fisheries regulations, such as catch-and-release and bag limits, which have been found to be inversely related to travel distance (Post & Parkinson, 2012). Failure to include the influence of travel distance may lead to inaccurate portrayals of angler behaviour and undermine management efforts.

Despite growing interest in preference heterogeneity, investigation of the spatial patterns of behaviour that result from the specification of preference heterogeneity is underdeveloped in the recreational fisheries literature. To my knowledge there are only two examples where preference heterogeneity was explored through spatially explicit fisheries models. First, Hunt et al. (2011) as part of an examination into the sensitivity of a spatially structured Walleye (*Sander vitreus*) fishery to varied angler behaviour and overall effort, systematically varied the modelled importance of catch rate (a measure of catch-orientation) and harvesting efficiency (a measure of angler skill). Increasing the importance anglers placed on catch led anglers to shift their effort more quickly as stocks declined and resulted in fewer overexploited or collapsed fish stocks. When harvesting efficiency increased, the dispersal of angler effort across the landscape was not sufficient to offset increased catch rates, and the number of stocks that were overexploited or collapsed increased. Second, March et al. (2014), developed an angler typology based on angler specialization and catch-orientation and compared variations in the anglers' perception of fishing quality within a marine recreational fishery. Anglers with different specifications of specialization and catch-orientation were found to value different areas of the fishery, with trophy anglers attracted to locations in deep water, while generalists preferred areas closer to shore. While the study took place across a single waterbody, heterogeneity of angler preferences resulted in the spatial segmentation of angler effort. In both studies, the influence of preference heterogeneity, as measured by catch-orientation and specialization, led to distinct patterns of angler effort that could not have been realized in a non-spatial application.

Understanding of the role of preference heterogeneity in patterns of angler effort can also be gained from other fields of research. Studies from land use modelling have illustrated that varying the specification of preference heterogeneity of prospective homeowners results in distinct spatial patterns of housing development (Brown & Robinson, 2006). Relative to a model with homogeneous preferences, a model that incorporated homeowner heterogeneity resulted in smaller, condensed patches of housing development that were more dispersed across a hypothetical landscape. If the shift in development patterns associated with greater preference heterogeneity were translated to a recreational fisheries context it would have important implications for recreational fisheries management. Increased angler effort on a few lakes may equate to increased fishing pressure on those lakes, and greater likelihood of stock overexploitation or collapse.

1.4. Research Objectives and the Structure of the Paper

Currently there is a lack of knowledge regarding how the specification of preference heterogeneity influences modeling of dynamic resource systems. Answering the question of how to specify preference heterogeneity within models and understanding of its impacts on model outcomes remains underexplored (Evans, 2012; Huang, Parker, Filatova, & Sun, 2014). The decisions regarding which characteristics of the individual or recreational experience to include and how to specify the heterogeneity of those characteristics is still largely an “art”, based on the researcher’s subjective perception of the system under study (An, 2012).

The importance of angler behaviour in recreational fisheries warrants exploration of the influence that preference heterogeneity has on spatial patterns of angler effort. Greater understanding in this area will help to quantify uncertainty surrounding angler behaviour (Fulton, Smith, Smith, & Van Putten, 2011), build on existing research on the spatial patterns of fishing pressure (Carpenter & Brock, 2004; Hunt et al., 2011; Post et al., 2008) and advance the evaluation of fisheries management policies and regulations (Gao & Hailu, 2010; Post & Parkinson, 2012).

The objective of my research is to examine how different specifications of angler preference heterogeneity affect modelled patterns of angler effort and fishing mortality within a dynamic recreational fisheries system. Through my research, I will determine if modelled patterns of angler effort become more concentrated on a subset of lakes as the heterogeneity of angler preference increases, and assess whether the range of fishing mortality rates (the fraction of a fish stock that dies in a year as a result of angling activities) increases as the heterogeneity of angler preferences increases. From research in land use modelling (noted in Section 1.3), I expect that increasing heterogeneity of angler preferences will lead anglers to concentrate their fishing trips on fewer lakes. Further, I expect that as the spatial patterns of angler lake choice become more concentrated on a subset of lakes, fishing mortality will increase on those lakes while declining on others.

In the following section, I outline a modelling approach that investigates the influence of varying specifications of preference heterogeneity on spatial patterns of angler effort and fishing mortality. Importantly, this approach tracks angler effort at the group level, revealing how different specifications of preference heterogeneity manifest in group level patterns of effort. I then detail the application of this model in the recreational Rainbow Trout (*Oncorhynchus mykiss*) fishery of the Omineca Wildlife Region, BC, Canada. This is followed by my results from an exploration of four different models of angler preference heterogeneity, and a discussion of the implications and limitations of my research. Reconciling the preferences of anglers with management objectives has long been a major challenge for fisheries researchers (Wilde & Ditton, 1991). My research contributes to this continuing integration and the improvement of recreational fisheries management and research.

Chapter 2.

Methods

2.1. Study Area and Fishery

The Omineca Wildlife Management Region (Zone 7A) is located in northeast British Columbia, Canada (Fig. 1). The region covers more than 13 million hectares, and includes more than 500 lakes containing Rainbow Trout (MOE, 2017b). Of these, 50 are regularly stocked by the Freshwater Fisheries Society of British Columbia (FFSBC), a non-profit agency charged with the conservation and management of BC's freshwater fisheries (FFSBC, 2017a). The Omineca Region is also home to an avid angling population, with up to 20,000 fishing licenses purchased annually (Stüssi & Maher, 2006). These local anglers make up most of the anglers in the region (95%), with many of these (70%) coming from the City of Prince George, the largest city in the region (Stüssi & Maher, 2006). Rainbow Trout is the dominant recreational fishery in the Omineca region, though Brook Trout and Kokanee are also popular (FFSBC, 2017). Rainbow Trout are targeted by 98% of Omineca anglers (Stüssi & Maher, 2006) and have been found to comprise 70% of the recreational harvest (Levey & Williams, 2003). Those angling for Rainbow Trout in the Omineca region are subject to a daily quota of 5 fish, and are restricted to single barbless hooks on all waterbodies (FLRNO, 2017). There are also lake specific regulations covering seasonal openings and closures, restrictions on engine type and power, the number of fishing lines per person, and the area(s) open to fishing (FLRNO, 2017).

I chose the Omineca region for this research as it has a single major population centre (Prince George) which is home to most of the anglers in the region (Stüssi & Maher, 2006). This made it reasonable for me to assume all anglers from the Omineca region were located in Prince George, and subsequently ensured that travel distance to each lake for those anglers was reasonably accurate in the model. Further, the recreational Rainbow Trout fishery in the Omineca region has been extensively studied, providing a wealth data on anglers and fish populations in the region (MOE, 2017a; Post, 2011; Stüssi & Maher, 2006). I limited my study to 77 stocked and wild Rainbow Trout lakes that were identified using FFSBC stocking reports (FFSBC, 2017c), spatial data from the Fisheries Information Summary System (MOE, 2017b), and through discussion with FFSBC staff (Fig. 2).

Figure 1. **The Omineca Region and Lower Mainland within the province of British Columbia, Canada**

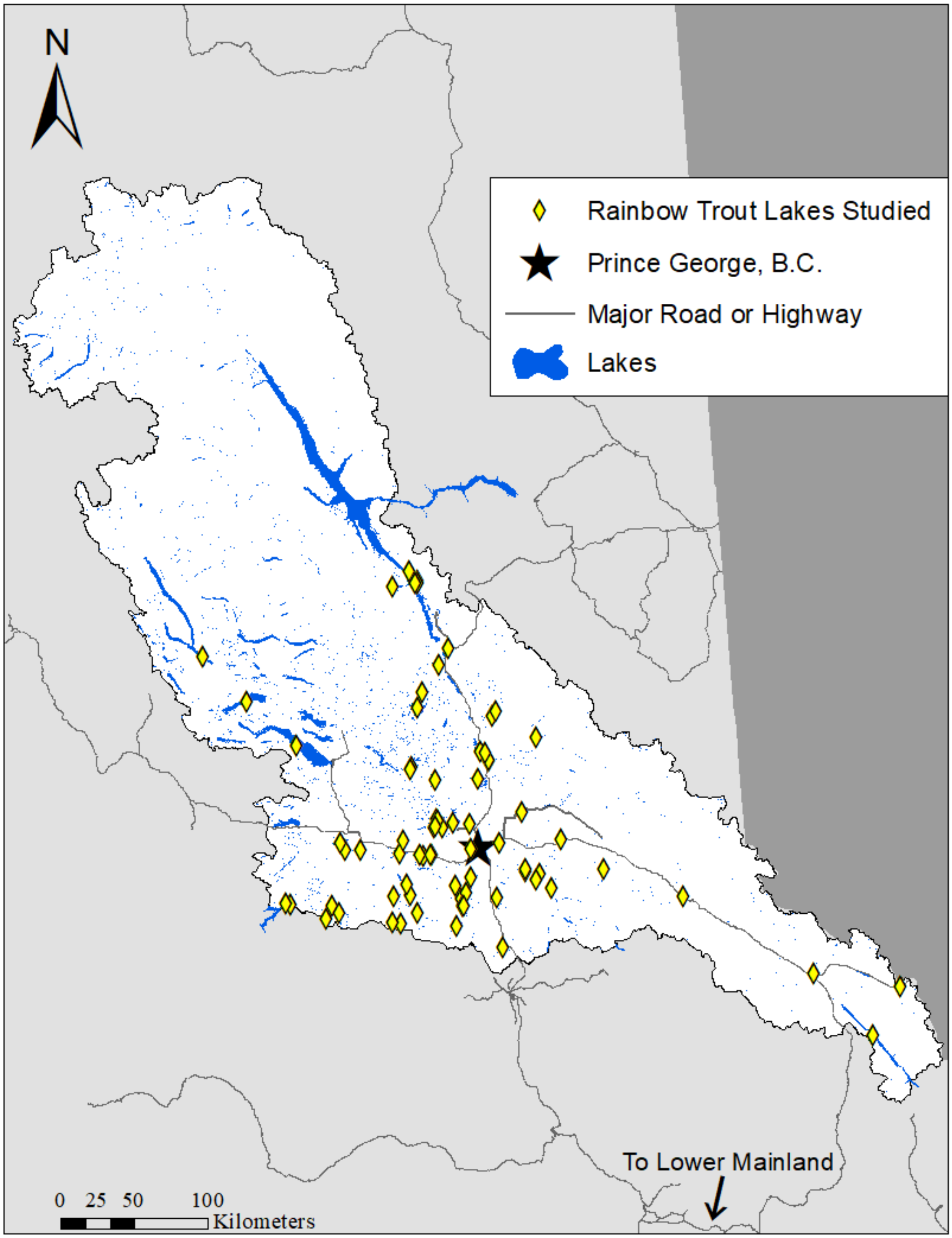

Figure 2. **Rainbow Trout Lakes included in the Agent-based Model**

2.2. Model Overview

To understand the influence of preference heterogeneity on spatial patterns of angler effort and fishing pressure, I developed an agent-based model that integrated heterogeneous angler preferences and dynamic Rainbow Trout populations within a spatially structured recreational fishery. The agent-based model (ABM) was built on preferences estimated from a discrete choice experiment that incorporated intra-angler, inter-angler, and unobserved heterogeneity. The ABM was coupled to an age-structured Rainbow Trout population model parameterized with observed data. This choice of modelling approach was guided by my understanding of the recreational Rainbow Trout fishery. First, individual preferences are the foundation of angler decision-making, and preferences are heterogeneous (Aas & Ditton, 1998; Arlinghaus et al., 2014). Second, the fishery is a spatially structured system, encompassing multiple fishing sites embedded across a landscape but interconnected by the decisions of anglers (Carpenter & Brock, 2004; Hunt et al., 2011; Post et al., 2008). Third, the interactions between anglers and fish stocks form complex relationships and feedbacks (Ward et al., 2016). In the following paragraphs, I outline how this understanding informed my chosen modelling approach.

Where decision-making is grounded in the heterogeneous preferences of individuals, and individual decisions manifest as landscape scale patterns, systems should be modelled at the scale of the individual (Fenichel et al., 2013; Gilbert, 2008). Accordingly, I adopted an ABM approach, which can represent individuals as autonomous agents and account for preference heterogeneity (Macal & North, 2010). Simple behavioural rules and interactions can replicate relationships and feedbacks, giving rise to complex patterns of behaviour at landscape scales (Macal & North, 2010).

However, agent behaviour is dependent on the behavioural rules developed by the researcher, which, if not grounded in sound behavioural theory, may introduce unrealistic representations of angler decision-making (Jager & Janssen, 2003; Macal & North, 2010). I chose to ground agent behaviour in a discrete choice experiment developed by Dabrowska et al. (2017). Discrete choice experiments offer a flexible and theoretically robust foundation on which to base individual behaviour (Bruch & Atwell, 2013; Hunt, Kushneriuk, & Lester, 2007). Further, several methods have been developed to account for preference heterogeneity in DCE and the behavioural models estimated from them (Swait, 2007; Train, 2009).

I coupled the agent-based model of angler behaviour to an age-structured population model of Rainbow Trout, where the fish population is segmented and tracked by age class. My motivation for using an age-structured population model was twofold. First, employing a structured model of fish populations is important where angler preferences are heterogeneous and anglers may prefer diverse fishing experiences (e.g. varying catch rates, fish size) (Fenichel et al., 2013). Second, incorporating the structure of Rainbow Trout stocks, where variables such as mortality rates and fecundity vary with age, allows for more realistic fluctuations in abundance and structure (Briggs et al., 2010; Tuljapurkar, Caswell, Nisbet, & de Roos, 1997). This in turn allows for more realistic relationships and feedbacks between anglers and fish populations.

The model I developed can be conceived of as three parts: (1) four behavioural models estimated from a discrete choice experiment, (2) an agent-based model, and (3) a Rainbow Trout population model (Fig. 3). I will expand on each in turn in the following sections. First, I will detail discrete choice experiments and the development of probabilistic behavioural models that can account for heterogeneous angler preferences. I will then discuss agent-based modelling, its advantages and challenges, before describing structured population models. Finally, I will detail how I operationalized the model for application in the Omineca region, and the methods I used to verify, validate, and analyse model results.

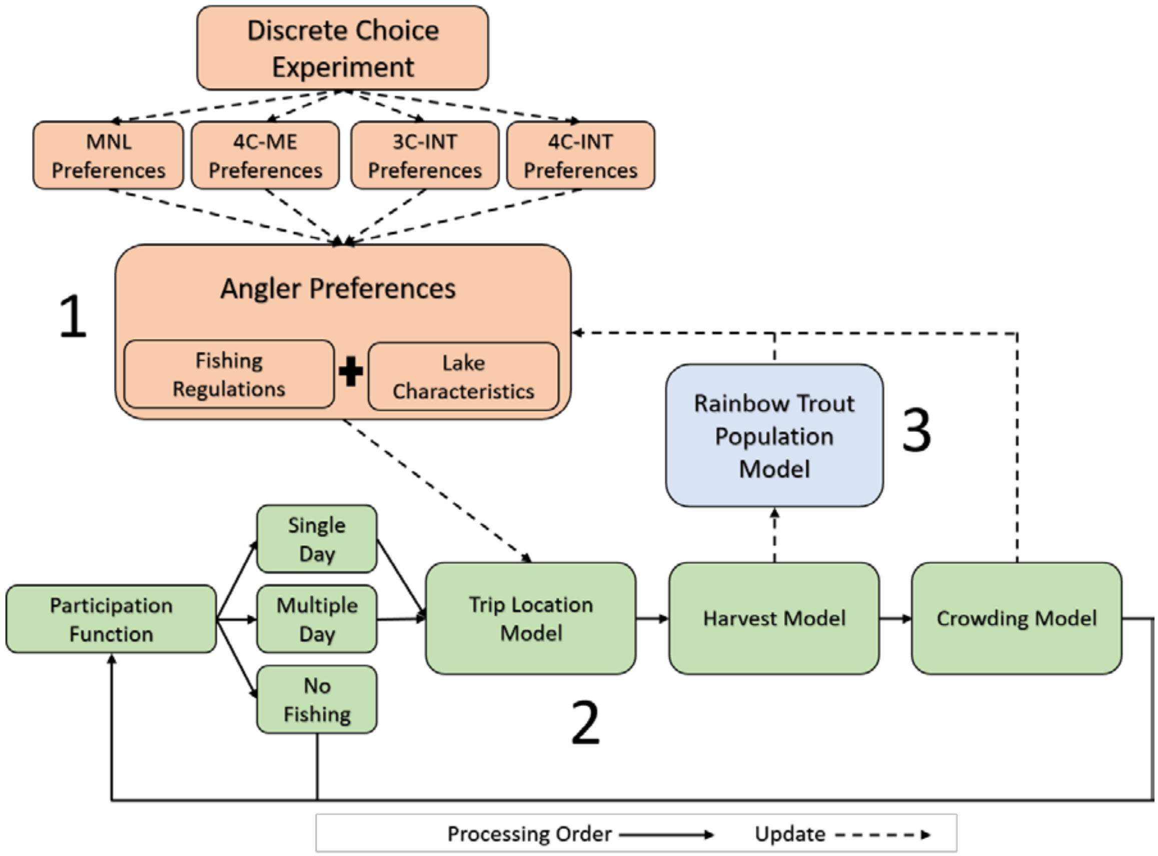

Figure 3. Conceptual Model of the Agent-based Model

2.3. Discrete Choice Experiments

Discrete choice experiments (DCE) follow a stated preference choice modelling approach to estimate angler preferences (Aas, Haider, & Hunt, 2000). The DCE approach involves survey respondents selecting a preferred alternative from a set of mutually exclusive observed or hypothetical alternatives (choice set). The alternatives, such as lake sites, are described by a bundle of characteristics (attributes) that are hypothesized to be relevant to each individual's decision-making process (e.g. travel distance, presence of a boat launch). Each attribute is understood to provide the individual with a level of well-being, or utility. The individual derives utility from the consumption of the characteristics (attributes) of the alternative, rather than the alternative itself (Lancaster, 1966). For example, the utility an individual derives from an apple results (in part) from the attributes of colour, taste, and nutritional value. From this perspective, when making a choice, an individual is comparing the attributes of alternatives rather than the alternatives themselves (Lancaster, 1966).

The individual’s choice of alternative is based on their preferences for, and subsequently perceived utility of, the attributes of the alternative. It is assumed that individuals cognitively integrate the utility from each attribute to determine the total utility for each alternative (Aas et al., 2000). Relying on the assumptions that individuals are rational actors with perfect information of all alternatives (i.e. are aware of all sources of utility), individuals will choose the alternative that provides them with the greatest total utility (utility maximization). However, not all sources of utility known to the individual can be observed by the researcher (Manski, 1977). For the researcher, incomplete information of the attributes, the decision-maker, or both are unobserved influences on the individual’s decision-making process, and prevent the researcher from making definitive statements regarding the individual’s future behaviour (Manski, 1977). However, applying Random Utility Theory (RUT), researchers treat unobserved influences as random variables with a defined distribution (further detail provided below). This results in probabilistic behavioural models (Random Utility Models), which allows the researcher offer predictions of individual behaviour (Manski, 1977).

A notable advantage of stated preference methods is that when describing alternatives researchers are not limited to attributes for which there is observed data (Louviere, Hensher, & Swait, 2000). Instead researchers can describe alternatives with attributes that may be hard to measure but still relevant to decision-makers (Louviere et al., 2000). The freedom from observed data has the additional benefit of allowing researchers to evaluate individual behavioural responses to hypothetical alternatives such as new regulations, or environmental changes (Louviere et al., 2000).

This hypothetical nature of stated preference Discrete Choice Experiments can be criticized for introducing hypothetical bias (Arlinghaus & Mehner, 2005). Hypothetical bias arises when there are inconsistencies between an individual’s stated intention and their behaviour (Hensher, 2010), and reviews of past stated preference studies have found substantial and systemic hypothetical bias (List & Gallet, 2001; Murphy, Allen, Stevens, & Weatherhead, 2005). Hypothetical bias is introduced into stated preference applications when there is a perceived lack of consequence for respondents, constraints on respondent behaviour are overlooked or omitted, the attributes are not seen as realistic or relevant by respondents, respondents act strategically to manipulate outcomes, or where respondents are unsure of their choice but respond regardless (Loomis, 2011; Hensher, 2010; Haab, Interis, Petroli, & Whitehead, 2013). Numerous *ex ante* and *ex post* methods have been developed to correct for hypothetical bias and addressing it remains a prominent field of inquiry (Loomis, 2014). However, it is recognized that hypothetical bias is heavily influenced by the context in which the study is being applied and the methods being used (Hensher, 2010; Loomis, 2014). As such, hypothetical bias remains a challenge in stated preference applications.

It has also been argued that stated preference DCE represent close-ended questions that limit choice options, shaping a respondent's understanding and decision-making through the choice options that are presented (Arlinghaus & Mehner, 2005; Hensher, 2010). The alternatives included in a DCE and the attributes used to describe them are pre-determined and chosen with a focus on the behavioural, regulatory, or environmental issues of interest to researchers. This omits alternatives that individuals may have considered, includes alternatives that individuals may not have considered, and limits the attributes that influence decision-making (Arlinghaus & Mehner, 2005). Past studies of fisheries regulations that have employed open-ended questions have discovered that anglers consider a wider variety of potential regulations than traditionally included in a DCE (Arlinghaus & Mehner, 2003). To overcome the limitations imposed by closed-ended questions, researchers can include open-ended questions to uncover important influences that may not have been adequately addressed in the DCE (e.g. Arlinghaus & Mehner, 2003).

Undoubtedly, stated preference methods still have challenges to overcome. However, stated preference is one of the few methods available to develop knowledge of future, unknown behaviour in response to planned or unplanned changes for which observed behaviour is insufficient (Loomis, 2014). Results should be viewed with a critical eye but should not be dismissed as they may yet offer important insights for policy development and evaluation (Loomis, 2014).

2.3.1. Random Utility Models

Random Utility Models (RUM) are behavioural models based on utility maximization and RUT that aim to replicate observed behaviour or predict future behaviour. Within RUM, the utility of an alternative i is given by U_i, and the observed and unobserved sources of utility are expressed as V_i and ε_i, respectively, such that[2]:

$$U_i = V_i + \varepsilon_i$$

Using a linear form, the observed utility can be expanded to identify utility the individual believes they will derive from each attribute of the alternative:

$$V_i = \beta_{0i} + \beta_{1i} f(X_{1i}) + \beta_{2i} f(X_{2i}) \cdots + \beta_{Ki} f(X_{Ki})$$

where β_1 is the coefficient associated with the attribute X_1, and K is the total number of attributes describing alternative i. The term β_{0i} is the alternative-specific constant which corrects the model predictions of alternatives to equal the observed frequency of choice from the data. Attributes enter the utility expression through $f(\ldots)$ to account for non-linear relationships (i.e. logarithmic, quadratic) that may better describe the relationship between the attribute and derived utility (Hensher et al., 2005). For example, the marginal utility of catching a fish that is one centimetre larger may decrease as the size of the fish caught increases. In this instance, a logarithmic function would better describe the relationship between the attribute and derived utility.

The above utility expression represents a Main Effects model that estimates coefficients for each attribute in isolation. For example, within recreational fisheries a Main Effects model would estimate the preference for the attributes of trip duration (single day or multiple days) and travel distance separately. However, an individual's preference for the distance they are willing to travel may depend on whether their trip lasts a day or a week. Accounting for the interaction between attributes, or between attributes and characteristics of the individual, will account for that variability in preferences. Subsequently, to include Interaction Effects, the above expression can be rewritten as:

$$V_i = \beta_{0i} + \beta_{1i} f(X_{1i}) + \beta_{2i} f(X_{2i}) + \beta_{3i} f(X_{1i} X_{2i}) \cdots + \beta_{Ki} f(X_{Ki})$$

where $\beta_{3i} f(X_{1i} X_{2i})$ is the interaction effect between attributes X_{1i} and X_{2i}.

[2] Notation follows Hensher, Rose, & Greene (2005).

With an understanding of the sources of utility, the probability that an individual may choose an alternative can be calculated. That an individual chooses one alternative (i) over all others $(j = 1, \dots, J)$ assumes that an individual chooses the alternative with the maximum utility, such that:

$$U_i > U_j$$

$$(V_i + \varepsilon_i) > (V_j + \varepsilon_j)$$

Rearranging to place observable and unobservable utility together:

$$(V_i - V_j) > (\varepsilon_j - \varepsilon_i)$$

Since ε cannot be observed, a definitive statement regarding this equation cannot be made. Instead, ε is treated as a random variable in line with RUT, and the probability of an individual choosing an option can be calculated as:

$$P_i = P\big[\big(\varepsilon_j - \varepsilon_i\big) < \big(V_i - V_j\big) \; \forall \, j \in j = 1, \dots, J; \; i \neq j\big]$$

where P_i is the probability of the individual choosing alternative i, from the set of alternatives j.

The probability of an individual choosing an alternative can be estimated using the multinomial logit model (MNL) (McFadden, 1974). The MNL is simple, easy to implement in predictive applications, and widely used (Louviere et al., 2000). To apply the MNL, the error terms (unobserved utility) are assumed to be independent and identically distributed (IID) and follow an extreme value type 1 distribution (EV1) (e.g. Aas et al., 2000; Oh, Ditton, Gentner, & Riechers, 2005). The probability of an individual choosing an alternative can then be expressed as:

$$P_i = \frac{e^{\mu V_i}}{\sum e^{\mu V_j}}, \qquad \forall \, j \in j = 1, \dots, J; \; i \neq j$$

where V_i is observed utility for alternative i, and μ is the scale parameter ($\mu > 0$) which is inversely proportional to the standard deviation of the unobserved utility (Swait, 2007). Where the utility function is linear-in-parameters, values of μ cannot be separated from β

(Swait, 2007). To identify the values of β, researchers often assume that the scale parameter is fixed at unity across all individuals (Swait, 2007).

2.3.2. Preference Heterogeneity in Random Utility Models

The Main Effects MNL does not account for preference heterogeneity as it assigns the same preferences to all individuals in the population. However, as has been previously highlighted (Section 1.2), individuals likely have heterogeneous preferences which result in complex behavioural patterns, and a more realistic representation of preference heterogeneity is important for recreational fisheries management (e.g., Johnston et al. 2010).

To overcome the limitations imposed by homogenous preferences, preference heterogeneity can be represented within RUMs as either continuous, discrete, or both (Swait, 2007; Train, 2009). A popular RUM approach is the Mixed Logit model, which is a flexible modelling approach that can represent preference heterogeneity as either continuous or discrete distributions (Train, 2009). Where preference heterogeneity is treated as a continuous distribution, individual preferences for each attribute vary randomly along a defined distribution (e.g. normal, log normal, triangular, or uniform) with an estimated mean and standard deviation (Train, 2009). Often referred to as Random Parameters Logit (RPL), in this method, individual specific preferences (β_g) are unknown to the researcher (Train, 2009). Instead, the probability than an individual will choose an alternative is a weighted average of the standard MNL model estimated for different values of β (Train, 2009). As such, the probability that individual g choose alternative i is:

$$P_{gi} = \int \left(\frac{e^{\mu V_{gi}}}{\sum e^{\mu V_{gj}}} \right) f(\beta) d(\beta)$$

where $f(\beta)$ is the distribution of preferences (β) with values $\theta(\tilde{\beta}, \sigma_\beta)$, also known as the mixing distribution (Train, 2009).

In providing the mean and standard deviation of utility for each attribute, an RPL model offers a description of the extent of preference heterogeneity (Hensher & Greene, 2003; Hunt, 2005). However, in its standard form the RPL approach does not explicitly identify the sources of heterogeneity (Boxall & Adamowicz, 2002; Hunt, 2005).

Nevertheless, advanced applications of RPL have identified sources of heterogeneity by incorporating observed characteristics into estimations of individual preferences (Greene & Hensher, 2003; Greene, Hensher, & Rose, 2006), while others have shown that analyzing estimated preferences with respect to observed characteristics (e.g. age, origin) can offer insights into the sources of preference heterogeneity (Hunt et al., 2005).

Random utility models can also incorporate preference heterogeneity discretely through the segmentation of the population into groups with identical preferences (Bhat & Koppelman, 2003; Train, 2009). Representing heterogeneity discretely assumes that a population can be divided into a finite number of mutually-exclusive groups (Bhat & Koppelman, 2003). Segmentation of the population can be carried out exogenously (deterministic) or endogenously (probabilistic) (Bhat, 1997). Exogenous segmentation is established *a priori* using a limited number of sociodemographic variables understood by the researcher to capture variation in preference (Bhat, 1997). While the researcher is free to use as many variables as they like, practically speaking they are limited as the number of segments grows rapidly with each additional segmenting variable (Bhat & Koppelman, 2003). The advantage of exogenous segmentation with sociodemographic variables is that it is relatively easy to apply (Bhat & Koppelman, 2003). However, exogenous segmentation may suffer from arbitrariness, incompleteness, and discreteness (Bhat, 2002). Segmenting a population *a priori* requires the researcher to create discrete segments for continuous variables, often defining threshold values, delineating segments and the number of segments arbitrarily (Bhat, 2002). Exogeneous approaches may also be incomplete as it is unlikely that preference heterogeneity will align with sociodemographic variables, thus preventing exogeneous methods from capturing all relevant heterogeneity (Bhat, 2002). Finally, the assumption that the individuals in a population can be assigned to discrete classes each with identical preferences limits the researcher's ability to identify the sources of utility (Bhat, 2002).

An alternative, endogenous segmentation approach is the latent class model (LCM), sometimes referred to as a finite mixture model[3]. A LCM identifies and incorporates unobserved sources of preference heterogeneity into estimates of individual preferences by grouping the population using their choice behaviour (Swait,

[3] A Latent Class Model is a variation of a Mixed Logit model where the mixing distribution, $f(\beta)$, takes on discrete rather than continuous values (Train, 2009).

1994). The LCM approach assumes that choice behaviour is informed by unobservable, or latent, perceptions and attitudes as well as observable sociodemographic variables, and that these aspects are associated with latent classes or groups (Swait, 1994). A maximum likelihood function is used to assign an individual a membership probability for each class in a population, and it is often assumed that the individual belongs to the class for which they have the greatest probability. Just as with exogeneous segmentation, through a LCM, preferences in each class are identical. However, the LCM approach ensures differences in preferences between classes are maximized. This approach has the advantage of basing grouping on the choice behaviour of interest that may be more relevant to managers and researchers (Boxall & Adamowicz, 2002; Swait, 1994).

Following the approach developed by Swait (1994), class membership is determined through a membership likelihood function that incorporates latent perceptions, latent attitudes, and sociodemographic variables:

$$Y_{sg} = \gamma_s Z_g + \zeta_{sg}, \qquad s = 1, \ldots, S$$

where γ_s is a vector of parameter weights for class s, Z_g is a vector of latent perceptions, latent attitudes, and observed sociodemographic variables for individual g, and ζ_{sg} is the error term. Like a MNL, the error term is treated as a random variable and is almost always assumed to be IID with an EV1 distribution. Thus, the probability that an individual belongs to a given class can be calculated as:

$$W_{sg} = \frac{e^{\gamma_s Z_g}}{\sum_{o=1}^{S} e^{\gamma_o Z_g}}$$

With this class membership equation established, the joint model of latent class membership and choice behaviour is:

$$P_{isg} = \sum_{s=1}^{S} P_{isg} W_{sg}$$

$$P_{isg} = \sum_{s=1}^{S} \left[\frac{e^{\beta_{is} X_{ig}}}{\sum e^{\beta_{js} X_{ig}}}\right] \left[\frac{e^{\gamma_s Z_g}}{\sum_{o=1}^{S} e^{\gamma_o Z_g}}\right]$$

where P_{isg} is the probability that individual g chooses alternative i given that they belong to class s, and β_{is} are the class-specific parameter weights for class s.

A LCM does not define the number of classes within a population. Instead, it is up to the researcher to determine the appropriate number of classes to represent a population. To select the appropriate model, and number of classes, LCM are frequently assessed using information-theoretic criteria. Guided by the principle of parsimony, that is, the effort to balance model bias and model variance (overfitting and underfitting), information-theoretic criteria are used to ensure that the inferences made from the chosen model can be considered valid (Burnham & Anderson, 2002). The objective is to minimize the information lost when statistical models are developed from data on real-world systems (Burnham & Anderson, 2002). Measures such as the corrected Akakie Information Criteria (AICc) and Bayesian Information Criteria (BIC) quantify the amount of information added or lost for each candidate model relative to other model specifications, with researchers often choosing the model with the least information lost (Burnham & Anderson, 2002). However, these statistical measures are suggestive rather than prescriptive, and the decision regarding which model to choose ultimately falls to the researcher (Wedel & Kamakura, 2000).

How to represent preference heterogeneity in RUMs rests with researcher and no one approach has been found to be unequivocally better suited to the task (Greene & Hensher, 2003; Swait, 2007). Further, the representation of heterogeneity should not be regarded as an either-or proposition. The combination of continuous and discrete representations of preference heterogeneity in RUMs is a developing area of research (e.g. Bujosa, Riera, & Hicks, 2010; Greene & Hensher, 2013). Regardless of the method chosen, all of the approaches detailed above can offer important insights into the diversity of individual preferences (Swait, 2007).

2.4. Agent-based Modelling

Recreational fishing is an individual activity that results in landscape scale patterns of angler behaviour. It has been argued that where the relationship between individual decisions and regional patterns of behaviour is the focus of research, and the decisions of individuals are rooted in their preferences, the system under study should be simulated at the scale of the individual or "agent" (Fenichel et al., 2013; Gilbert, 2008). This allows the researcher to account for individual heterogeneity (Fenichel et al., 2013), observe the emergence of landscape scale patterns at multiple spatial and temporal scales, and understand the causal links between individual decisions and landscape scale patterns (Gilbert, 2008).

Agent-based modelling (ABM), also known as individual-based modelling in ecology, is an effective means to capture the relationship between individual behaviour and landscape scale patterns. It simulates the dynamics of a system from a bottom-up approach, rooted in the behaviours of individuals. Individuals are represented by agents whose actions are governed by behavioural rules specified by the researcher. Behavioural rules can be formed from theory alone or be empirically grounded, and remain static or evolve through agent learning (Bruch & Atwell, 2013). Agents can be programmed to interact with each other and with their environment, and their future actions can be influenced by previous interactions. These dynamics can explicitly capture the feedbacks between individuals and the environment that define recreational fisheries. Further, the feedbacks often give rise to complex spatial and temporal patterns of behaviour that were not explicitly included in behaviour rules (Macal & North, 2010). Thus, ABM counters assumptions that patterns seen at a regional scale result from the simple aggregation of the characteristics of component parts (Bruch & Atwell, 2013). The ABM approach can capture and explore the interdependencies between individuals within a system, across temporal and spatial contexts, and as a result is a powerful tool to explore the consequences of individual behaviour (Bruch & Atwell, 2013).

Though ABM has been applied across diverse fields, there are core characteristics shared by all applications. Agent-based models always include agents, an environment, and a set of relationships that define the ways in which an agent can interact with their environment and other agents (Macal & North, 2010). Agents can be defined as individuals, small groups (e.g. households), or large institutions (e.g. government agencies) (Macal & North, 2010). The system being examined and the nature of the research being undertaken will shape the scale agents are modelled at. The agents themselves are autonomous decision-makers, who are self-contained (unique, identifiable from other agents) and maintain a “memory” that describes their current state (Macal & North, 2010). Finally, ABM requires a theory of agent behaviour to guide each agent’s decision-making processes. This may be normative, driven by behavioural theory, or based on observed behaviour (Macal & North, 2010).

Agent-based models can also offer the researcher additional flexibility in modelling recreational fisheries. Agents can be heterogeneous in their behavioural rules, and goal-oriented and adaptive such that they are not only reactive to change but seek their goals through evolving means (Macal & North, 2010). Further, ABM can be structured to impose bounded rationality on agents, addressing critiques surrounding models of hyper-rational actors (perfect information, unlimited cognitive abilities) which are seen as unrepresentative of realistic decision-making (Fagiolo, Moneta, & Windrum, 2007; Gilbert, 2008).

Despite the advantages and flexibility offered by ABM, challenges remain in model characterization and evaluation. The modeller is required to make subjective decisions regarding the simplification of complex behaviours (Bonabeau, 2002) and the definition of behavioural rules (Janssen & Ostrom, 2006) that allow results to be understood and related to existing literature. The process of abstraction and simplification also creates challenges for model evaluation. While models can be internally valid (perform as programmed), it may be difficult to compare results from an abstract model to observational data, limiting the ability to assess model accuracy and ultimately, the model's relevance to management actions (Fagiolo et al., 2007). Additionally, there is a threat that complexity contained within an ABM confers an unwarranted degree of legitimacy or objectivity to the model (Glicksman, 2008). The complexity and the extent of interactions in ABM make it difficult to ascertain if the model is faithfully representing the system in question (Oreskes, 2003). That the results "look right" may hide errors or disguise the level of uncertainty surrounding model variables and relationships (Smajgl & Barreteau, 2014). Modellers in ABM continuously balance efforts towards a greater alignment with real-world systems and the interpretability and relevance of their results (Janssen & Ostrom, 2006).

Efforts towards a more realistic depiction of real-world dynamics in ABM has placed increased emphasis on agent behavioural rules based on empirical data. It is argued that creating accurate representations of real-world individuals is crucial to ABM modelling efforts as it enhances the structural (internal) validity of the model (Holm, Lemm, Thees, & Hilty, 2016), and may provide stronger explanations of the causal mechanisms within the ABM (Boero & Squazzoni, 2005). However, researchers continue to struggle to achieve more realistic depictions of real-world individuals, and translate model results to generalized conclusions about real-world processes (Bruch & Atwell, 2013).

Random Utility Models, such as those derived from Discrete Choice Experiments, have been noted as offering researchers a flexible and theoretically robust method to empirically ground the rules governing agent behaviours (Bruch & Atwell, 2013; Hunt, Kushneriuk, et al., 2007). Thus, agent behavioural rules are based on the choices of real-world actors. Further, RUMs, such as MNL or LCM, are easy to implement in a computational environment.

Initial efforts in recreational fisheries have confirmed the value of an approach that integrates ABM and RUM. It has been found to be an effective tool to investigate angler learning and behaviour at the scale of individual lakes, and communicate results to managers and the public (Hunt, Kushneriuk, et al., 2007). The ABM-RUM approach also allows researchers to explore “what if?” scenarios, model uncertainties, and assess results in terms meaningful changes in the distribution of angler utility, or well-being (Gao & Hailu, 2010; Loomis, Bond, & Harpman, 2008). While efforts to date in recreational fisheries are limited, the advantages noted above will likely spur further applications.

2.5. Age-structured Population Models

Complementing the representation of social dynamics, a robust fisheries population model is required to simulate realistic dynamics of population size and composition. The size and abundance of the target species are an important input into angler decision-making and the preservation of the fish stock is a necessary management goal.

It has been argued that the behaviour and physiology of the individuals of the species being studied should form the foundation for population dynamics modelling as opposed to observed population abundance or patterns (Metz & Diekmann, 1986; Tuljapurkar et al., 1997; Turchin, 2003). This approach rests on the belief that population level patterns are rooted in individual behaviour that varies over age or life-stage, and can only be understood through individual based mechanisms and theories (Turchin, 2003). Further, by linking population dynamics to individual behaviours, researchers can go beyond predictions of population abundance to offer insight into the mechanisms and patterns the drive abundance (Newman et al., 2014). As such, they offer explanations for observed patterns which are of more interest to wildlife managers (Newman et al., 2014).

Structured population models have been used extensively to link individual life characteristics and population level dynamics (Briggs et al., 2010; Caswell, 2001; Newman et al., 2014). The life characteristics of the individual's life cycle, or vital rates, such as birth, growth, maturation, mortality, and reproduction are reduced to simple numerical representations, each with a clear, operational definition (Caswell, 2001; Turchin, 2003). These vital rates can be measured directly, grounding structured population models in observed population dynamics (Tuljapurkar et al., 1997).

Structured population models replicate the composition of a population and the dynamics that arise from it. Individuals are partitioned into discrete classes according to life stage or age class, each with their associated vital rates (Briggs et al., 2010). This recognizes that individuals within the population will respond differently to stresses, such as predation or competition, depending on their age, sex, or developmental stage (Tuljapurkar et al., 1997), but strikes a balance between representing the individual and generalizing vital rates for the population (Cushing, 2009). By dividing the population into classes, structured population modelling can replicate oscillations in population numbers over time, as well as delayed impacts to abundance and structure that result from class-specific responses to changes in the environment (Briggs et al., 2010).

The development of a structured population model creates challenges for the modeller. The generalization of a species' vital rates may ignore variation between individuals, and between locations, detracting from the accuracy of the model (Turchin, 2003). It has been noted that there is often more variation within a population then between populations (Cushing, 2009). Further, discretizing a population into classes whose growth or development is not easily demarcated relies on the judgement of the modeller, influencing results (Briggs et al., 2010; Tuljapurkar et al., 1997). It should be recognized that the focus of the research will shape the structure of the population model and model outcomes.

The application of structured population modelling can be illustrated through a simple example in recreational fisheries. If a fish population for a given lake (i) at a certain time (t) is represented by $N_{i,t}$, and subsequently the discrete classes (c) in that population are represented as $n_{i,c,t}$, then the relationship between classes and the population can be expressed as:

$$N_{i,t} = \left[n_{i,1,t} + n_{i,2,t} + \ldots n_{i,c,t}\right]$$

and subsequently, the population at a future time can be expressed as:

$$N_{i,t+1} = f_c\left(n_{i,1,t}, n_{i,2,t}, \ldots, n_{i,c,t}\right)$$

where $f_c(\ldots)$ is a function relating past populations to future ones, and the difference between time periods (the time-step) is determined by the modeller depending on the species' life cycle and research being pursued (Turchin, 2003).

The relationship between past and future populations is influenced by mortality, recruitment, and growth. When all these are considered, the relationship between age classes and population from the present (t) and a future time period ($t + 1$) can be expressed as:

$$N_{i,t+1} = n_{i,1,t}(A_1)\left(R_{i,1,t}\right) + n_{i,2,t}(A_2)\left(R_{i,2,t}\right) + \cdots n_{i,c,t}(A_c)\left(R_{i,c,t}\right) + (ST_{i,t})$$

where A_c is class-specific mortality, $R_{i,c}$ is class-specific fecundity, or the per capital number of offspring from class c reaching class 1 at time $t + 1$, and $ST_{i,t}$ is the number of fish stocked. Growth applies to this relationship indirectly, by altering reproductive productivity (i.e. $R_{i,c,t}$) or vulnerability to fishing pressure (fishing mortality). Of note, the above equation represents a closed system which omits the influence of immigration or emigration from population dynamics.

2.6. Model Specification

In this section, I detail the specification of the Angler and Rainbow Trout sub-models (Parts 2 and 3 in Fig. 3). I first review the Angler sub-model, providing detail of the estimation of angler preferences and the angler's (agent's) decision-making process.

I then describe the age-structured population model, including the methods used to incorporate growth, fecundity, mortality, and stocking.

2.6.1. Anglers

In my ABM, an agent's decision-making process comprised two linked decisions; whether to participate and which lake to visit (conditional on participation). The decision to participate was determined by the probability an angler will go on a single day trip, a multi-day trip (3 days)[4], or not participate (the Participation Function in Fig. 1). I derived these probabilities from anglers' stated number of days spent on single day trips and multiple day trips collected as part of the DCE (Dabrowska et al., 2017).

If the angler selected a single or multi-day trip, the angler's preferences for the attributes of a lake site determined their lake choice (the Trip Location Model in Fig. 1). Angler preferences were estimated from a DCE that collected 1,854 survey responses from anglers active between 2011 – 2012 (Dabrowska et al., 2017).[5] Dabrowska et al. (2017) estimated several discrete choice models, including variations of LCM which represent heterogeneity in agent preferences by segmenting the population into distinct angler classes or groups.[6] From this, I developed four different specifications of angler preference heterogeneity based on MNL and LCM estimations. The 4 Class Main Effects model only included unobserved sources of heterogeneity, while the Interaction Effects models included unobserved utility and interactions between the attributes of alternatives and inter-angler (Specialization, Origin) and intra-angler (Trip Duration) heterogeneity. I ranked the models from most homogeneous to most heterogeneous according to the number of coefficients used to define angler preferences (Table 1). In this application, additional coefficients resulted from the inclusion of additional of sources of heterogeneity. As such, a greater number of coefficients represents greater preference

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[4] I assumed that anglers from the Lower Mainland only took multi-day trips as the travel distance to the Omineca region would prevent them from spending the observed average fishing effort (5.4hrs) on a single day trip.

[5] I have included a list of the attributes used to describe potential fishing locations (i.e. lakes) in Appendix A.

[6] I have included the angler preferences estimated by Dabrowska et al. (2017) in Appendix C.

Table 1. Preference Heterogeneity Represented by Each Choice Model

Model	Name	Number of Coefficients	Rank 1 (Most Homogeneous) 4 (Most Heterogeneous)
Multinomial Logit Model	MNL	16	1
4 Class Main Effects Model	4C-ME	64	2
3 Class Interaction Effects Model	3C-INT	210	3
4 Class Interaction Effects Model	4C-INT	280	4

heterogeneity. Importantly, the ranking of models is ordinal and the differences in the number of coefficients are not meaningful.

To account for the influence of travel distance on angler decision-making, I used creel survey data from the Omineca region to divide anglers into three starting locations: Omineca region, Lower Mainland (a Metropolitan Area), and Other Management Regions (Stüssi & Maher, 2006; Post, 2011).[7] For the attribute of travel distance, as well as catch and size, I coded the attribute levels from the DCE logarithmically to reflect the diminishing return of utility (see Arlinghaus, Beardmore, Riepe, Meyerhoff, & Pagel, 2014), while all other attributes were coded linearly.

With a lake selected, the Harvest Model calculated total number of fish caught for each angler at each lake based on the density of Rainbow Trout, time spent at that lake in a day (static for all anglers), and a catchability coefficient which incorporates the angler's level of skill (Eq. 1 & Eq. 2). I condensed the equations I used into Table 2 and included them at the end of this chapter. A selectability function determined the size of the Rainbow Trout caught, which addresses the varying vulnerability of fish by age (Eq. 3). For computational simplicity, the modelled angler only remembered the average size of all fish harvested at a given lake for a given day. If an angler travelled to a lake and did not catch a fish, they retained the memory of fish size from their last visit. While the catch equation determined the number of Rainbow Trout an angler can catch, I capped the number of fish an angler could harvest from a given lake at the bag limit for the lake. I regarded any fish above the bag limit as catch and release. However, the angler remembered the total number of fish caught, not just those harvested.

[7] Tables detailing how I allocated anglers by region and class are in Appendix A.

For modelling purposes, I reframed the attribute of crowding as encounters, where an encounter occurred when an angler could not exploit the area they would exploit in a day (exploitable area) without also exploiting the area of another angler. In practice, the area exploitable by an angler varies by location, gear, and the angler themselves, and as such no universal threshold dictating when an encounter occurs exists. In this application, I calculated encounters as the product of angler density and the lesser of either a given lake's area or the angler's exploitable area (Eq. 4).

Following a visit to a lake, the angler updated their memory of the attributes for size of fish, catch, and the number of encounters (crowding) for that lake based on their experience. The modelled anglers did not share information, and as such each angler acted in isolation, only interacting with each other indirectly through changes in the fishery.

2.6.2. Rainbow Trout

In the following section, I detail the age-structured population model that I developed to represent Rainbow Trout population dynamics. The model is linear and deterministic, and simulates population abundance, as well as the weight and length of Rainbow Trout in each age class (i.e weight-at-age and length-at-age). For simplicity, I modelled each lake as a closed system and Rainbow Trout were not able to immigrate or emigrate.

I used a von Bertalanffy Growth Model to calculate the growth (in) of Rainbow Trout (Eq. 5) (von Bertalanffy, 1938). For a subset of lakes, I obtained the values for $L_{\infty i}$, and φ_i from ongoing research (D. Varkey, personal communication, November 17, 2016), or derived them from length-at-age data retrieved from EcoCat (MOE, 2017). For the remaining lakes, values of $L_{\infty i}$were randomly selected from a normal distribution with the mean and standard deviation taken from observed $L_{\infty i}$. For φ_i values, I used the mean from observed φ_i. From a review of fish stock assessments in the region, I assumed that Rainbow Trout die at 9 years old (MOE, 2016). As such, the model tracks ages 0+ to 8+, with ages 0+ and 1+ in streams and ages 2+ to 8+ in lakes[8].

[8] Age 1+ indicates that a fish is between 1 and 2 years of age.

Recruitment in Rainbow Trout lakes differed depending on whether the lake was a wild population or stocked. Only those lakes with wild populations were naturally reproducing, and I assumed that stocked lakes were composed solely of triploid (sterile) Rainbow Trout. At stocked lakes, I defined recruitment ($R_{(s)t}, t = 0,1,2,\dots,T$) as the number of fish entering the model in age class 1+. I used stocking reports from the Freshwater Fisheries Society of British Columbia (FFSBC) for the Omineca region from 2001 to 2011 to calculate a 10-year average of stocking events. I converted fry and fingerling to yearling through a monthly instantaneous mortality rate $(e^{(-0.6*1/12)})$, while Spring and Fall catchables were unaltered. The model added yearlings to each stocked lake on December 31 of each year, while Spring and Fall catchables were added on June 1 and October 1 respectively. In contrast, initial recruitment for wild lakes ($R_{(w)0}$) was based on the length of inlet streams for each lake. I established a 5% gradient as the maximum slope suitable for Rainbow Trout habitat (Hartman & Miles, 2001), and a maximum distance of 10km as the farthest distance that could contribute to recruitment. I assumed that each 1,000m of stream length produced 500 yearlings in unfished systems (no fishing mortality). I determined subsequent recruitment in wild lakes $(R_{(w)t}, t = 1,2,\dots,T)$ with a Ricker recruitment function (Eq. 7) (Ricker, 1975). To establish fecundity, I assumed that 100% of Rainbow Trout aged 4+ to 8+ were sexually mature and that the sex ratio was 1:1 (Bustard, 1989). I set per capita egg production through a weight-to-egg function (Nicholls, 1958) (Eq. 8) where weight-at-age was based on length-at-age (Eq. 6).

I simulated annual spawning as a single day event set to May 1 to correspond with the average observed start of spawning (MOE, 2008). I applied a spawning mortality of 50% to all sexually mature Rainbow Trout following spawning, and a natural mortality rate of $1 - (e^{-0.6})$ to all Rainbow Trout at the end of every year (B. van Poorten, personal communication, December 16, 2016).

To establish the initial length-at-age, weight-at-age, and population structure for each lake in the study area, I used observed length-at-age data and R_0, as defined above. I determined the population structure of the Rainbow Trout populations using lake specific recruitment (R_0) and the rate of natural mortality (Eq. 9 & Eq. 10).

2.7. Model Implementation

I set the ABM to operate on a daily time-step, for 365 days a year, and ran it from an unfished state until it had reached had reached equilibrium, where angler patterns of effort were relatively similar year-to-year. I determined that the model had reached equilibrium when increasing the length of the model run did not result in significant variation of the standard deviation of angler effort at each lake over the final 30 years. A model run of 70 years was found to satisfy this condition, as the standard deviation of angler effort at any given lake averaged 14 days of fishing (effort) over the last 30 years.

To reduce bias that I may have introduced through initial parameterization, I set the initial coded values for lake based attributes (Crowding, Size of Fish, Catch) for all lakes to the highest attribute level included in the DCE. This presented each lake as pristine, with far greater utility than would be realized based on the conditions at each lake. This ensured that every angler would visit each lake, discover the fishing conditions for themselves, and base future decisions on their experiences rather than parameters set arbitrarily.

I coded the ABM in R version 3.4.0 (R Core Team, 2017) and ran it on the WestGrid network operated by Compute Canada.

2.8. Verification and Validation

I used a two-part process to verify and validate model results: first, I verified model code through systematic assessment of the model and its sub-models to ensure they performed as intended. Second, I assessed the correspondence of model processes to observed behavioural patterns and processes using a one-factor-at-a-time (OFAT) sensitivity analysis, visually comparing model results (Appendix B). The OFAT approach is effective in revealing linear or non-linear relationships between single parameters and model outcomes, and testing whether results are based on strong assumptions concerning single parameters (ten Broeke, van Voorn, & Ligtenberg, 2016). Class-specific catchability coefficients, Rainbow Trout abundance, and the area exploitable by an angler were selected for sensitivity analysis. I concluded that a model was valid if it responded as expected given the changes to initial parameterization.

2.9. Analysis

To understand the influence of preference heterogeneity on spatial patterns of effort, I analyzed angler effort (days fished) using the Simpsons Index (λ), and fishing mortality using the instantaneous fishing mortality rate (F). The Simpsons Index is a measure of the degree of concentration of entities into a given number of types (Simpson, 1949). For my purposes, entities are days fished (effort) and types are the lakes included in my study. The Index (λ) equals the probability that two trips drawn from a distribution of angler effort across all lakes (with replacement) are from the same lake (Simpson, 1949). If all trips taken in a year were on the same lake, the probability would equal 1 (i.e. 100%). Thus, an increase in the Simpsons Index denotes an increase in the concentration of angler effort.

To understand the impact of angler effort on fish stocks, and assess whether increasing preference heterogeneity resulted in different spatial patterns of fishing mortality, I used instantaneous fishing mortality rates (F) to measure fishing mortality. While empirical observations have shown that fishing mortality declines exponentially in proportion to abundance, the instantaneous fishing mortality rate is effective at representing mortality over a year by converting this exponential relationship into a linear one through logarithmic transformation (Miranda & Bettoli, 2007). This allows the researcher to accurately interpolate fishing morality for any time within a year, assuming constant fishing pressure (Miranda & Bettoli, 2007). The instantaneous fishing mortality rate compares the total number of fish caught at a lake in a year (C) to the average number of fish in that lake in that year ($\widetilde{N}$) (Eq. 12) (Ricker, 1975).

In my research, while F denotes increased fishing pressure and therefore increased risk of stock collapse, this risk is conditional on whether the lake is wild or stocked. Regardless of the values of F, stocked lakes were immune to collapse due to annual stocking events. Further, increased risk is different from high risk. A minor increase in fishing mortality at a lake with a large fish population would not be said to place it at high risk of collapse. I used instantaneous fishing mortality rate only to compare fishing mortality among lakes and across models, and assess whether increasing preference heterogeneity results in different spatial patterns of fishing mortality.

Table 2. Model Equations

Name	Eq.	Formula	Notes
Catch equation	1	$C = \left(\frac{N}{Area}\right) * E * q$	C is catch (# of RT) $N/Area$ is fish density (fish/ha) E is effort (5.4 hrs – constant for all anglers) q is the catchability coefficient
Catchability Coefficient	2	$q = \frac{0.1}{\left(1 + e^{-\frac{D_s - 50}{20}}\right)}$	q is the catchability coefficient D_s is angler class-specific average annual days fished (Included in Appendix A)
Selectability	3	$SL_{ic} = \frac{1}{(1 + e^{(-0.05*(L_{ic} - (L_{\infty i}*0.6)))})}$	SL_{ic} is the probability of catching a fish of age class c in lake i L_{ic} is the size of fish of age class c and in lake i $L_{\infty i}$ is the theoretical maximum length (in) for RT in lake i
Encounters	4	$Enc_{ti} = \frac{G_{ti} - 1}{Area_i} * \min\{Area_i, Expl\}$	Enc_{ti} is the number of encounters experienced by all anglers on lake i at time t G_{ti} is the number of anglers $Area_i$ is the lake area (ha) $Expl$ is the area an angler can exploit during angling day (ha)
Von Bertalanffy Growth Model (length-at-age)	5	$L_{tic} = L_{\infty i} + \left(L_{t-1,i,c-1} - L_{\infty i}\right) * e^{\varphi_i}$	L_{tic} is the length (in) of age class c at lake i at time t $L_{\infty i}$ is the theoretical maximum length (in) for RT in lake i φ_i is the growth rate determining how quickly RT approach $L_{\infty i}$
Weight-at-age	6	$WT_{tic} = 0.00001 * L_{tic}{}^3$	$WT_{i,c,t}$ is the weight (grams) of individuals in class c L_{tic} is the length (in) of RT at time t in lake i in class c

Ricker Recruitment Function (Ricker, 1975)	7	$R_{it} = \alpha_i * EGG_{it} * exp(-\beta_i * E_{it})$ $\alpha = \vartheta * \phi_{\epsilon_0}$ $\beta = \frac{\ln(\alpha * \phi_{\epsilon_0})}{(R_0 * \phi_{\epsilon_0})}$	ϕ_{ϵ_0} is the fecundity incidence function in an unfished state (Walters & Martell, 2003) EGG_{it} is total eggs in lake i at time t For lakes that did not have length-at-age data, I applied average α and β.
Weight-to-egg Function (Nichols, 1958)	8	$egg_{ict} = (1.6 * WT_{ict} - 81.83) * \frac{n_{ict}}{2}$ $EGG_{it} = \sum egg_{ict}$	$egg_{i,c,t}$ is number of eggs from class c $EGG_{i,t}$ is total eggs $WT_{i,c,t}$ is the weight (grams) of individuals in class c $n_{i,c,t}$ is the number of individuals in class c i is lake c is age class t is time
Population Initialization. Age 1+	9	$n_{ic} = R_{(s)0}, \quad c = 1$ $n_{ic} = R_{(w)0}, \quad c = 1$	n_{ic} is the number of individuals in class c $R_{(s)0}$ is the number of recruits in stocked lakes $R_{(w)0}$ is the number of recruits in wild lakes
Population Initialization. Age 2+ to age 8+	10	$n_{ic+1} = n_{ic} * (1 - e^{-0.6}),$ $c = 1,2, \ldots, 7$	n_{ic} is the number of individuals in class c
Simpsons (Diversity) Index	11	$\lambda = \sum_{i=1}^{J} \frac{p_i}{p_j}$	p is number of days fished per year i is an alternative (i.e. lake) j is a set of alternatives (i.e. lakes in a region) J is the total number of alternatives in set j

Instantaneous Fishing Mortality Rate (Ricker, 1975)	12	$Z = 1 - e^{-F}$ $F_i = -\log(1 - \frac{\sum C_i}{\widetilde{N}})$	Z Instantaneous mortality assuming no natural mortality $\widetilde{N}_i$ Average annual abundance at lake i C_i Catch at lake i in a year

Chapter 3.

Results

3.1. Distribution of Angler Effort by Model

My results suggest that accounting for greater sources of preference heterogeneity will lead anglers to concentrate their effort on fewer lakes. Models with greater preference heterogeneity showed a concentration of effort on fewer lakes, with values for the Simpsons Index increasing from 1.652 in the MNL to 3.275 in the 4C-INT. In other words, the probability that two trips from the same year were on the same lake increased from 1.652% to 3.275%. Given that there were 77 lakes available to anglers and approximately 48,000 days of fishing each year, this can be viewed as a substantial increase. Notably, the 4C-ME model saw only a very slight increase (1.698) when compared to the baseline MNL model.

Table 3. Simpsons Index (λ) of Angler Effort ($\times\ 10^{-2}$)

MNL	4C-ME	3C-INT	4C-INT
1.652	1.698	2.935	3.275

Values of the Simpsons Index suggests that angler effort became more concentrated as greater sources of heterogeneity were accounted for. However, such simple statistical measures are of limited use to fisheries managers and researchers. More helpful is an understanding of how anglers allocated their fishing trips spatially across the region, both as a population and specific angler groups.

In comparing the distributions of effort, increasing preference heterogeneity was associated with angler effort shifting from a more uniform distribution across all lakes to one where effort was concentrated on several lakes (Fig. 3). The number of lakes that received greater than 1,000 angler days per year (dashed line) declined as preference heterogeneity increased (12 for MNL, 11 for 4C-ME, 10 for 3C-INT, and 7 for 4C-INT). At the same time, effort on the most visited lakes increased. For example, angler effort on lake 54 in MNL, the baseline model, was approximately 2,000 days per year. As preference heterogeneity increased, effort increased to approximately 6,000 days per year in 4C-INT. Similar patterns were seen on lakes 63 and 67. Spatially, this concentration of effort was concentrated on lakes closer to the City of Prince George (PG) (Fig. 4). Whereas the 4C-ME model saw effort increase at lakes dispersed across the landscape, increases in effort were limited to lakes within 200km and 100km for the 3C-INT and 4C-INT models respectively. However, not all lakes within these distances experienced an increase in angler effort, with many seeing small declines. In viewing these results, recall that the total number of days fished was fixed for each model and was constrained to be equal across all models. Thus, the decline in angler effort on several lakes coupled with the increase of angler effort on select others represented a concentration of angler effort as preference heterogeneity increased.

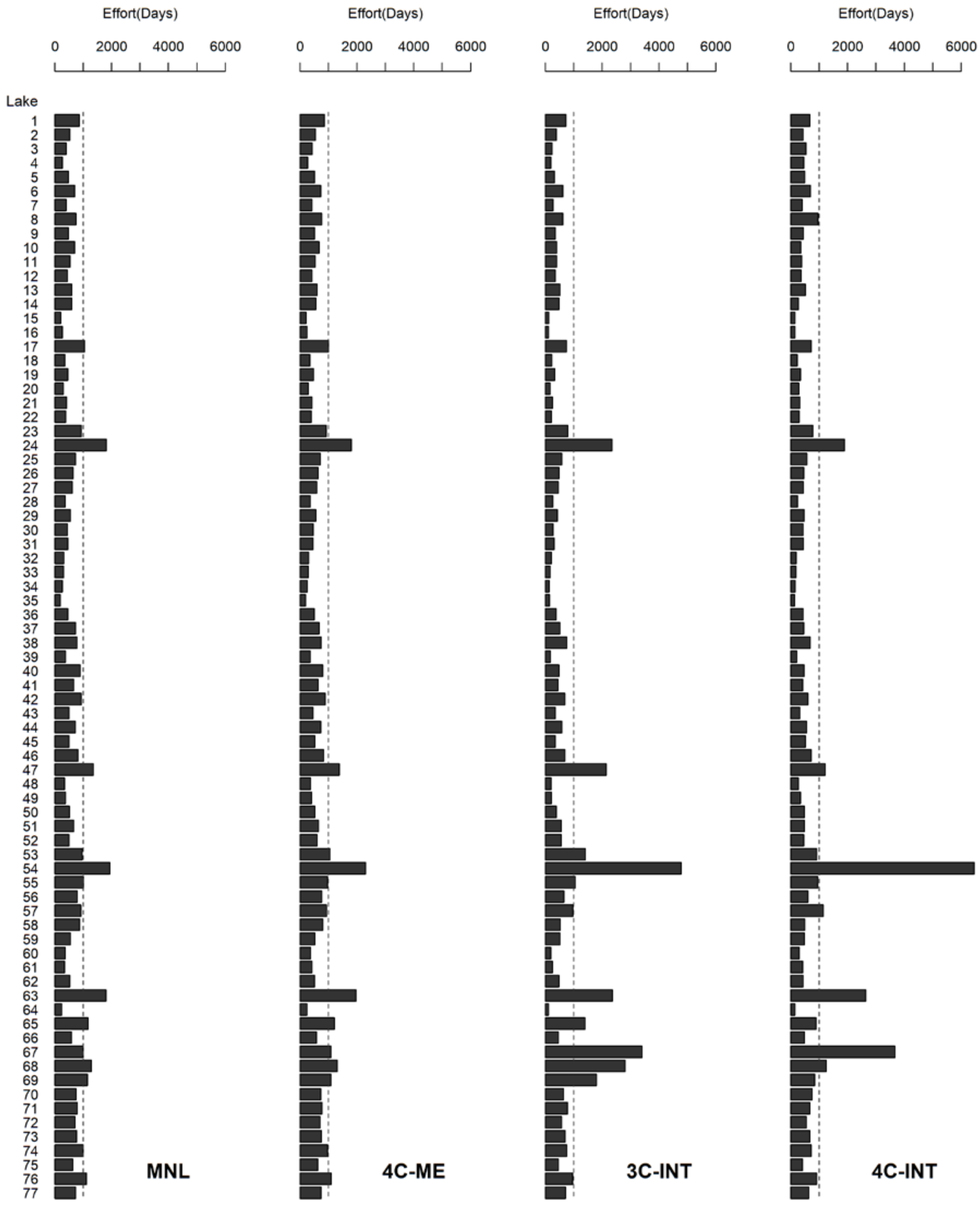

Figure 4. Distribution of Angler Effort (Days) by Model. Dashed grey line indicates 1,000 days of fishing per year.

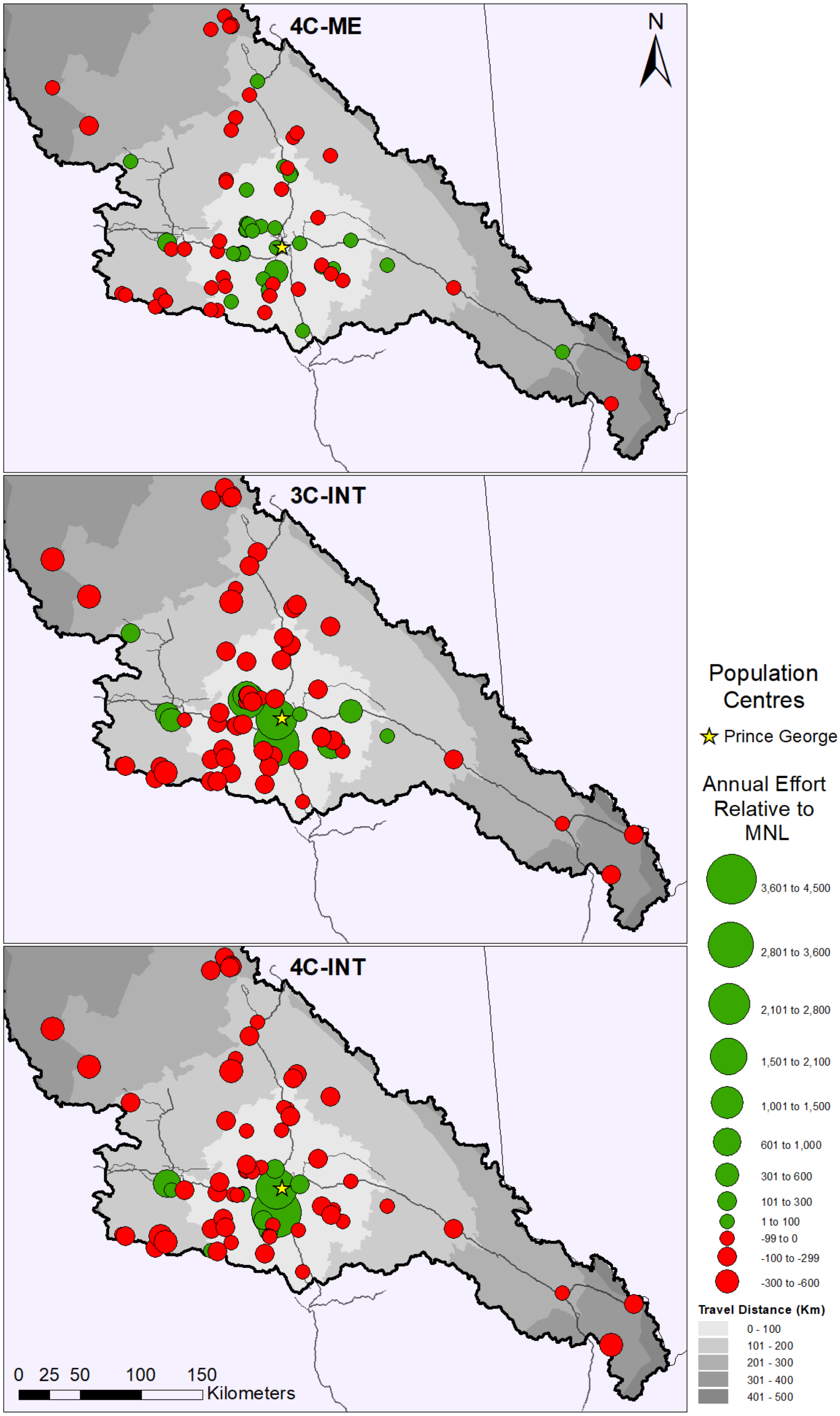

Figure 5. Map of the Change in Annual Angler Effort Relative to the MNL

3.2. Distribution of Angler Effort by Class

Population level patterns of behaviour indicate that increased preference heterogeneity led to concentrated angler effort on a subset of lakes. However, anglers had distinct preferences that influenced their choice of a lake, and high angler effort at a lake may be attributable to a smaller subset of the angler population. Managers must identify and understand these different angler groups (or classes) to develop targeted and effective management actions.

Because LCM groups anglers into classes with distinct preferences, I expected distinct spatial patterns of effort for each class. Further, I expected models with the greatest heterogeneity (3C-INT and 4C-INT) to predict more diverse spatial patterns of class effort. To account for differences in the number of anglers in each class, I transformed angler effort to relative effort, which is the percentage of total class effort expended at a lake per year. Relative effort by class for 4C-ME, 3C-INT, and 4C-INT models is presented in Figures 3 – 5.

Each model was characterized by a degree of dissimilarity between patterns of class effort. However, as preference heterogeneity increased, the differences between patterns of effort became more pronounced. Class patterns of effort differed in two ways. First, at low preference heterogeneity, the lakes that received the most effort were the same across classes. As preference heterogeneity increased, the lakes that received the greatest effort differed between classes. For example, in the 4C-ME model, where preferences were the least heterogeneous, lakes 24, 54, and 63 received high relative effort in all four classes. In contrast, angler effort in Class 3 of 3C-INT was greatest on lake 67, while angler effort for Class 1 and Class 2 was greatest on lake 54. A similar pattern emerged in 4C-INT, where angler effort in Class 1 and 4 was highest on lake 54, while angler effort on Class 2 and 3 was highest on lake 67.

Second, the models also differed in the degree to which class effort was concentrated on a subset of lakes (Table 4). In the 4C-ME model, only Class 3 concentrated their effort to any degree (λ = 4.534). In the 3C-INT model, both Class 2 (λ = 4.840) and 3 (λ = 4.590) had a greater concentration of effort, while in the 4C-INT model Class 4 spent a considerable number of days fishing on a subset of preferred lakes (λ = 21.730).

Table 4 **Simpsons Index (λ) of Angler Class Effort ($\times\ 10^{-2}$)**

	4C-ME	3C-INT	4C-INT
CLASS 1	1.646	2.338	2.325
CLASS 2	1.886	4.840	3.982
CLASS 3	4.534	4.590	3.851
CLASS 4	1.433	-	21.730

Patterns of class effort also expressed a degree of similarity regardless of the specification of preference heterogeneity. Where class effort was concentrated, it was on lakes closer to the major population centre (PG) (Fig. 8 - 10). In both the 3C-INT and 4C-INT models where effort concentration was greatest (see Table 3), the preferred subset of lakes was near PG. That angler effort became increasingly concentrated on lakes closer to PG as preference heterogeneity increased (see Fig. 4) resulted from the behaviour of all angler classes, rather than one or two. However, some classes were less influenced by travel distance. For example, in the 4C-INT model, effort from Class 2 was concentrated around PG while effort from Class 4 was still substantial at lakes approximately 100km to the west of PG.

Different representations of angler preference heterogeneity led to distinct spatial patterns of effort. Including greater preference heterogeneity revealed that angler classes likely preferred different lakes, and concentrated their effort on those lakes to varying degrees. However, though the influence of travel distance was not equal among classes, all classes in all models preferred lakes that were relatively close to the City of Prince George.

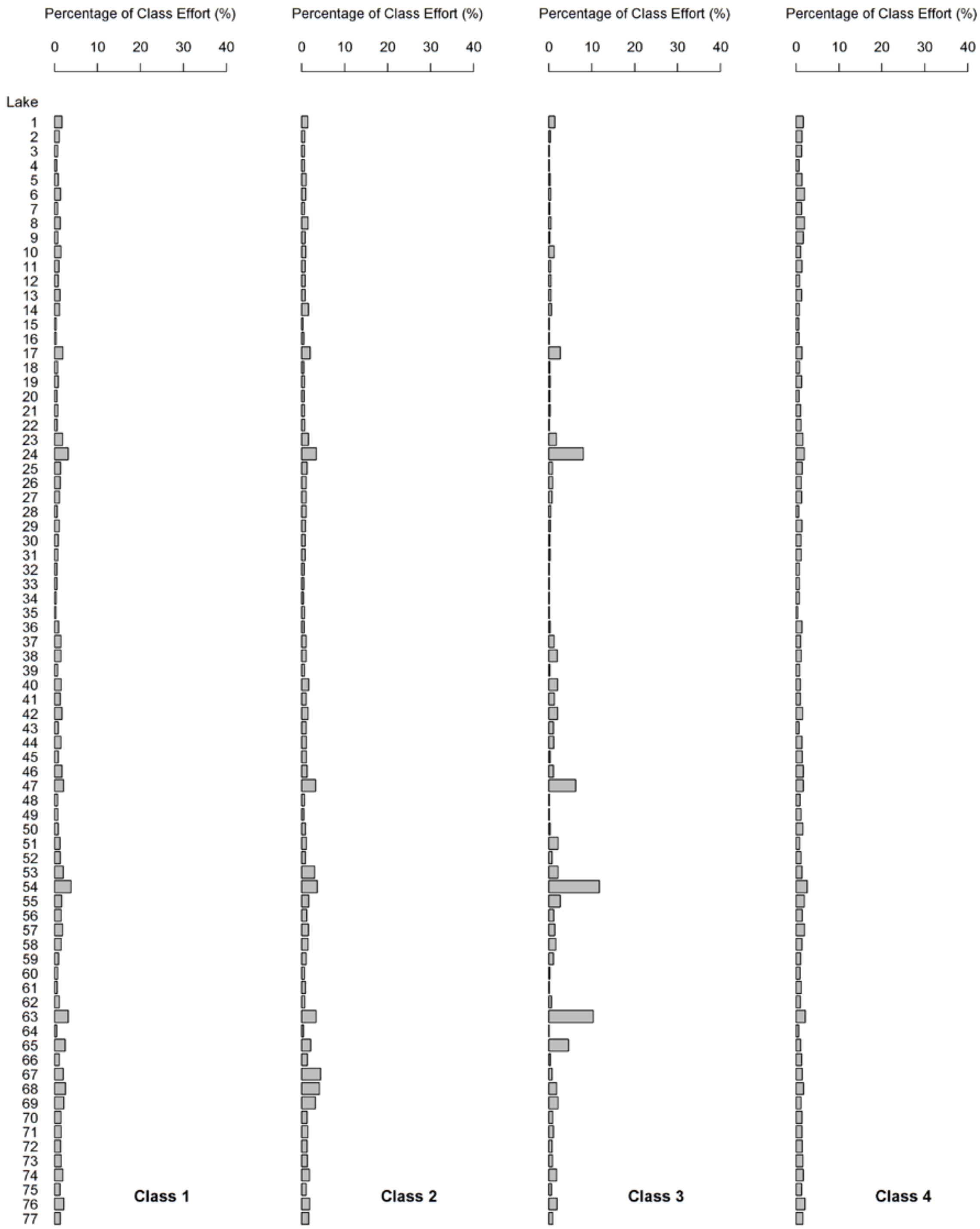

Figure 6. 4C-ME - Distribution of Angler Effort by Class (% of total class effort)

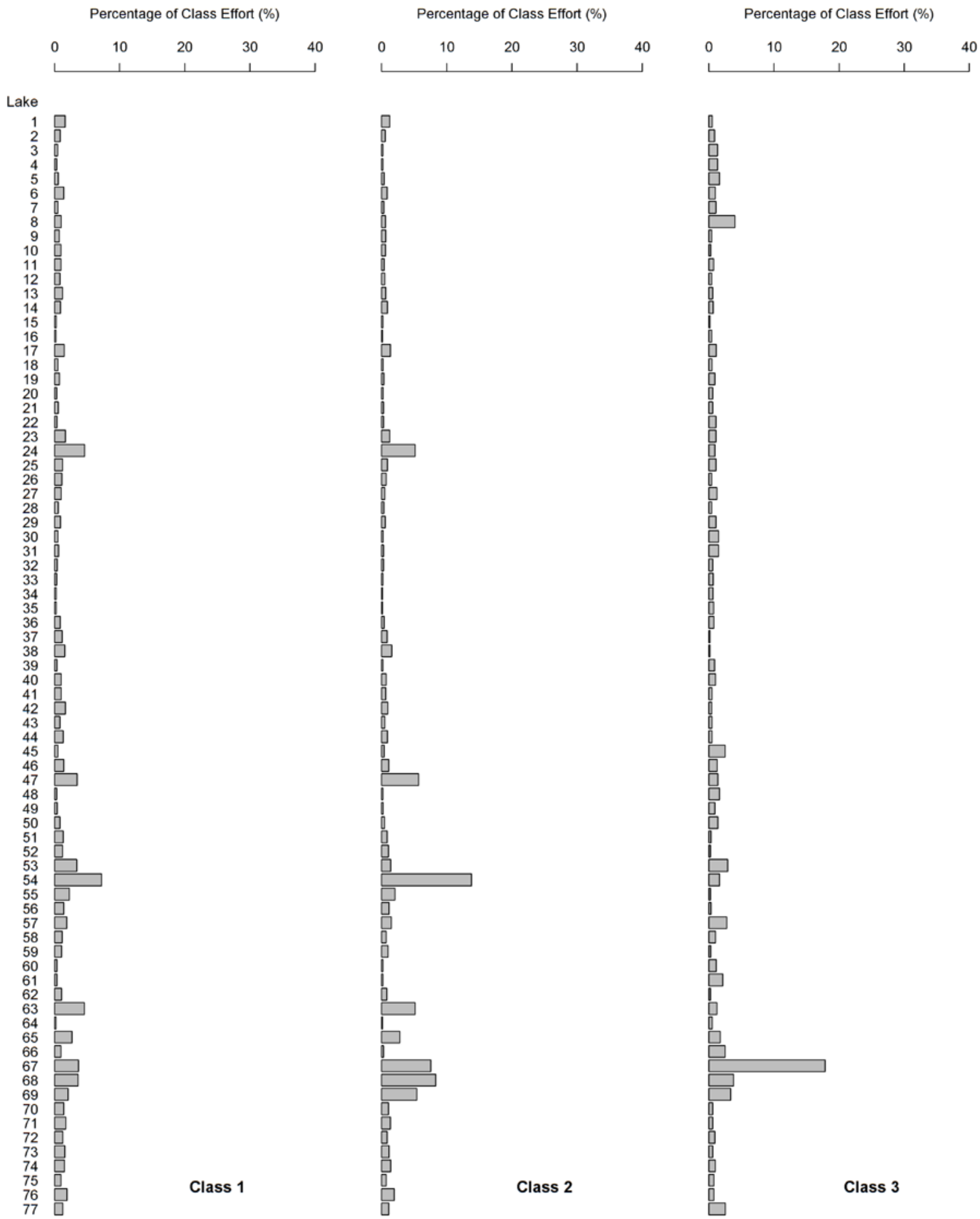

Figure 7. **3C-INT - Distribution of Angler Effort by Class (% of total class effort)**

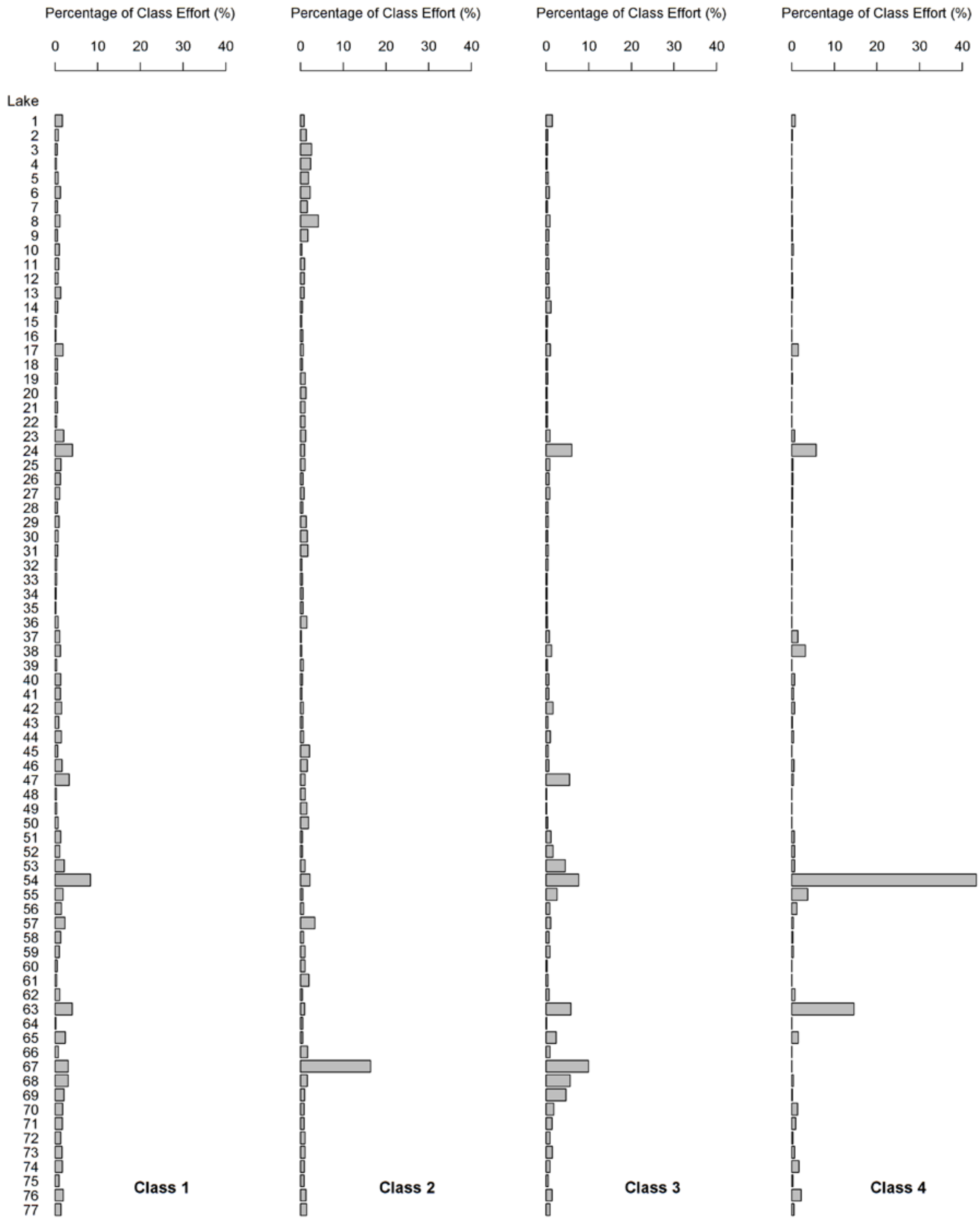

Figure 8. **4C-INT - Distribution of Angler Effort by Class (% of total class effort)**

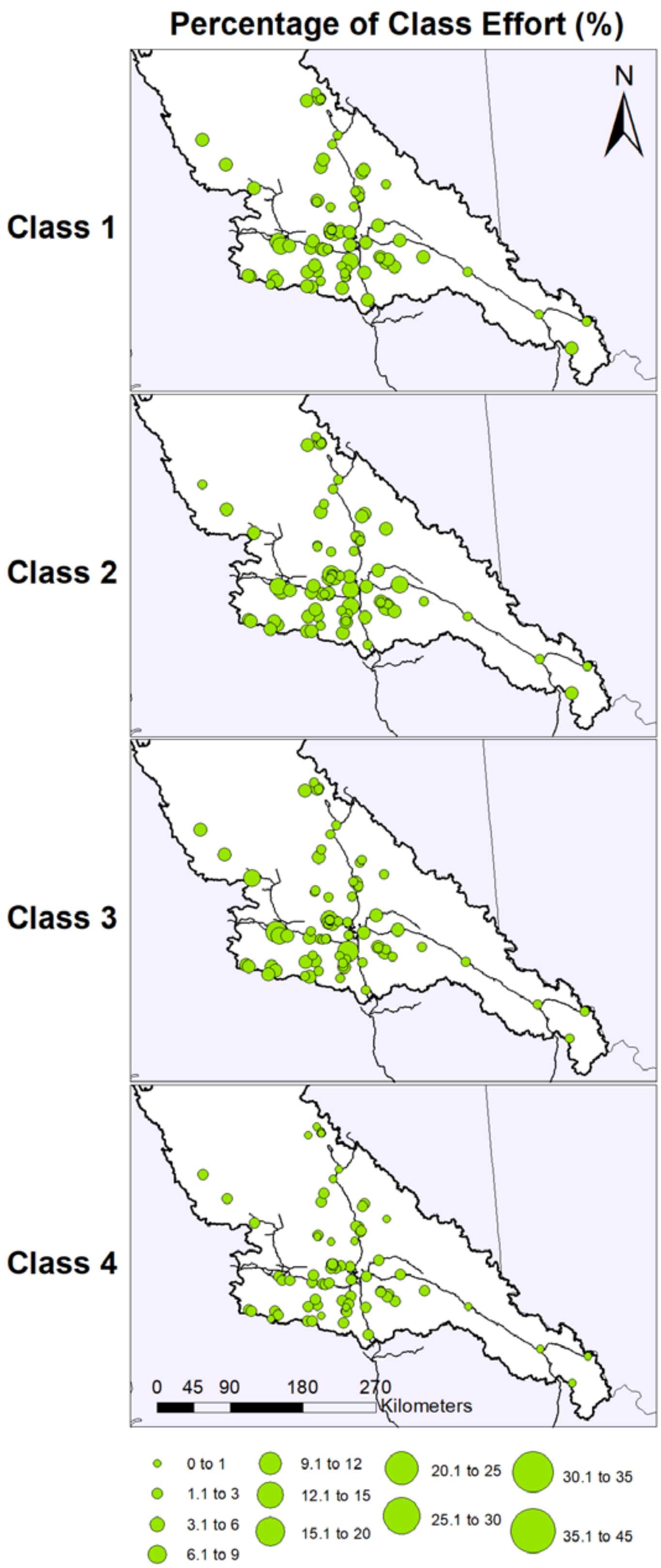

Figure 9. Map of 4C-ME Relative Angler Class Effort

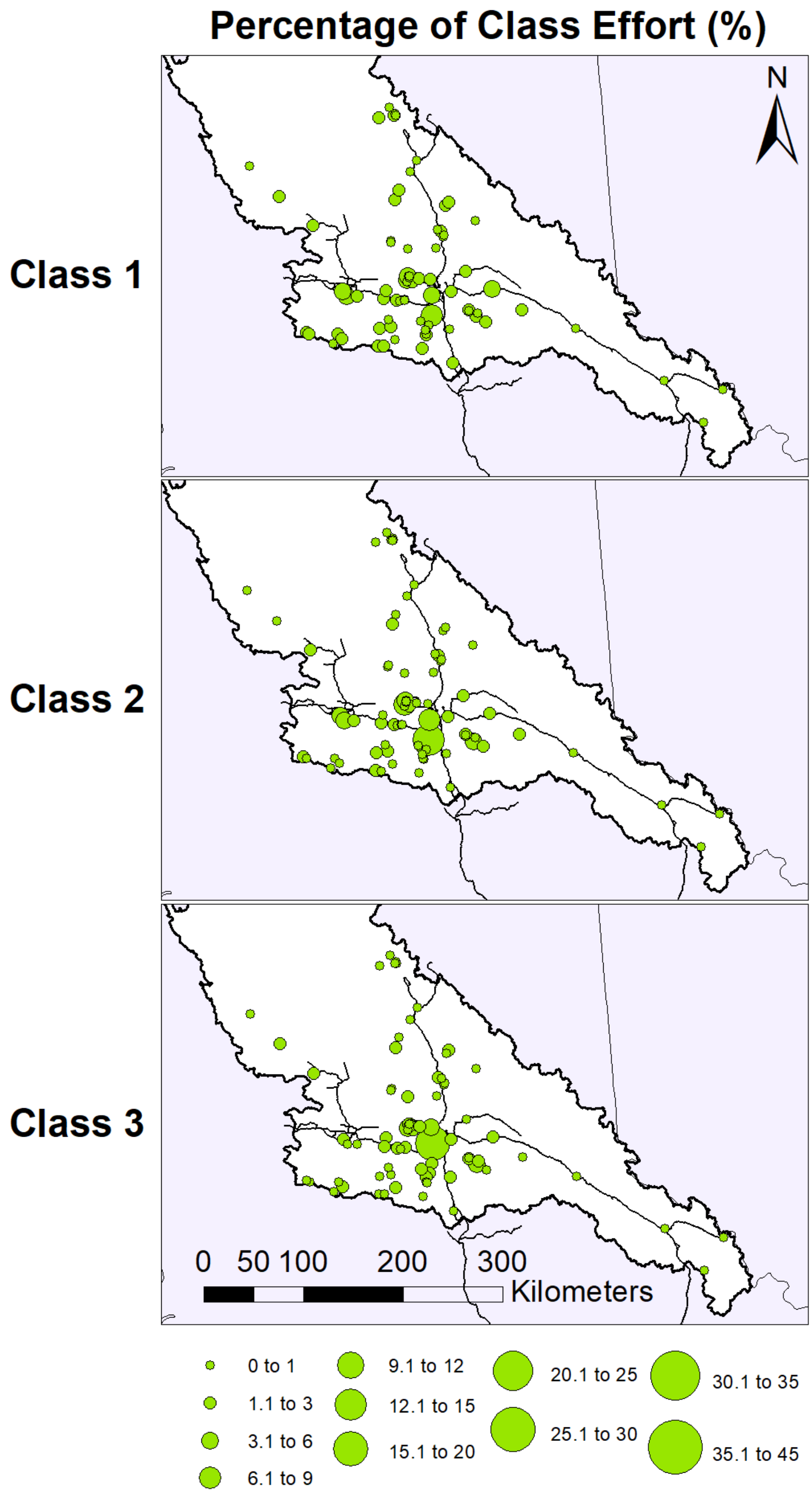

Figure 10. Map of 3C-INT Relative Angler Class Effort

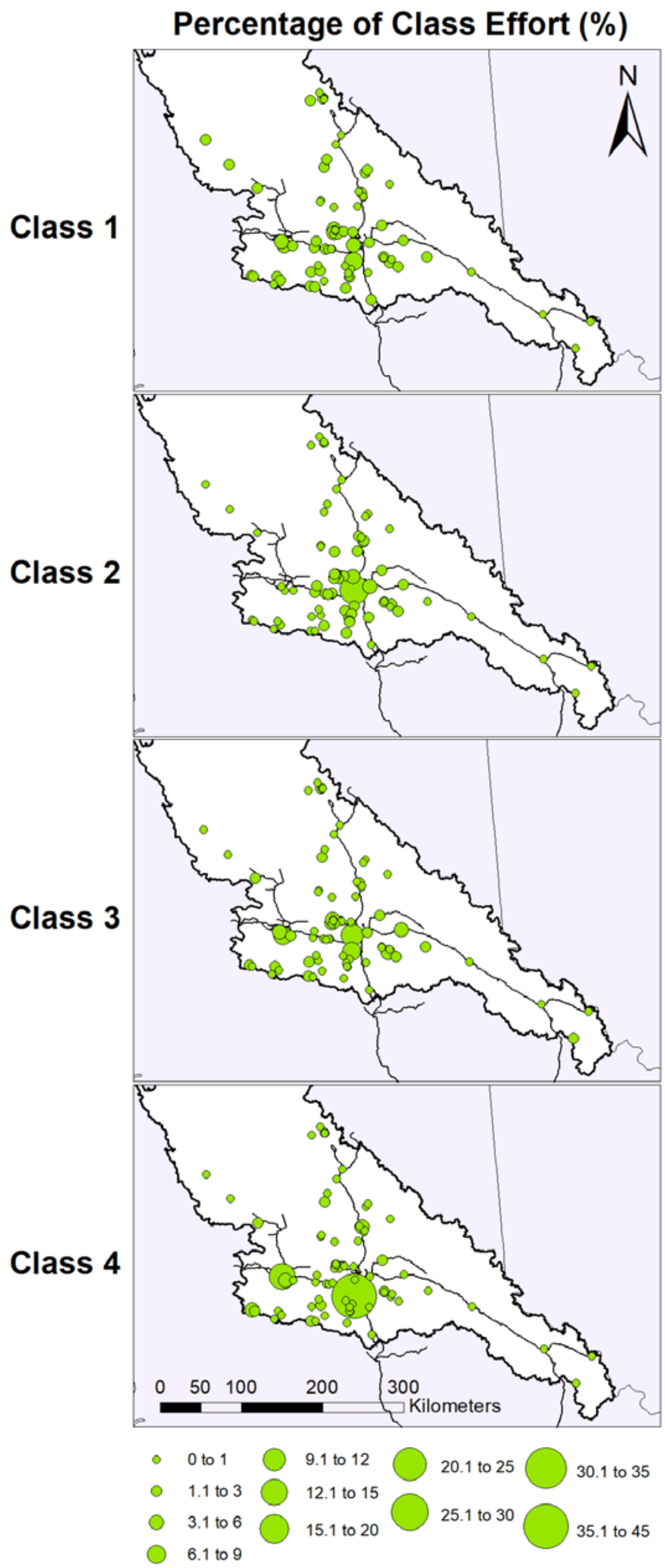

Figure 11. Map of 4C-INT Relative Angler Class Effort

3.3. Instantaneous Fishing Mortality Rate

To connect patterns of angler effort to their influence on fish stocks, I investigated whether the concentration of angler effort on a subset of lakes resulted in a greater range of fishing mortality across the landscape. I expected that as the heterogeneity of angler preferences increased and angler effort became more concentrated on a subset of lakes, those lakes would see high fishing mortality, while other lakes where effort declined would see lower fishing mortality. As such, the range of fishing mortality rates across the landscape would increase as angler preference heterogeneity increased. Using instantaneous fishing mortality rate (F), I compared each model to the baseline model (MNL) (Fig. 11). I subtracted lake specific values of F produced by the baseline model from the corresponding lake in each model. In Figure 5, where F is 0, modelled values of F were equal to the baseline model. Values of F greater than 0 indicate that fishing mortality increased at the lake, while values of F less than 0 indicate that fishing mortality decreased at the lake.

The range of instantaneous fishing mortality rates was different for each model (dashed lines), but contrary to my expectations the range of F did not increase as the heterogeneity of angler preferences increased. The 4C-ME model had a range of 0.527 and included increased fishing mortality rate at several lakes. The 4C-INT model, which had the greatest heterogeneity of preferences, had a range of 0.943, with a decline in fishing mortality rate at a substantial number of lakes, with small increases in fishing mortality at a few lakes. Unexpectedly, the 3C-INT model presented the largest range of fishing mortality rates (1.646). Approximately 10 lakes declined in F of 0.5 or greater, while several increased in fishing mortality to approximately 0.25.

The spatial distribution of instantaneous fishing mortality rates resembled angler patterns of effort, but differed in several notable aspects (Fig. 12). First, increases in F were not constrained to lakes close to PG in any of the models, and values of F were not as sensitive to travel distance as greater sources of preference heterogeneity were accounted for. Further, the magnitude of the increase in values of F at lakes near PG did not align with the increase in angler effort (see Fig. 4). There were large declines in F at lakes near PG in 3C-INT model, but declines were less on those same lakes in the most heterogeneous, 4C-INT model.

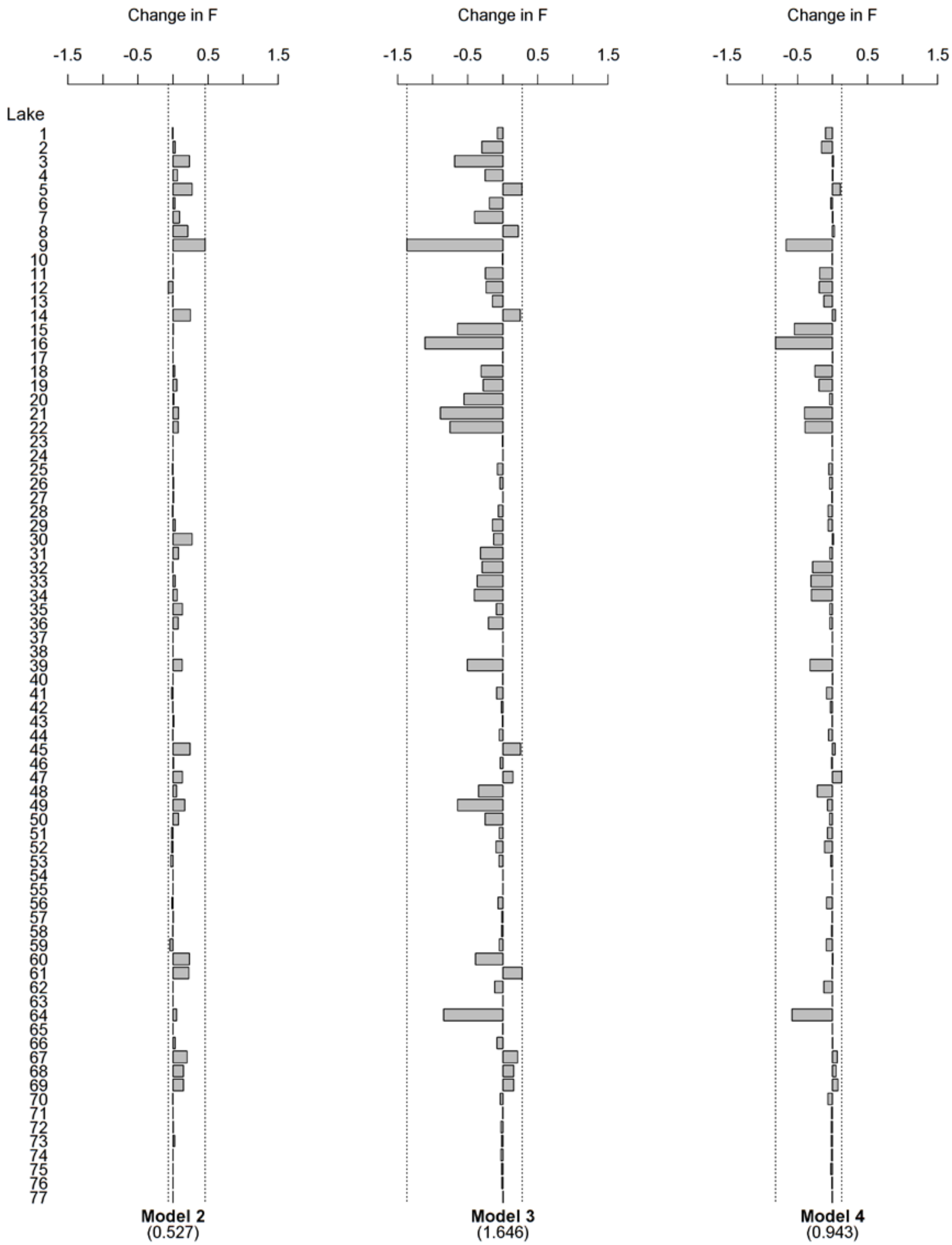

Figure 12. Instantaneous Fishing Mortality Rate (F) Relative to the Baseline (MNL) Model.

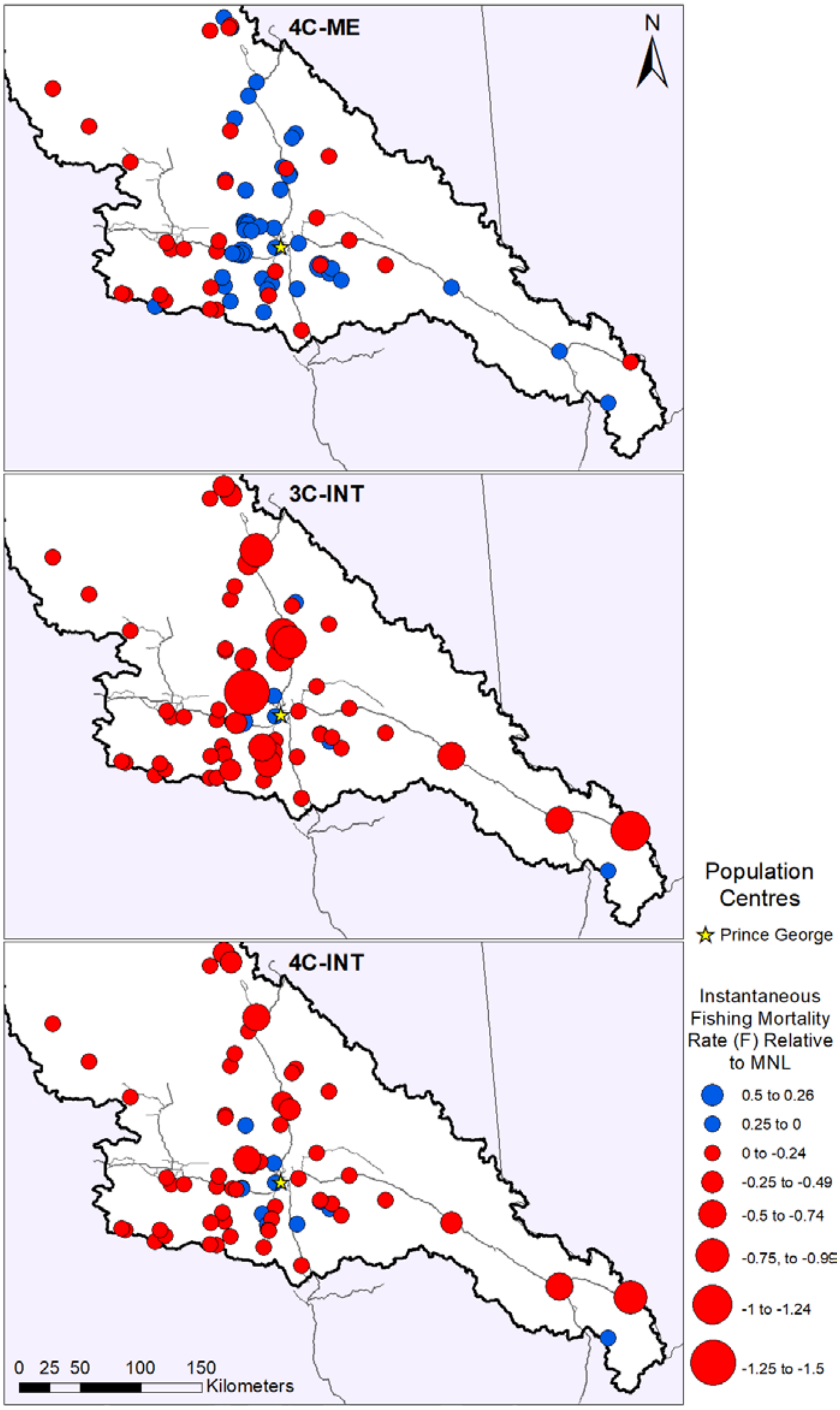

Figure 13. **Map of the Instantaneous Fishing Mortality Rates Relative to the Baseline (MNL) Model.**

I carried out a sensitivity analysis to explore what influence catch efficiency (catchability coefficient), Rainbow Trout populations, and the anglers' exploitable area had on my results. The sensitivity analysis revealed that my models were sensitive to catch efficiency and fish abundance. An increase in the range of catch efficiency ($\sigma_D = 0, 5, 9$) resulted in shifts in angler effort among those lakes that received high effort, and an increase in the range of instantaneous fishing mortality rates (F). When the populations of Rainbow Trout were altered from 50% of initial values to 200% of initial values, angler effort moved from more evenly distributed among all lakes to become more concentrated on a subset of lakes, with an increase in the range of F. Finally, altering the anglers' sensitivity to the presence of other anglers by adjusting the area they could exploit in a single day (5ha, 10ha, 20ha) had limited effects on the spatial distribution of effort and F.

In review, increasing preference heterogeneity led to distinct spatial patterns of angler effort. As preference heterogeneity increased, anglers increasingly concentrated their effort on a smaller subset of lakes that were relatively close to the major population centre. However, increased preference heterogeneity did not change which lakes received the most or least effort. The patterns of angler effort seen at the population level resulted from the lake site choices of different angler classes. In each model, some classes showed a tendency to distribute effort evenly to all lakes, while others concentrated effort on a few lakes. Further, angler classes differed in terms of which lakes were most preferred, with different classes of anglers drawn to different lakes, though all preferred lakes that were relatively close to the major population centre. Finally, the distinct spatial patterns of angler effort generated by each model resulted in different rates of fishing mortality, though these did not correlate to changes in preference heterogeneity. While fishing mortality rates increased on those lakes that received increased effort, increases and declines in F were less influenced by distance from the City of Prince George. The following section discusses these results, identifies the limitations of this study, and examines opportunities for future research.

Chapter 4.

Discussion

Understanding how spatial patterns of angler effort and fishing mortality vary as greater preference heterogeneity is captured by a model is lacking in the recreational fisheries literature. Accounting for preference heterogeneity has been identified as a critical avenue of research in fisheries management (Fenichel et al., 2013). Studies in land use modelling indicate that variation in preference heterogeneity can lead to different spatial patterns of behaviour (i.e. housing development) (Brown & Robinson, 2006) suggesting that increasing preference heterogeneity could have significant implications for other applications such as recreational fisheries (Johnston et al., 2010; Johnston et al., 2013). To address this gap in the literature, I developed an agent-based model (ABM) and compared modelled angler effort from four different choice models that accounted for increasing degrees of heterogeneity, using the recreational Rainbow Trout fishery in the Omineca Wildlife Management Region of British Columbia. I used the models to determine if estimated patterns of angler effort become increasingly concentrated on a subset of lakes when greater sources of preference heterogeneity are accounted for, and to assess whether the range of fishing mortality rates increases with the heterogeneity of modelled angler preferences, relative to a baseline model.

Some but not all specifications of angler preference heterogeneity led to different patterns of angler effort relative to a baseline model (MNL). Where a single source of heterogeneity was included, spatial patterns of angler effort were relatively uniformly distributed across the landscape and did not differ significantly from the baseline model. However, when multiple sources of heterogeneity were included, patterns were significantly different, and increasing the number of sources of heterogeneity resulted in increasingly concentrated spatial patterns of angler effort. Finally, as more sources of preference heterogeneity were accounted for the range of fishing mortality rates increased, though overall these rates were not correlated with increases in preference heterogeneity.

4.1. Population Patterns of Effort

Applications of choice models in recreational fishing have shown that accounting for heterogeneity reveals greater variation in preferences among anglers (Carlin, Schroeder, & Fulton, 2012; Provencher & Bishop, 2004) and altering the specification of preferences can lead to different spatial patterns of effort and impacts to the fishery (Hunt et al., 2011; March, Alós, & Palmer, 2014). My results align with and extend this understanding of angler preferences, demonstrating that distinct patterns of effort arise from diverse angler preferences where anglers are represented as individuals, and interact with each other and a dynamic fisheries landscape. Further, the trend towards greater concentration of angler effort on a subset of preferred lakes seen in my results is analogous to the trend towards the concentration of housing development in clusters realized in land use modelling (Brown & Robinson, 2006). That the results from my model aligned with previous recreational fisheries literature and reproduce results from similar research in other fields lends validity to the emergent patterns of angler effort seen in my results and the modelling approach used.

The distinct patterns of modelled angler effort resulted from the increasing concentration of effort on a preferred subset of lakes. As greater sources of preference heterogeneity were accounted for, effort increasingly shifted from lake sites farther away from the City of Prince George (PG) to a subset of lakes closer to PG. Importantly, this subset of preferred lakes was the same across all models. Previous studies in recreational fisheries have established an inverse relationship between effort and travel distance, such that effort is expected to decline as travel distance increases (Post et al., 2008). Further, in studies where the sources of heterogeneity were systemically varied, spatial patterns of angler effort ranged from more concentrated to more diffuse, but regardless of parameterization, angler effort was more heavily concentrated on lakes close to a major population centre (Hunt et al., 2011). My results demonstrate a similar pattern with effort concentrated on the same subset of lakes near PG in all models. My results suggest that accounting for greater preference heterogeneity 1) may not alter which lakes receive the most effort, but only the magnitude of effort they receive, and 2) may increase angler aversion to travel distance. It is important to note, however, that not all lakes near PG received greater angler effort as source of preference heterogeneity were added. This highlights the influence of other attributes of the fishing experience in shaping angler lake choice, and the importance of a modelling approach that incorporates multiple attributes of potential fishing sites.

The concentration of effort that arose from increasing preference heterogeneity can be attributed to the interaction of several factors: the order in which sources of preference heterogeneity were added, the underlying preferences of the population, the structure of the computer model, and the nature of the fisheries landscape. First, incorporating unobserved utility in all models grouped the population and allowed preferences for each group to diverge from population averages, freeing angler groups driven by one or two attributes to concentrate their effort. If unobserved utility had only been accounted for in the most heterogeneous model I suspect that the concentration of effort would have been far less pronounced in the other models.

Second, the preferences of the sampled population also influenced patterns of angler effort. If the sampled population were comprised of specialized anglers or possessed a strong orientation to catch large fish, the addition of these sources of heterogeneity would result in anglers prioritizing lakes that offered that experience. In contrast, if the population were primarily composed of novice or generalist anglers with a focus on consumption, their effort would have remained more evenly distributed.

Third, the structure of the model influenced patterns of effort. The model treated anglers as individuals whose decisions were based on individual knowledge and experience, such that each angler had a unique understanding of the landscape. The model limited angler perception of the landscape and restricted angler knowledge of catch, size of catch, and crowding. Anglers did not know which lake would maximize their utility. Instead, anglers based their decision on their personal experiences which varied between anglers. Previous research has shown that when anglers share information on the state of the landscape, thus increasing their fishing success (i.e. catchability), angler effort becomes more concentrated (Hunt et al., 2011). Thus, in this application, if anglers had a shared understanding of the landscape, either through perfect information or sharing of information, angler effort would likely have been more concentrated.

Finally, the nature of the fisheries landscape also influenced patterns of effort. If the lakes included in the model had been more similar, and were seen to offer relatively equal utility by each angler class, effort regardless of class would have been more evenly distributed. Conversely, if lakes had been significantly different from each other and offered widely varying utility, angler effort would have been more concentrated. Acknowledging all these factors, I can conclude that accounting for greater preference heterogeneity will lead to distinct patterns of effort, both at the population and class scale. However, my results are specific to the methods used and study area, and prevent strong conclusions regarding preference heterogeneity and related patterns of effort.

4.2. Class Patterns of Effort

Increasing preference heterogeneity brought sharper contrast to the differences between class-specific patterns of effort. As preference heterogeneity increased, different angler classes began to allocate effort to different lakes, and while some classes continued to evenly distribute their effort, others increasingly concentrated their effort on a small subset of lakes close to the City of Prince George. When these patterns are interpreted through the theory of recreational specialization, the class-specific patterns of effort aligned well with the existing understanding of anglers in recreational fisheries literature. For example, examining the model with the greatest preference heterogeneity (4C-INT) identifies specialist anglers who are driven by trophy fish and form “place attachment” (Class 4) (Bryan, 1977; Oh, Sutton, & Sorice, 2013) as well as generalists who are less site attached and focused on consumption (Class 1) (Bryan, 1977; Fisher, 1997). These types or classes of angler were more difficult to identify in models where preference heterogeneity was limited. The clarity brought to class-specific patterns of effort by capturing more preference heterogeneity allows researchers and managers to better understand the composition of angler effort across a recreational fishery.

The combination of class-specific patterns of effort with knowledge of class preferences provided by the DCE and the state of the fishery could provide a better understanding of potential risks of overexploitation and angler responsiveness to regulatory or environmental changes. For example, looking again to the trophy anglers (Class 4, 4C-INT), if analysis were limited to their class-specific pattern of effort, which was concentrated on a subset of lakes, it would suggest that fishing mortality was high and that those lakes face a greater risk of stock collapse. However, highly specialized trophy anglers have been shown in some studies to be less impactful to fisheries as they are more likely to practice catch and release, and are more accepting of restrictive regulations (Ditton & Oh, 2006; Hyman et al., 2017; although see Dorow et al., 2010 for contrasting results). In this example, high effort levels may not correspond with risk of overexploitation, and anglers may be more accepting of more stringent regulations. Knowledge of both the spatial pattern of angler effort and the nature of angler preferences allows managers to tailor regulations to the needs of specific anglers and lakes, ultimately improving their effectiveness. Using models that captured preference heterogeneity to a greater extent made this knowledge available by distinguishing class-specific patterns of angler effort.

4.3. Fishing Mortality

Increases in preference heterogeneity and the subsequent spatial concentration of effort did not correspond to increases in the range of the instantaneous fishing mortality rate (F). The impact of angler effort on fish stocks was moderated by class-specific catch efficiency (Hunt et al., 2011; Ward, Quinn, et al., 2013) and fish abundance (Johnson & Carpenter, 1994; Post et al., 2008). The inclusion of class-specific catchability had the effect of decoupling the relationship between angler effort and instantaneous fishing mortality rate. Rather than changes in angler effort, the changes in the range of F reflect a self-organized shift in the composition of anglers at each lake and the variable impacts different angler classes have on fish stocks (Johnston et al., 2010; Ward, Askey, & Post, 2013). Where less specialized anglers replaced those that were more specialized, fishing mortality would decline even if angler effort remained the same. That the concentration of effort by more specialized anglers on a subset of lakes did not lead to higher F, and thus greater ranges of F, is a product of the density dependent catch equation. Below a certain fish density, anglers were no longer able to catch fish, though the promise of catching larger fish continued to attract effort (Discussion of this issue is provided below). The difference between patterns of angler effort and F were pronounced for models that were significantly different from the baseline model. This suggests that increasing preference heterogeneity allows the model to portray the interplay between angler effort, catch efficiency, and fishing mortality, more clearly. However, the accuracy of this relationship cannot be confirmed.

4.4. Sensitivity Analysis

I explored the influence of catch efficiency, fish abundance, and angler sensitivity to crowding as I was required to make strong assumptions when including them in the ABM.[9] Catch efficiency, as determined by angler specialization, is known to vary among anglers and influence an angler's impact on the fishery (Ward, Quinn, et al., 2013). I varied the range of catch efficiency across the angling population in Models 2, 3, and 4. A wider range of catch efficiency only influenced spatial patterns of effort in models where preference heterogeneity was relatively high (3C-INT and 4C-INT) but increased the range of instantaneous fishing mortality rates (F) in all models. Changes in the patterns of effort resulted from more specialized angler classes concentrating their effort on a subset of lakes as their catch efficiency increased. However, the range of F did not increase because of this added concentration, but from declines in F on numerous lakes frequented by less specialized anglers with lower catch efficiencies. In other words, F increased because novice anglers caught less, not because specialized anglers caught more. An assessment of Rainbow Trout anglers in BC found a far greater range catchability values relative to those tested in the sensitivity analysis (Ward, Quinn, et al., 2013), suggesting that my ABM underestimated the diversity of catch efficiency in the angling population.

Variation of fish abundance significantly altered the patterns of effort of those anglers driven by fishing quality (catch, size of catch). Low abundance had the effect of creating equally poor fishing quality across the landscape. This effectively removed catch-related attributes from decisions on lake choice as lakes no longer differed in fishing quality. As a result, anglers driven by the catch or size of catch more evenly distributed their effort across the landscape. Conversely, increased abundance improved fishing quality and increased the utility derived from catch and size of catch. This led catch-driven anglers to concentrate their effort on a subset of lakes with larger fish.

Varying the anglers' sensitivity to crowding had no influence on spatial patterns of effort regardless of preference heterogeneity. I attribute this to the fact that my trip probability sub-model did not include consideration of trip timing. The probability that an angler would take a single or multiple day trip did not vary by season or by day of the

[9] I have included Sensitivity Analysis figures in Appendix B

week. This likely omitted fluctuation in participation over the year and underestimated crowding, which has been shown to peak during spring and summer months and on weekends (Hunt, Boots, et al., 2007; Provencher & Bishop, 2004). The inability of my model to replicate realistic crowding levels reduced the influence of the crowding attribute to the point where it no longer affected angler site choice.

4.5. Limitations and Future Research

The simplification of a complex Rainbow Trout fishery into a workable computer model cannot be achieved without introducing unrealistic artefacts and uncertainties. The use of a linear-in-parameters utility equation to determine lake choice and the structure of angler memory led to overestimates of effort at several lakes. First, at lakes that had poor fishing quality (Catch, Size of catch) and received low to moderate levels of effort, non-catch related attributes may have provided sufficient utility so that even if the fish stock experienced significant decline or collapse anglers continued to travel to that lake (Hunt et al., 2011; Post, 2013; Post et al., 2008). While a more realistic understanding would conclude that anglers would avoid a lake without fish, a linear utility equation places equal weighting on each attribute allowing preferences for non-catch attributes (e.g. travel distance, boat launch) to override catch related attributes. Second, at lakes that had poor fishing quality but received high effort, overestimates of effort resulted from the structure of angler memory. Anglers only remembered the size of the last fish they caught at each lake. An angler that caught a large fish early in the model run but failed to catch others on return trips would continue to perceive that lake as providing high utility from the size of catch attribute. For anglers that were driven by fish size, this attribute dominated other attributes and resulted in overestimates of effort. This explains why the range of F did not increase as expected given the concentration of angler effort – some anglers were concentrated at lakes with few catchable fish. The values for catch and size were coded logarithmically within the utility function to address this, but the relative influence of non-catch related attributes and the structure of angler memory limited success.

The findings of this study should be considered with respect to several restrictions imposed on anglers that abstracted from realistic decision-making processes. Anglers did not communicate or share information with each other, but operated as isolated individuals on the landscape. Social networks and the diffusion of information among anglers has been shown to play an important role in addressing uncertainty and ensuring catch success (Little & McDonald, 2007; Mueller, Taylor, Frank, Robertson, & Grinold, 2008). Further, I simplified the role of memory which influenced the perceived utility of alternatives. It is unlikely that fishing experiences from several years in the past have the same influence on angler decision-making as more recent memories. Finally, angler effort was held static throughout the model run, forcing anglers to fish even when fishing quality across the landscape was poor. A more realistic approach would allow anglers to respond to the quality of the fishery (as measured by catch and fish size) such that angler effort would fluctuate year-to-year (Johnson & Carpenter, 1994). Addressing one or more of these issues would constitute a significant step forward in understanding preference heterogeneity in recreational fisheries systems.

Chapter 5.

Conclusion and Policy Implications

The integration of heterogeneous angler preferences into recreational fisheries management plans is critical for their success. Angler preferences shape spatial patterns of angler effort and related impacts to the fishery. It has been suggested that failure to account for angler preferences in fisheries management plans may lead to overexploitation or collapse of fish stocks (Post, 2013). However, exploration of how the specification of preference heterogeneity in recreational fisheries models effects patterns of angler effort is limited. To address this, I developed an agent-based model and explored the specification of preference heterogeneity using four models of angler preferences estimated from a discrete choice experiment. My results show that varying the specification of preference heterogeneity revealed distinct patterns of effort, both for the population and for subgroups, and varied the impacts to fish stocks.

The results of my research support the shift away from one-size-fits-all management approaches by reinforcing that different anglers target different lakes, and can have different impacts on fish stocks. Previous research has called for an end to one-size-fits-all approaches to fisheries management noting that the application of uniform regulations to all lakes within a region may lead to overexploitation or stock collapse (Carpenter & Brock, 2004; Hunt et al., 2011; Post et al., 2008). In its place, researchers have advocated for an integrated and holistic management approach that combines a variety of policies and regulations that recognize varying angler preferences (Fulton, Smith, Smith, & Van Putten, 2011; Ward, Quinn, et al., 2013).

In British Columbia, this management perspective is being applied through lake specific regulations designed to create angler-specific lakes based on an angler typology (FFSBC, 2010). This program is motivated by the recognition that there are diverse users with diverse preferences and values, but also notes that knowledge of these preferences and their influence on recreational fisheries is lacking (MOE, 2007). Modelling approaches, such as the one I developed, could help address this lack of understanding and inform management efforts. Model results could provide greater understanding of the composition of anglers at each lake (angler effort by class) guiding lake specific regulations, identify the attributes that attract anglers, and suggest how anglers may reallocate their effort in response to regulatory or environmental change. These insights would aid efforts to align the range of fishing opportunities in the Omineca region with angler demand (MOE, 2007).

While there is considerable potential for modelling approaches, such as mine, to inform fisheries management efforts, decision-makers should consider model complexity and the corresponding uncertainty (Oreskes, 2003). To that end, modelling efforts should be integrated into a fisheries management framework that embraces model uncertainty. Initial studies have pointed to the value of an adaptive management approach informed by agent-based modelling (Loomis et al., 2008). Adaptive management accepts uncertainty, recognizing that the variables and relationships within natural systems are difficult to define and are constantly changing (Loomis et al., 2008). Within the adaptive management framework, models that account for preference heterogeneity could be used to narrow in on favourable outcomes, while projects (e.g. new regulations, or policies) applied to the fishery could inform modelling efforts, reducing model uncertainty by better defining the system, variables, and their relationships (Loomis et al., 2008). Through an adaptive management framework, the modelling approach presented above could inform lake specific regulations targeted at the anglers believed to visit, and then be refined through observation of angler behaviour and the status of the fish stock. The integration of models that account for preference heterogeneity into a fisheries management framework that embraces model uncertainty represents an effective and sound foundation from which to generate new knowledge of the fisheries system and make informed, science-based decisions concerning the future of a recreational fishery.

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Appendix A.

Supplemental Material to Methods

Table A1. DCE Attributes and Attribute Levels

Attribute	Description	Levels
Take	The bag limit for the lake	Catch and Release (0) 1 Rainbow Trout 4 Rainbow Trout 5 Rainbow Trout
Gear	The type of fishing gear permitted on the lake	No restrictions Single barbless hook Bait ban Fly fishing only
Lake	The size (ha) of the lake	Less than 1,000ha Greater than 1,000ha
Motor	The restrictions placed on boat motors	No restrictions 10 horsepower Electric only
Boat	The presence of boat launch facilities	No facilities Car top launch Trailer launch
Crowding	The number of anglers encountered	1 2 3 5
Size	The size of the fish caught (in)	<9” 10” to 14” 14” to 20” >20”
Catch	The number of fish caught	3 5 7 10
Travel Distance†	Total distance travelled to reach the lake (km)	

†Anglers from Other Management Regions (OMR) did not consider travel distance to the lake as their starting location was not defined

Table A2. Distribution of Anglers Observed in Creel Surveys of the Omineca Region (%)

Region	Post (2011) (n = 201)	Stüssi & Maher (2006) (n = 223)	Average
Omineca	97.02	95.96	96.46
Lower Mainland	0.5	1.35	0.94
OMR	2.49	2.69	2.59

Table A3. Distribution of Anglers Visiting the Omineca Region

Observed Effort* (Days)	Total Estimated Effort (Days)	*Region*	Angler Distribution (%)	Effort Distribution (Days)
31,849	49,764	*Omineca*	96.46	48,003
		LM	0.94	469
		OMR	2.59	1,291

*Observed Effort was obtained from FFSBC for 55 of 77 lakes and scaled up to estimate total effort assuming that the unobserved lakes received on average the same effort as the observed lakes.

Table A4. 4C-ME - Distribution of Anglers visiting the Omineca Region

Region	Effort Distribution (Days)	Class	Angler Class Distribution (%)	Class Effort Distribution (Days)	Angler Distribution (Anglers)
Omineca	48,003	1	50%	24,001	1,558
		2	24%	11,369	738
		3	9%	4,421	287
		4	17%	8,211	533
LM	469	1	41%	192	12
		2	20%	93	6
		3	23%	105	6
		4	17%	77	5
OMR	1,291	1	47%	609	39
		2	17%	220	14
		3	20%	259	16
		4	16%	201	13

Table A5. 3C-INT - Distribution of Anglers visiting the Omineca Region

Region	Effort Distribution (Days)	Class	Angler Class Distribution (%)	Class Effort Distribution (Days)	Angler Distribution (Anglers)
Omineca	48,003	1	61%	29,054	1,886
		2	34%	16,422	1,066
		3	5%	2,526	164
LM	469	1	58%	270	17
		2	30%	139	9
		3	13%	59	3
OMR	1,291	1	55%	707	45
		2	27%	348	22
		3	18%	235	15

Table A6. 4C-INT - Distribution of Anglers visiting the Omineca Region

Region	Effort Distribution (Days)	Class	Angler Class Distribution (%)	Class Effort Distribution (Days)	Angler Distribution (Anglers)
Omineca	48,003	1	45%	21,475	1,394
		2	29%	13,895	902
		3	14%	6,947	451
		4	12%	5,684	369
LM	469	1	38%	180	11
		2	26%	120	7
		3	22%	104	6
		4	14%	64	4
OMR	1,291	1	49%	631	40
		2	20%	253	16
		3	23%	302	19
		4	8%	103	6

Table A7. Trip Probability by Angler Region

Region	Single Day	Multiple Day	No Fishing
Omineca	3.69%	0.18%	96.13%
LM	0%	1.41%	98.58%
OMR	3.9%	0.01%	96.09%

Table A8. Days Fished Annually† per Angler by Model and Class based on Specialization Score‡α

	4C-ME			3C-INT			4C-INT		
	SD=0	SD=5	SD=9	SD=0	SD=5	SD=9	SD=0	SD=5	SD=9
Class 1	15.4	13.5	12.2	15.4	10.7	7.1	15.4	15.5	15.9
Class 2	15.4	8.1	2.5	15.4	12.6	10.5	15.4	15.5	15.8
Class 3	15.4	17.0	18.4	15.4	22.1	27.7	15.4	7.6	1.7
Class 4	15.4	21.8	27.2	-	-	-	15.4	21.7	27.0

† This only influenced the Catchability Coefficient (Eq. 2) and not the probability of single or multiple day trips.

‡ Calculation required subjective determination of standard deviation (SD). Standard deviation was varied through sensitivity analysis to test for influence. A SD greater than 9 led to Days Fished less than 1.

α Utility derived from participation increases with angler specialization (Arlinghaus & Mehner, 2004; C.-O. Oh, Ditton, Anderson, Scott, & Stoll, 2005), which results in increased participation (days fished annually) with increased specialization (Ditton, Loomis, & Choi, 1992; Johnston et al., 2010).

Table A9. Class-Specific Catchability Coefficient (q) (x 10^{-3})

	4C-ME			3C-INT			4C-INT		
	SD = 0	SD = 5	SD = 9	SD = 0	SD = 5	SD = 9	SD = 0	SD = 5	SD = 9
Class 1	1.506	1.389	1.315	1.506	1.227	1.049	1.506	1.515	1.537
Class 2	1.506	1.096	0.852	1.506	1.333	1.219	1.506	1.512	1.533
Class 3	1.506	1.608	1.711	1.506	1.985	2.467	1.506	1.073	0.819
Class 4	1.506	1.964	2.423	-	-	-	1.506	1.957	2.408

Table A10. Rainbow Trout Lakes

Lake ID No.	Lake Name	Lake Area (ha)
1	Grizzly West	136.83
2	Berman	44.28
3	Clear	11.04
4	Nelson	9.93
5	Kwitzil #1	3.54
6	Eena	54.32
7	Camp	25.54
8	Ferguson	16.57
9	Butterfly	6.20
10	Takla	2,660.38
11	Tureen	58.04
12	Teardrop	39.15
13	Chubb	67.14
14	Saddle #2	2.69
15	Little Lost	6.27
16	Witney	8.42
17	Carp	5,629.00
18	Butternut	33.97
19	Crystal	39.72
20	Boot	15.67
21	Emerald	14.23
22	Square	13.48
23	Cluculz	1,988.22
24	Nulki	1,621.91
25	Cobb	223.13
26	Tacheeda #1	376.93
27	Tacheeda #2	196.61
28	Wicheeda	53.19
29	Grizzly East	71.48
30	Otipemisewak	7.15
31	Lynx	26.81
32	Dina #2	29.53
33	Dina #3	20.90
34	43 Mile Pothole	19.50
35	Dina #7	7.53
36	Vivian	47.08
37	Hobson	66.27
38	Chief Gray	31.50
39	La Salle (West)	13.02
40	Trembleur	11,617.20

Lake ID No.	Lake Name	Lake Area (ha)
41	Burden	246.93
42	Finger	829.85
43	Lavoie	231.42
44	Lintz	217.84
45	Kwitzil #2	6.58
46	Ness	346.88
47	Byers	17.29
48	Tory	18.64
49	Mckenzie West	17.93
50	Kathie	43.55
51	Dina #1	224.82
52	Tumuch	138.06
53	Purden	807.54
54	Nadsilnich	511.12
55	Hart	54.12
56	Opatcho	39.69
57	Tabor	381.45
58	Tatuk	1,867.11
59	Mckenzie East	26.20
60	Sawmill	10.58
61	Bow	5.85
62	War	143.27
63	Tachick	2,129.08
64	Windy Point	8.54
65	Stuart	35,932.43
66	Trapping	42.17
67	Shane	5.13
68	Verdant	28.74
69	Tsitniz	10.48
70	Tagai	251.83
71	Sinkut	350.05
72	Punchaw	247.17
73	Pitoney	174.08
74	Naltesby	846.68
75	Little Bobtail	243.18
76	Eaglet	835.58
77	Bednesti	270.41

Appendix B.

Sensitivity Analysis

Table B1. Simpsons Index $(\lambda)$of Angler Effort $(x\ 10^{-2})$

	MNL	4C-ME	3C-INT	4C-INT
Catchability SD = 0	1.672	1.748	3.120	3.304
Catchability SD = 9	1.654	1.665	4.762	3.625
RT Pop. 50%	1.567	1.615	2.535	2.921
RT Pop. 200%	1.690	1.720	3.765	2.855
Exploitable Area 5ha	1.649	1.687	2.906	3.280
Exploitable Area 20ha	1.655	1.705	2.944	3.297

Angler Effort by Model

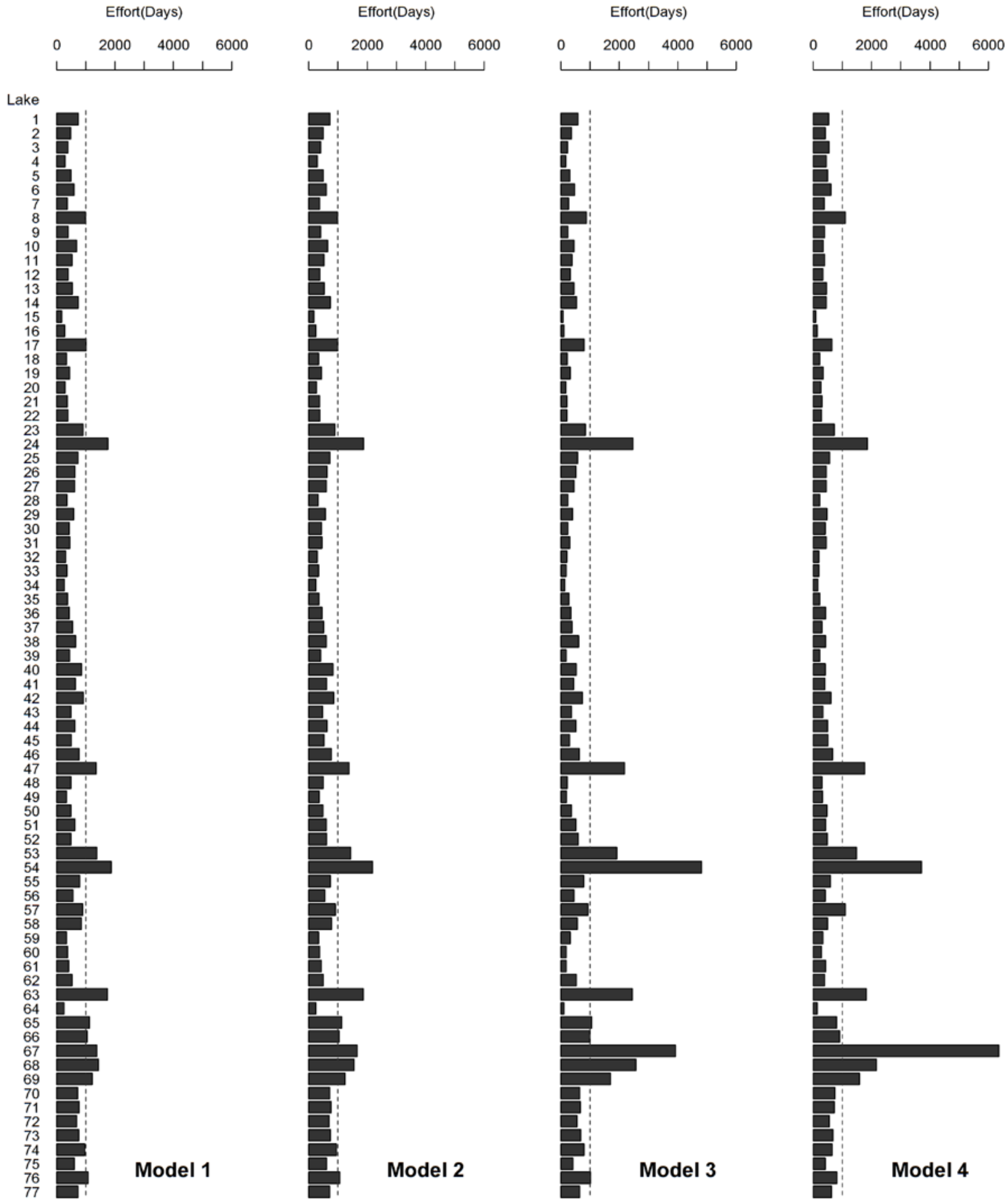

Figure B1. **Sensitivity Analysis: Angler Effort with Specialization SD = 0**

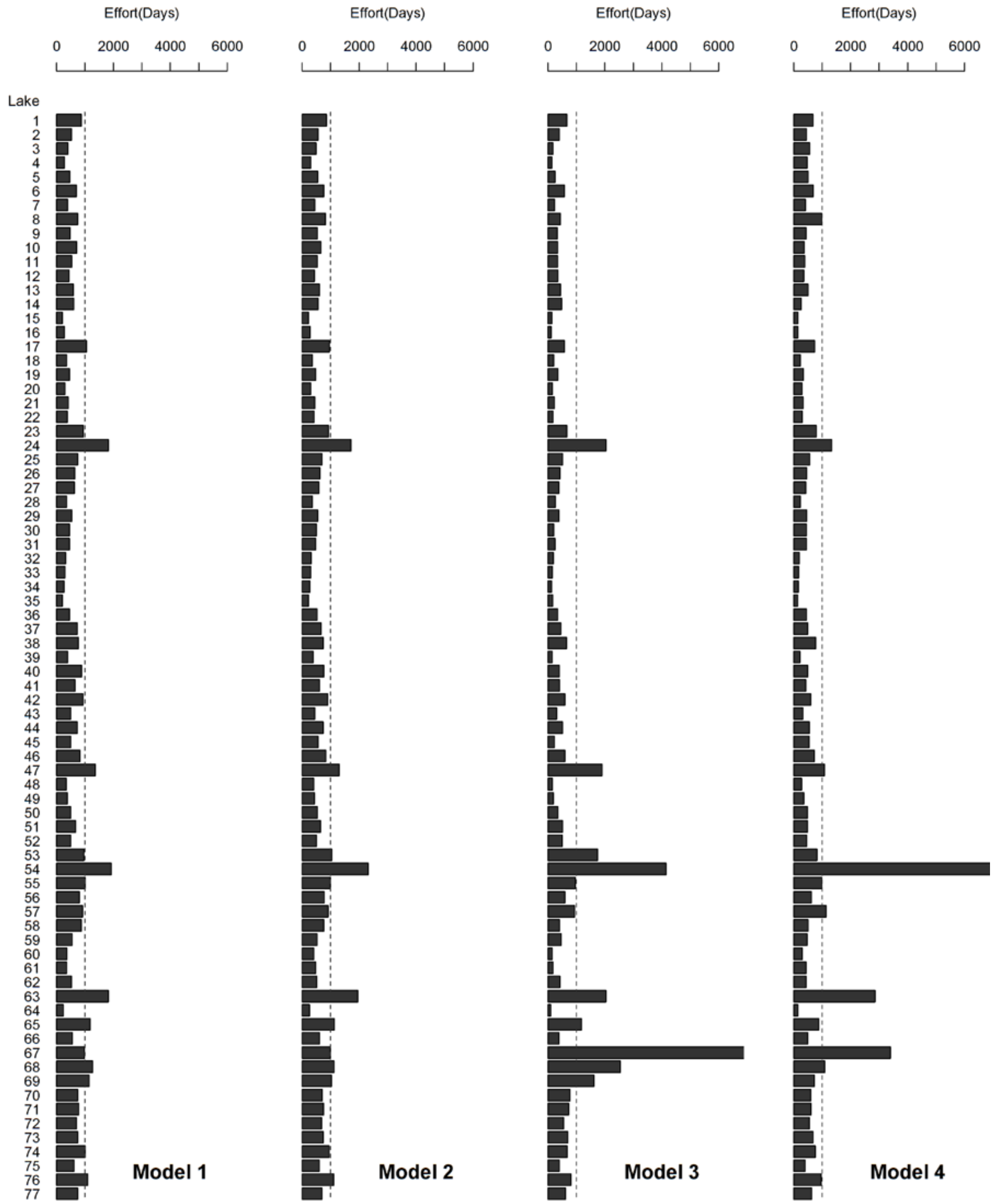

Figure B2. Sensitivity Analysis: Angler Effort with Specialization SD = 9

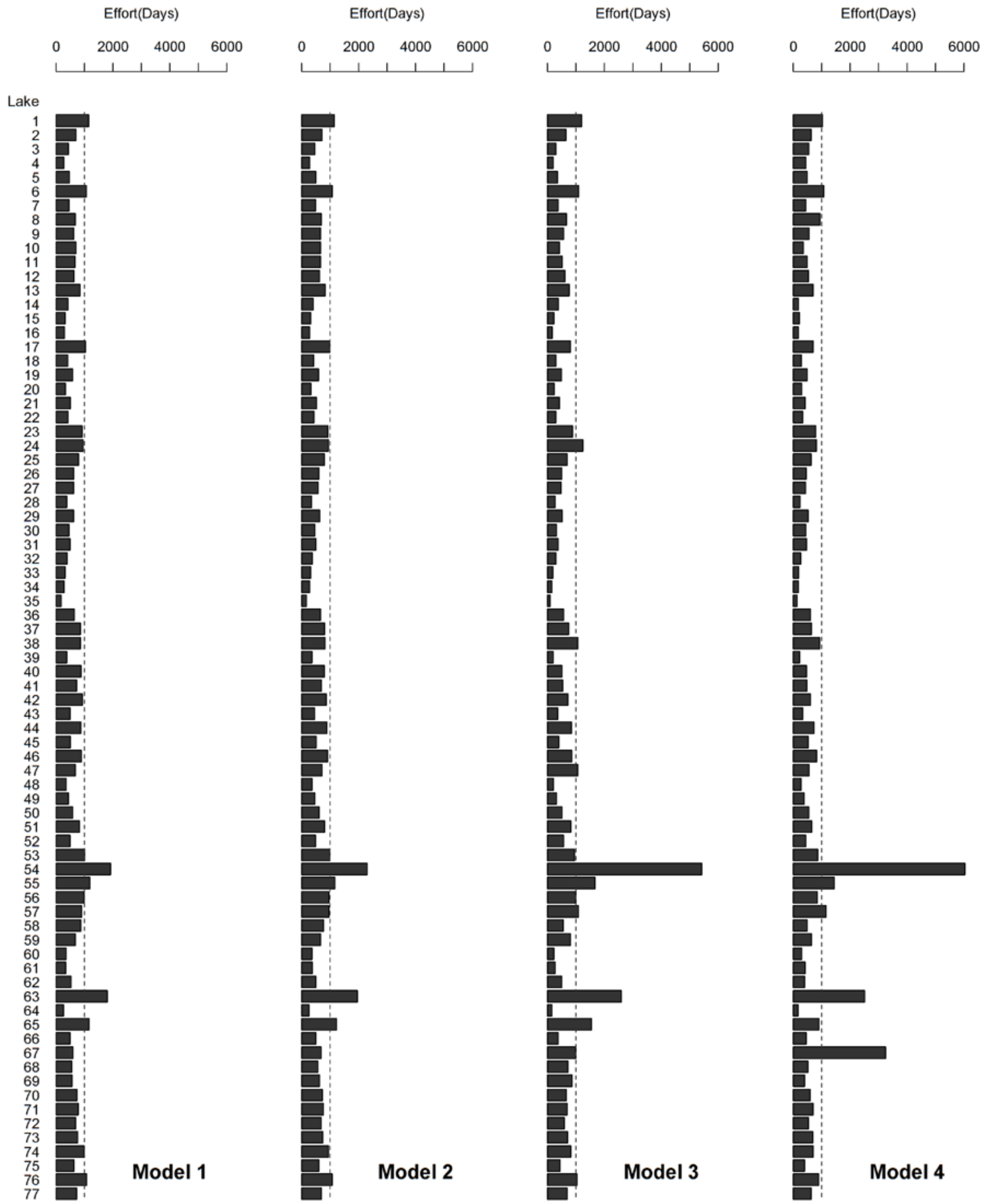

Figure B3. **Sensitivity Analysis: Angler Effort with RT Pop. 50% of Initial Value**

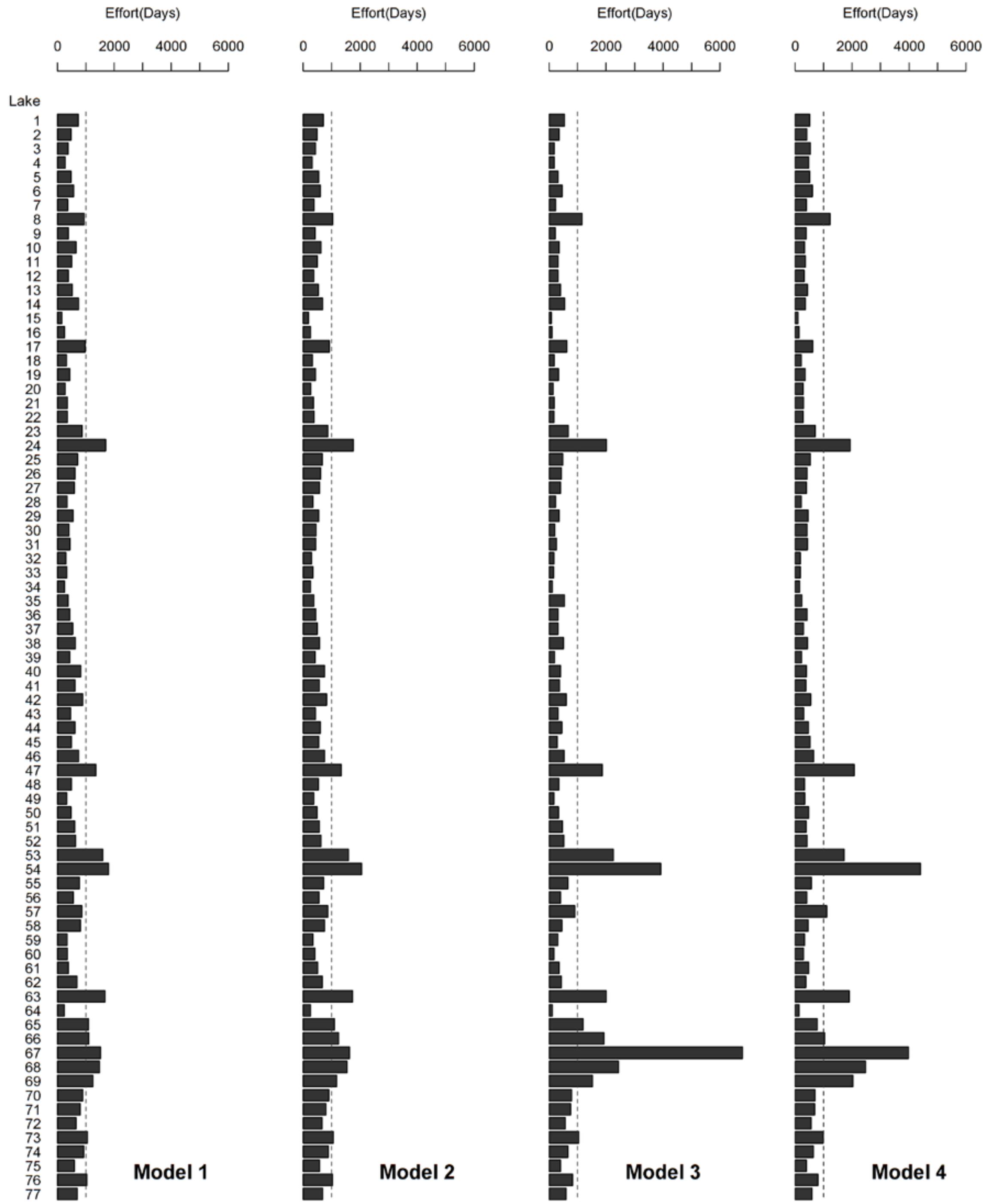

Figure B4. Sensitivity Analysis: Angler Effort with RT Pop. 200% of Initial Value

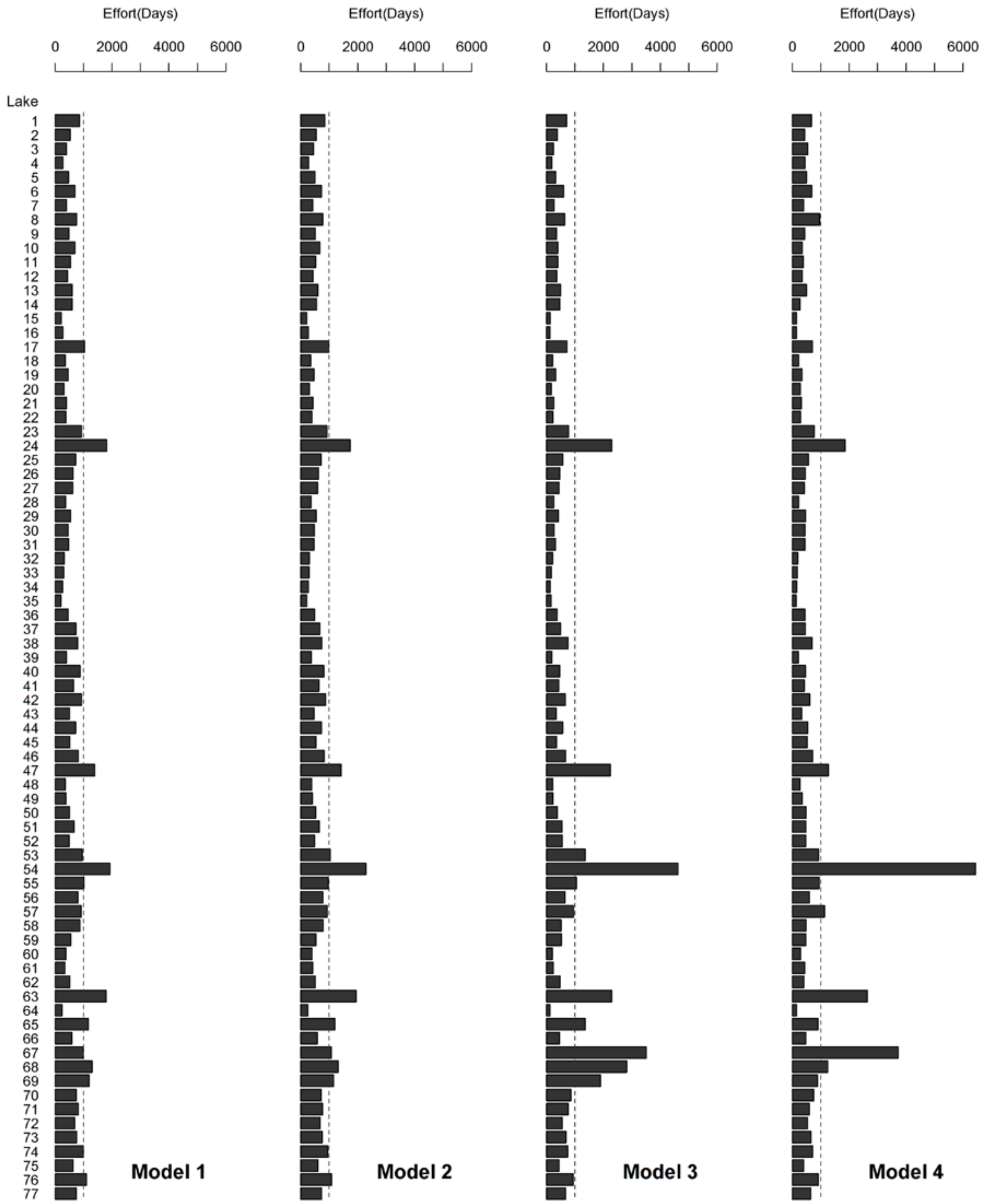

Figure B5. Sensitivity Analysis: Angler Effort with Exploitable Area = 5ha

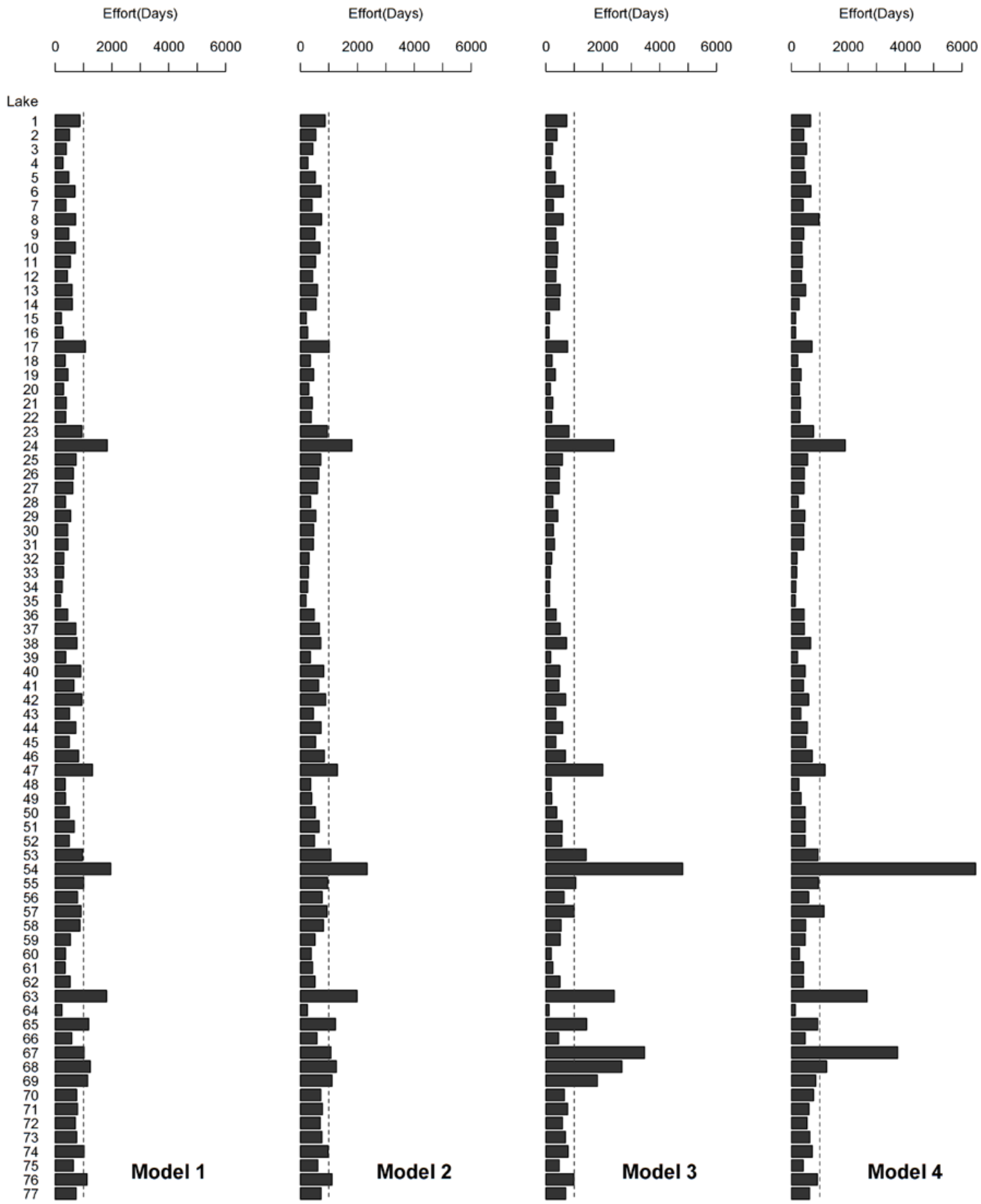

Figure B6. **Sensitivity Analysis: Angler Effort with Exploitable Area = 20ha**

Angler Effort by Class by Model

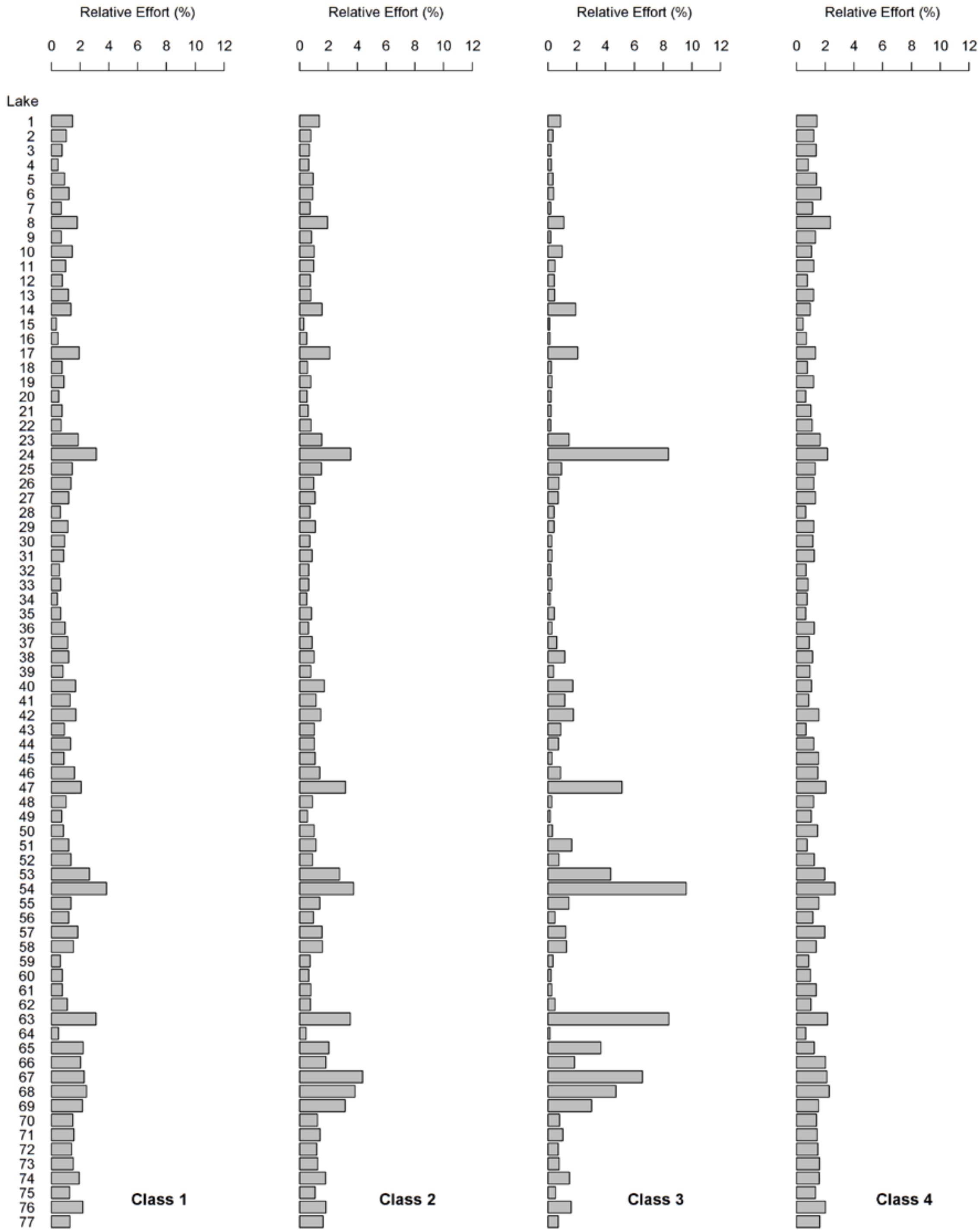

Figure B7. **4C-ME - Sensitivity Analysis: Class Effort with Specialization SD = 0**

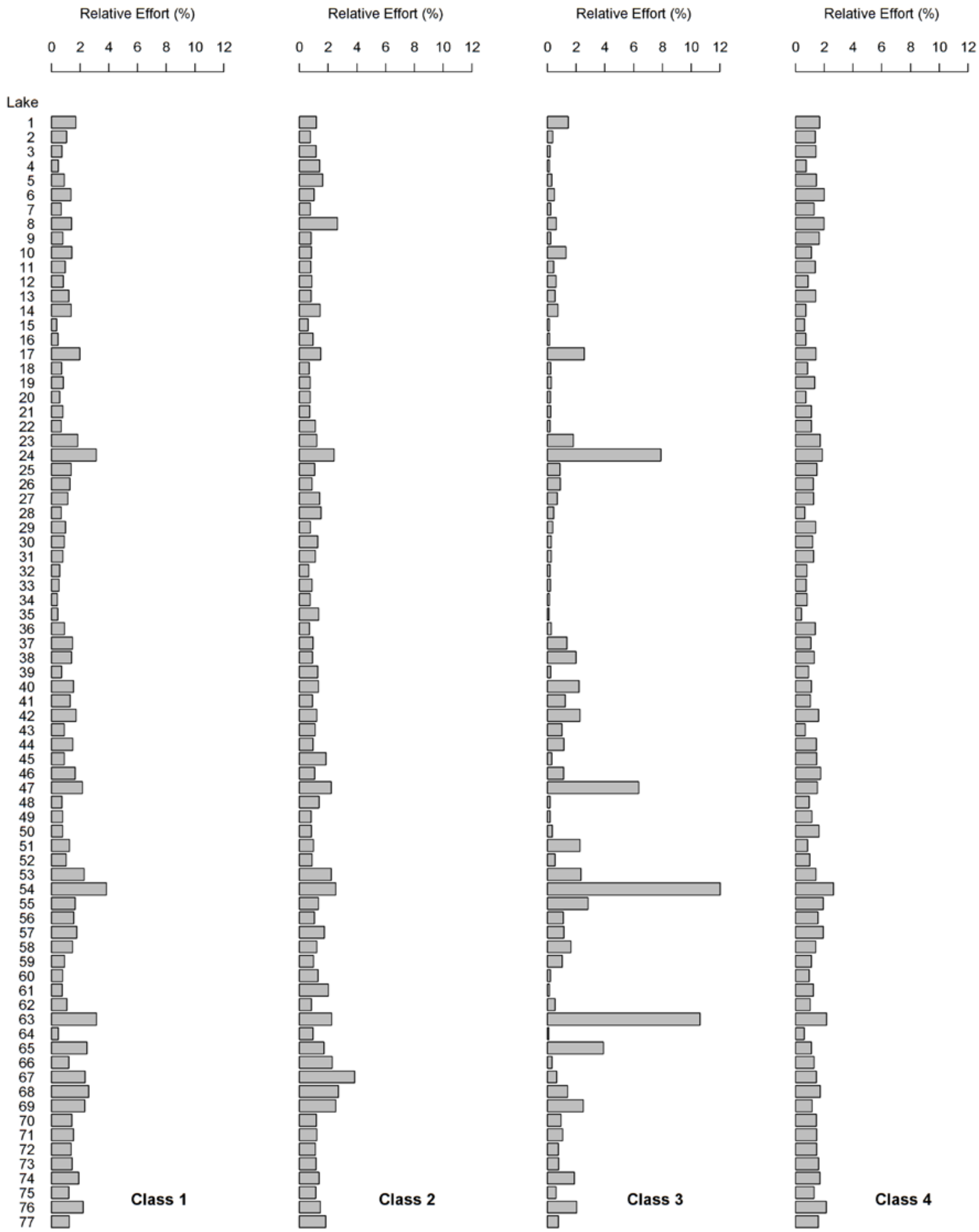

Figure B8. **4C-ME - Sensitivity Analysis: Class Effort with Specialization SD = 9**

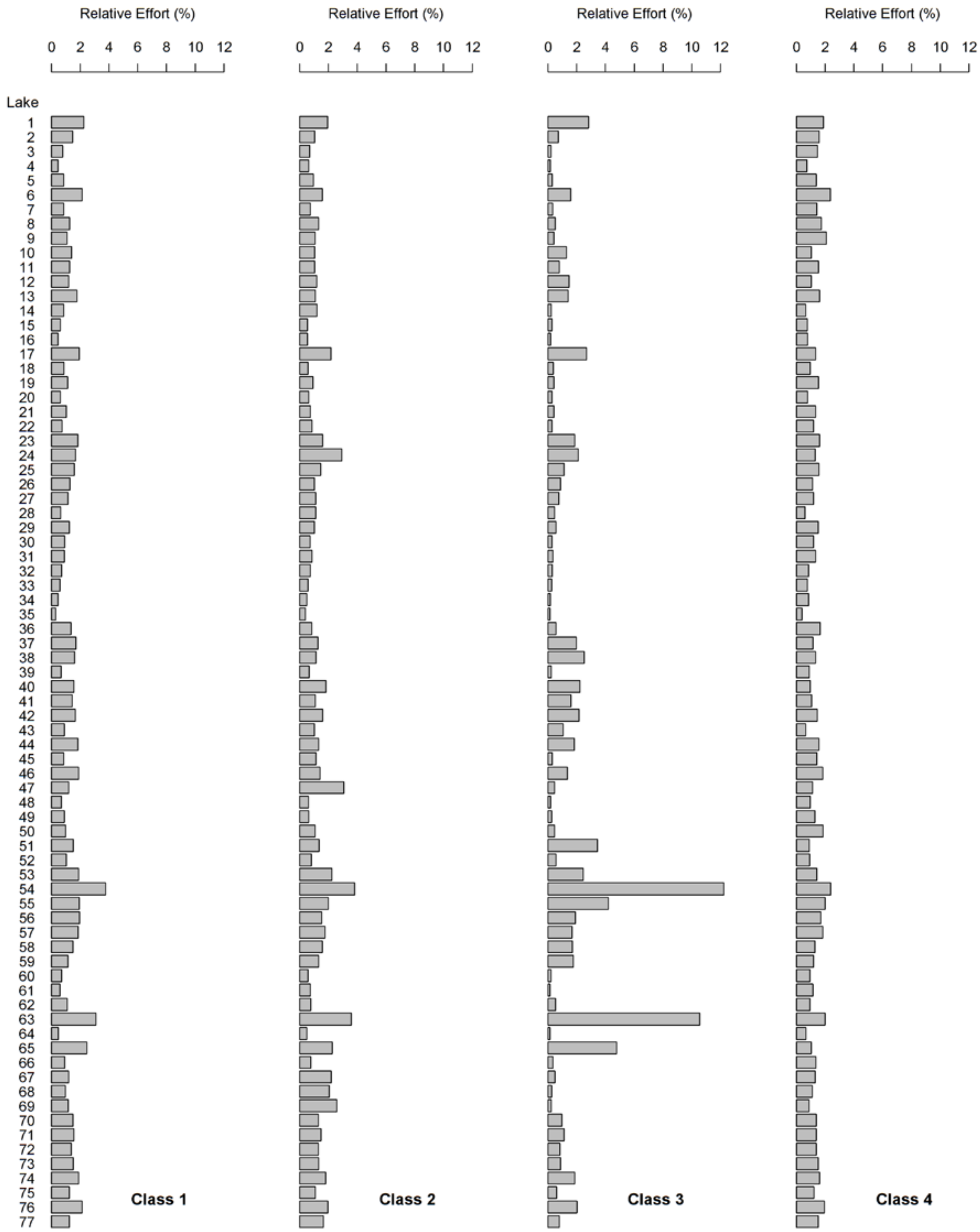

Figure B9. **4C-ME - Sensitivity Analysis: Class Effort with RT Pop. 50% of Initial Value**

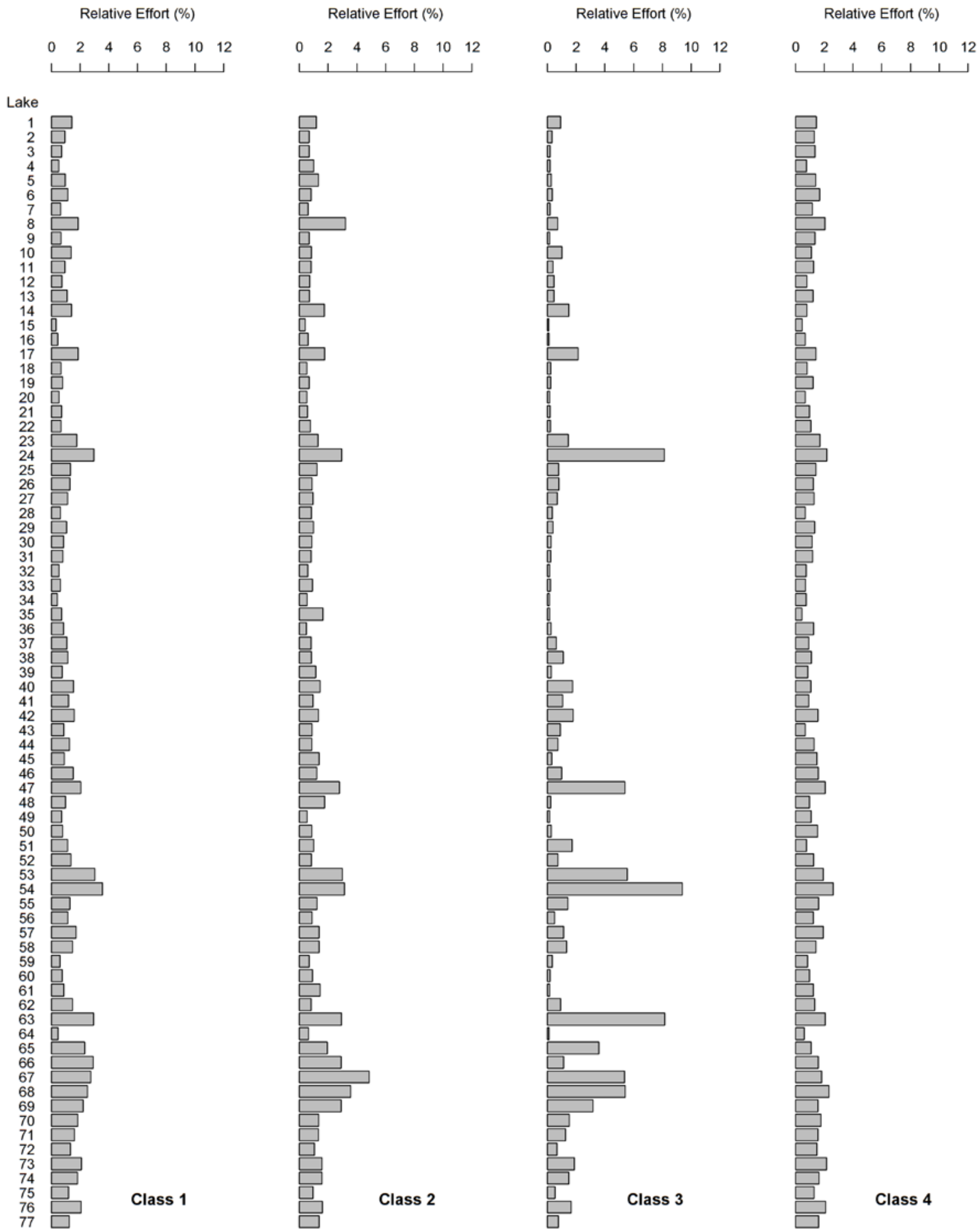

Figure B10. 4C-ME - Sensitivity Analysis: Class Effort with RT Pop. 200% of Initial Value

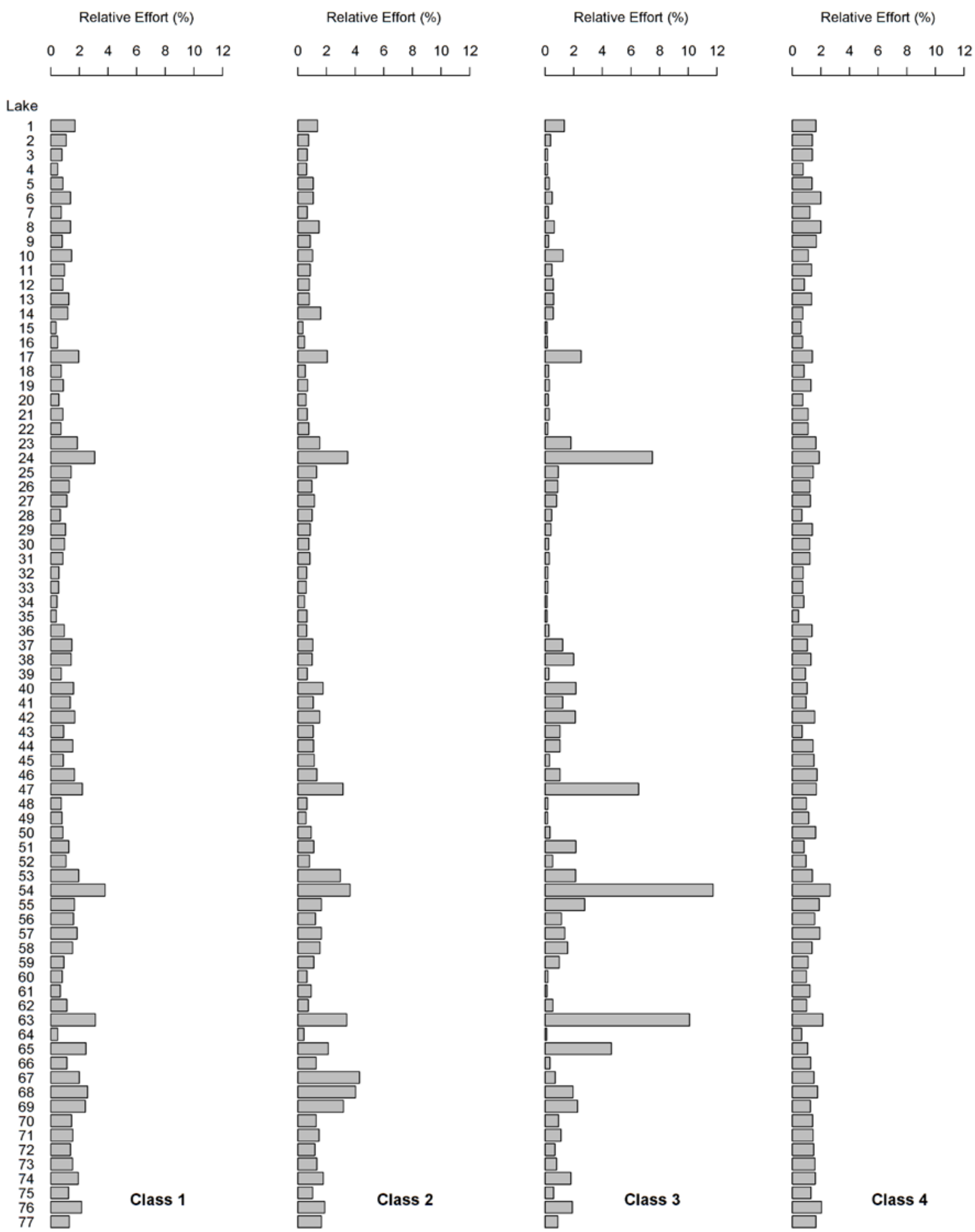

Figure B11. 4C-ME - Sensitivity Analysis: Class Effort with Exploitable Area = 5ha

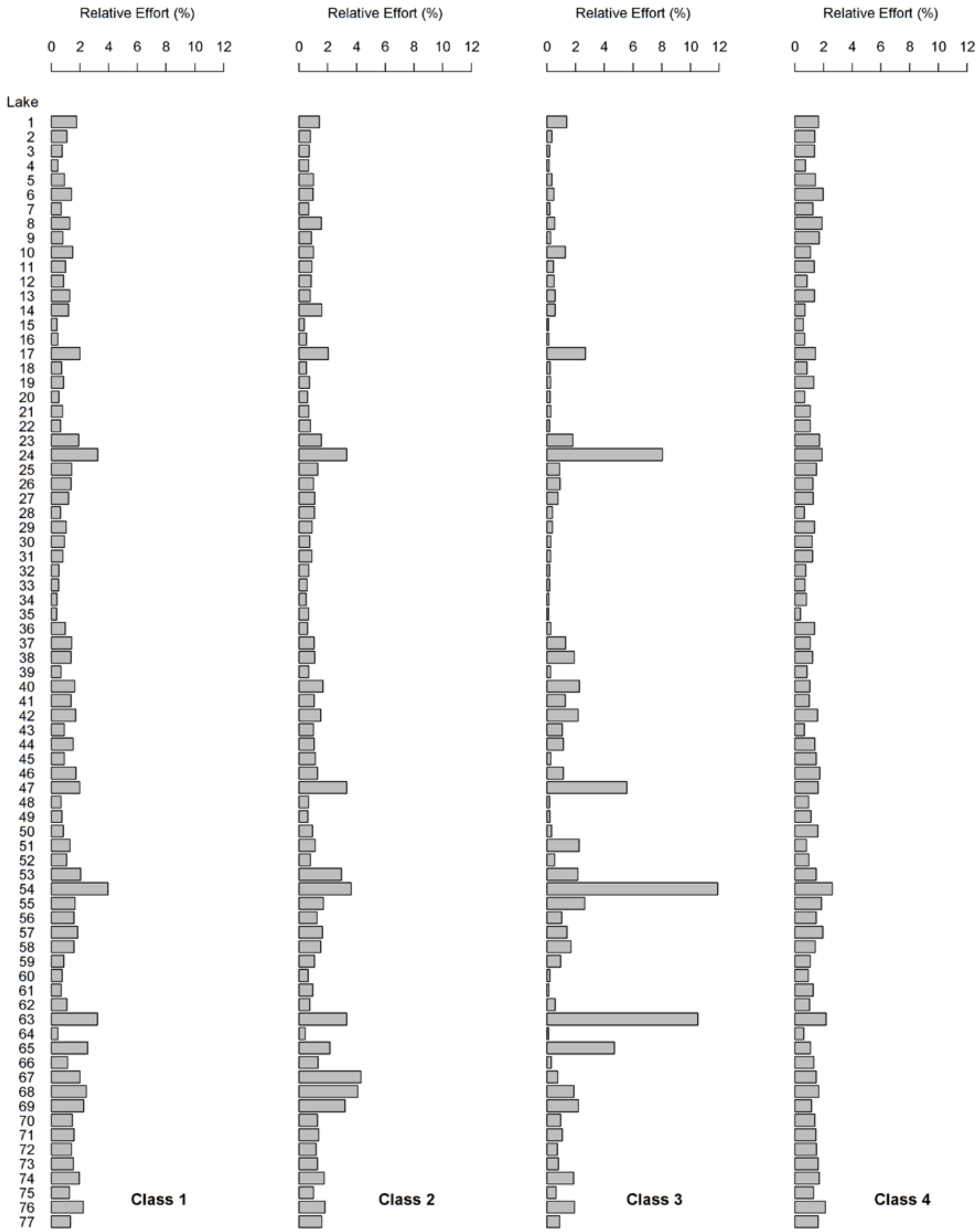

Figure B12. 4C-ME - Sensitivity Analysis: Class Effort with Exploitable Area = 20 ha

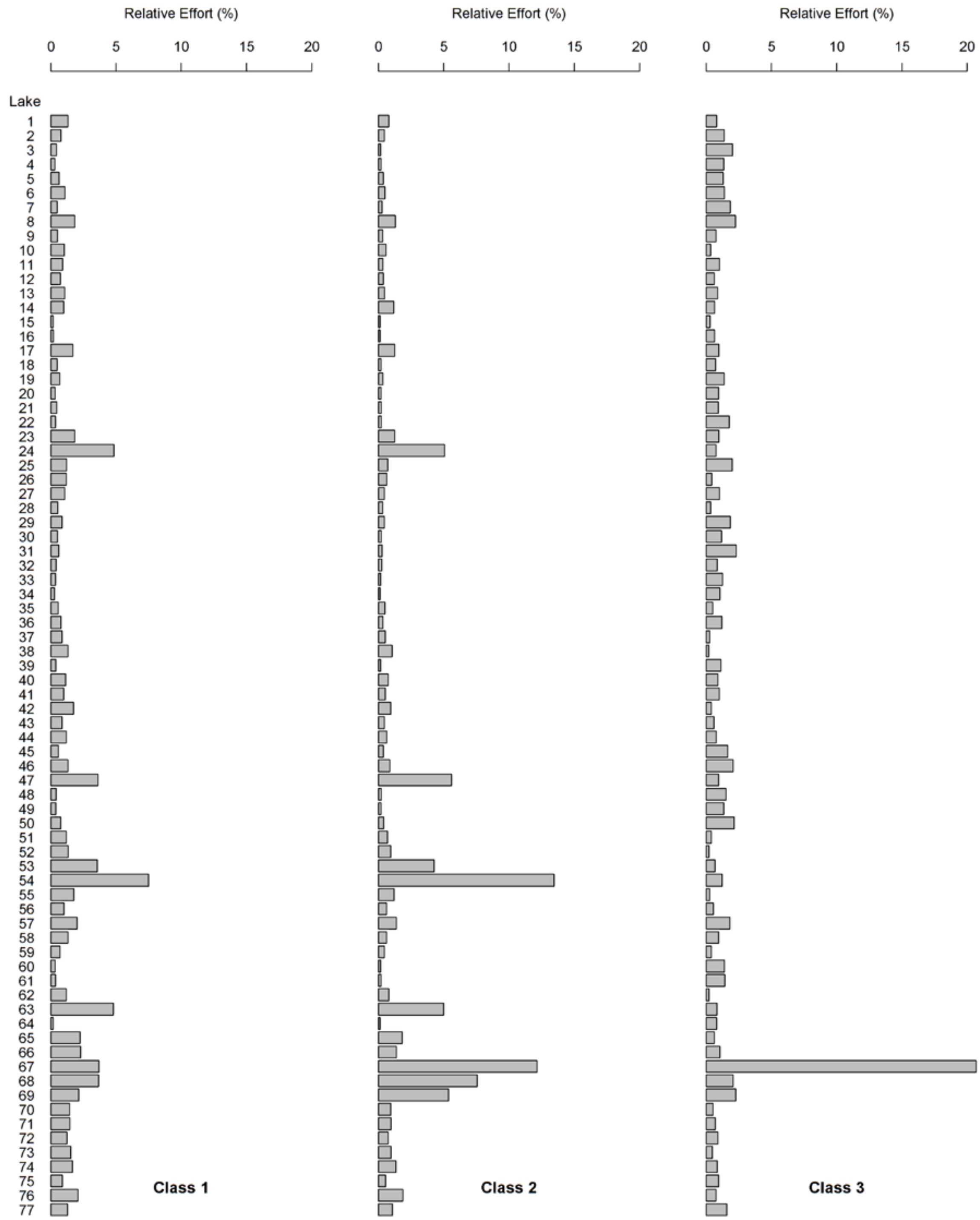

Figure B13. 3C-INT - Sensitivity Analysis: Class Effort with Specialization SD = 0
***Note rescaled x-axis**

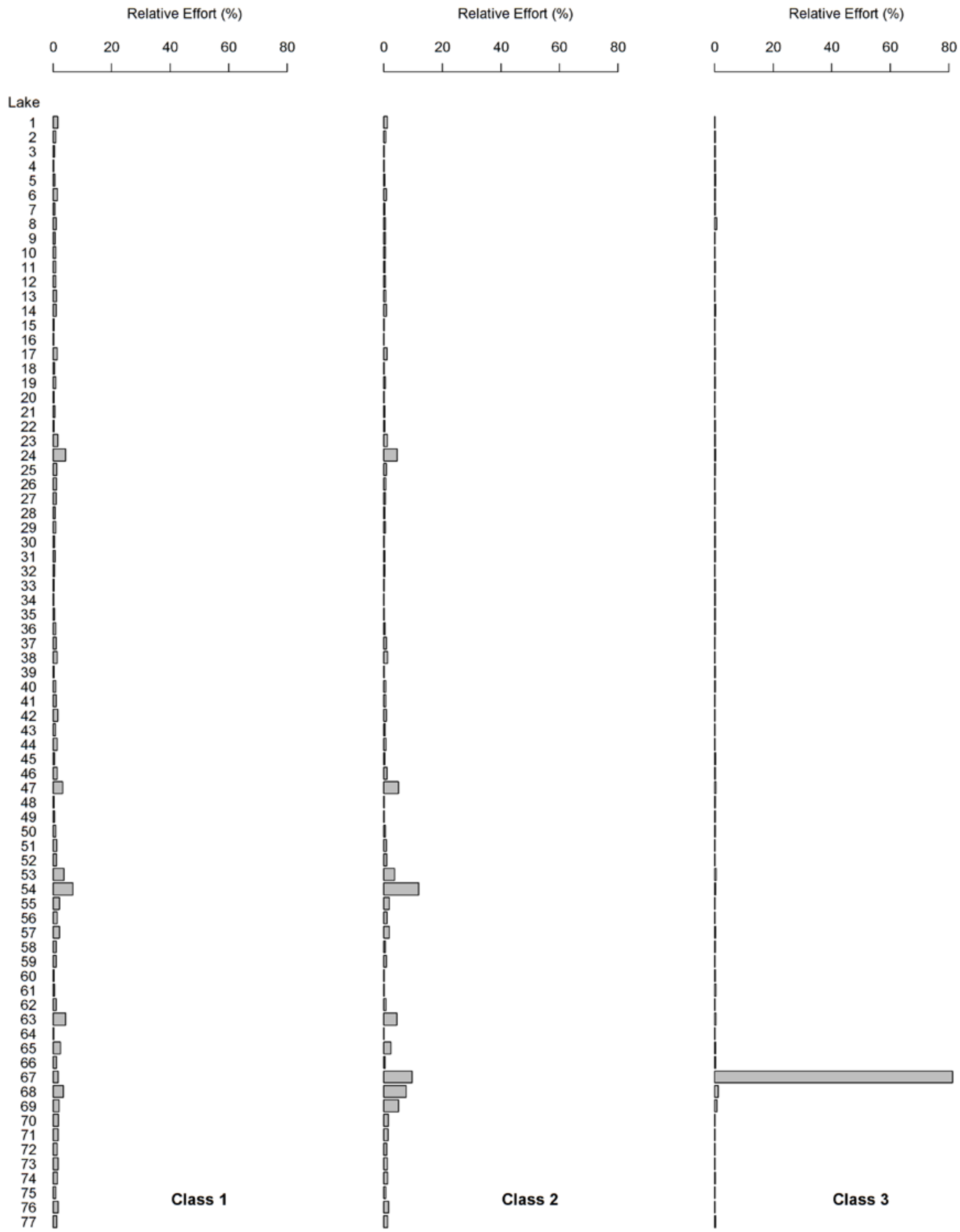

Figure B14. 3C-INT - Sensitivity Analysis: Class Effort with Specialization SD = 9
***Note rescaled x-axis**

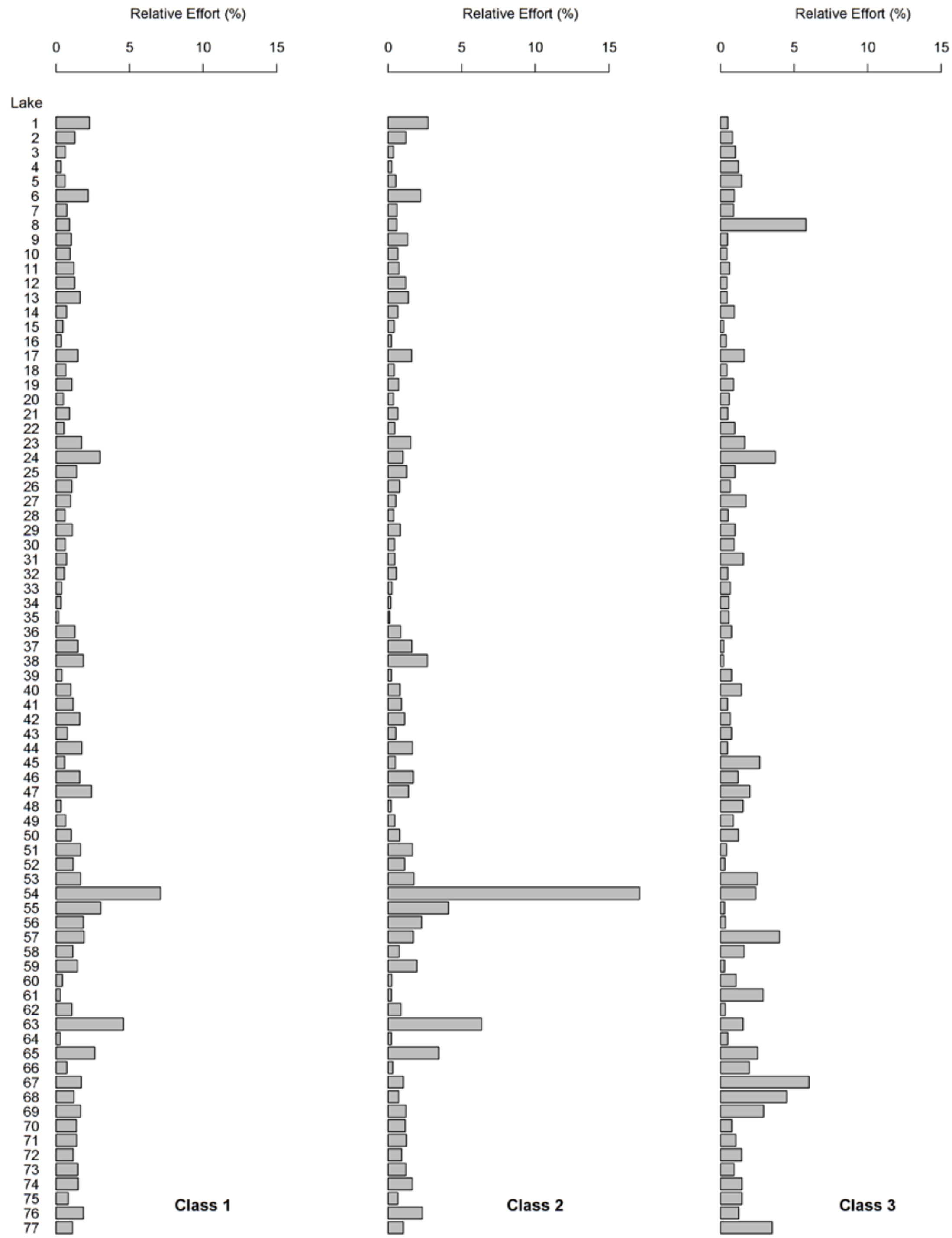

Figure B15. 3C-INT - Sensitivity Analysis: Class Effort with RT Pop. 50% of Initial Value

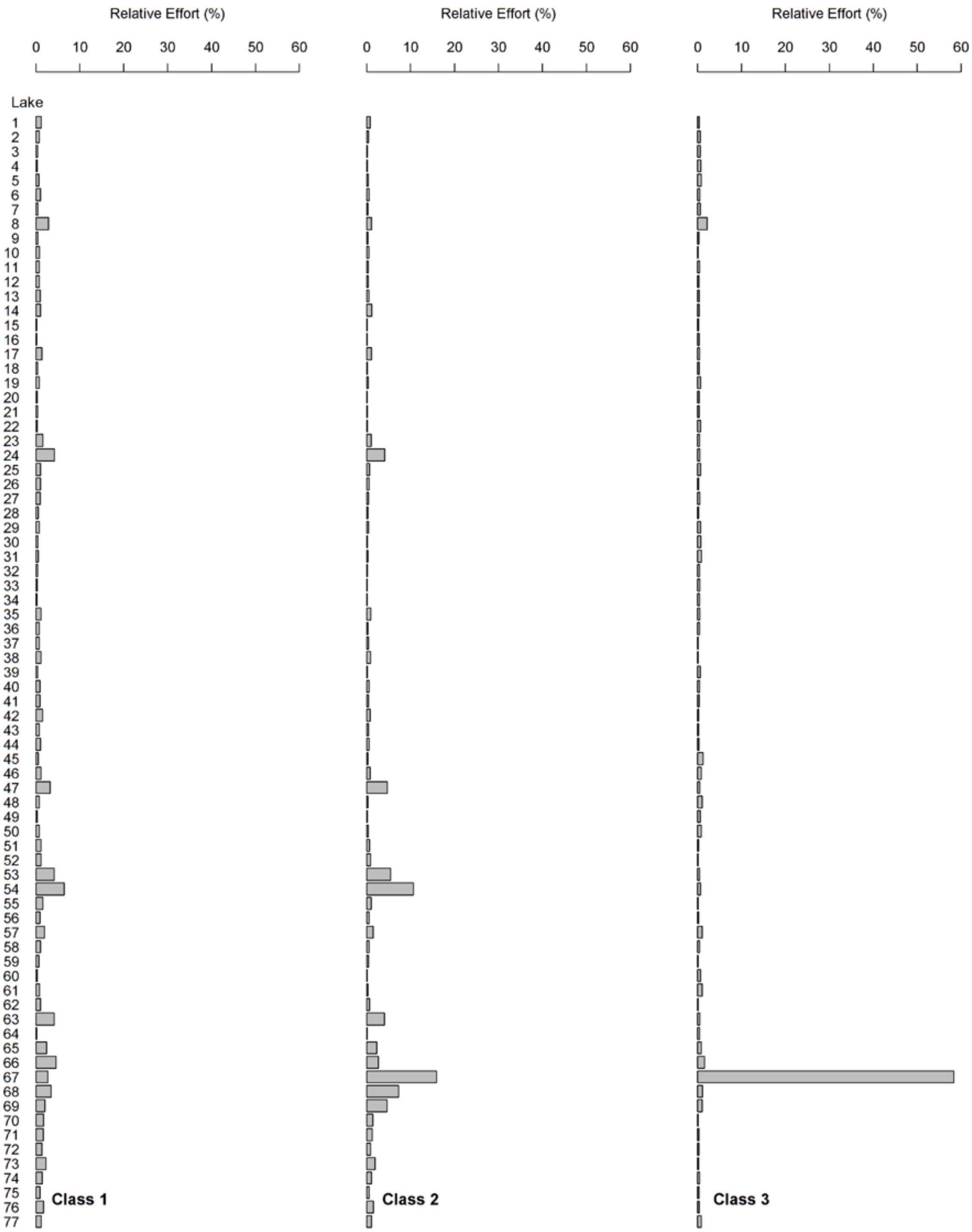

Figure B16. 3C-INT - Sensitivity Analysis: Class Effort with RT Pop. 200% of Initial Value. *Note rescaled x-axis

Figure B17. 3C-INT - Sensitivity Analysis: Class Effort with Exploitable Area = 5ha

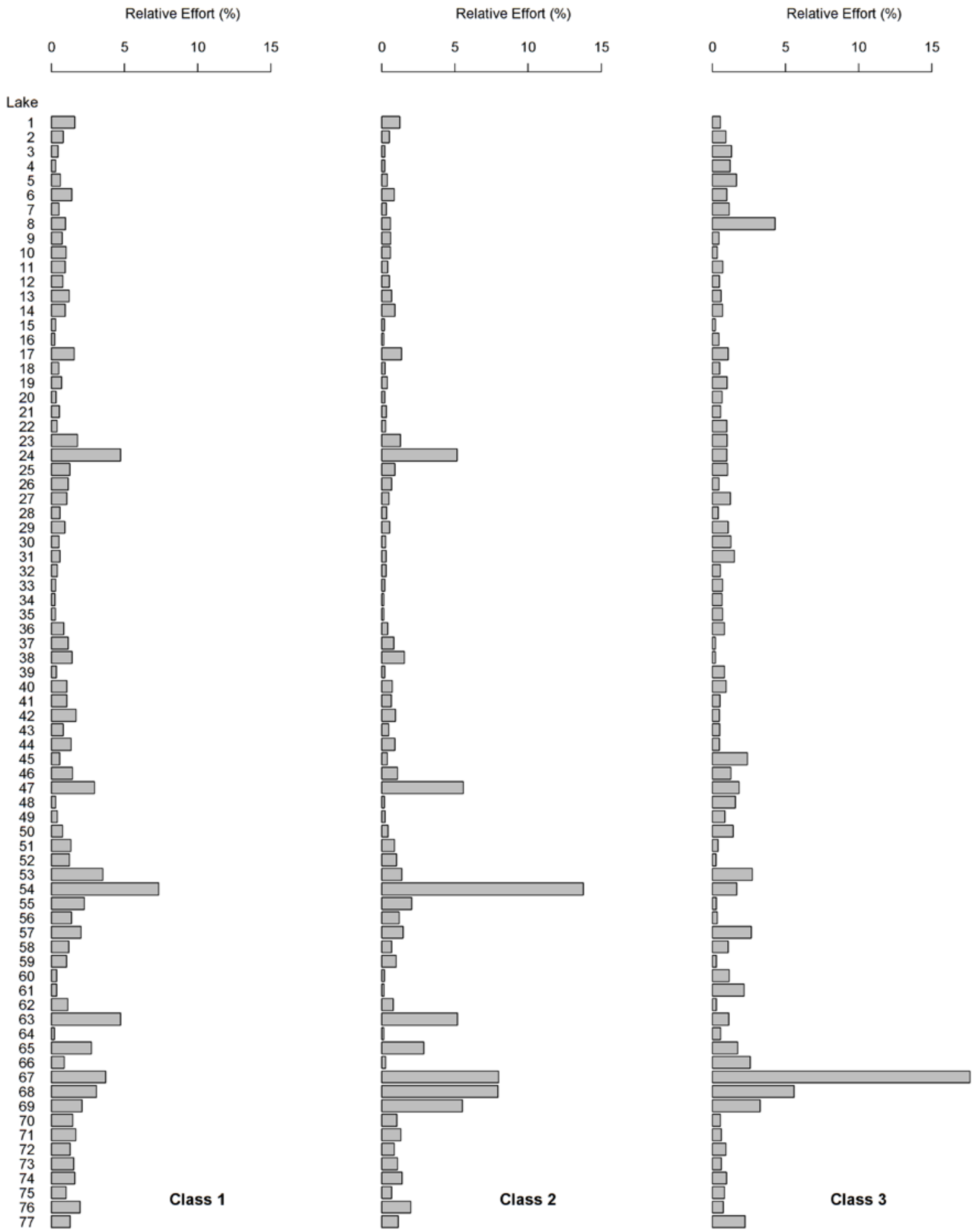

Figure B18. 3C-INT - Sensitivity Analysis: Class Effort with Exploitable Area = 20ha

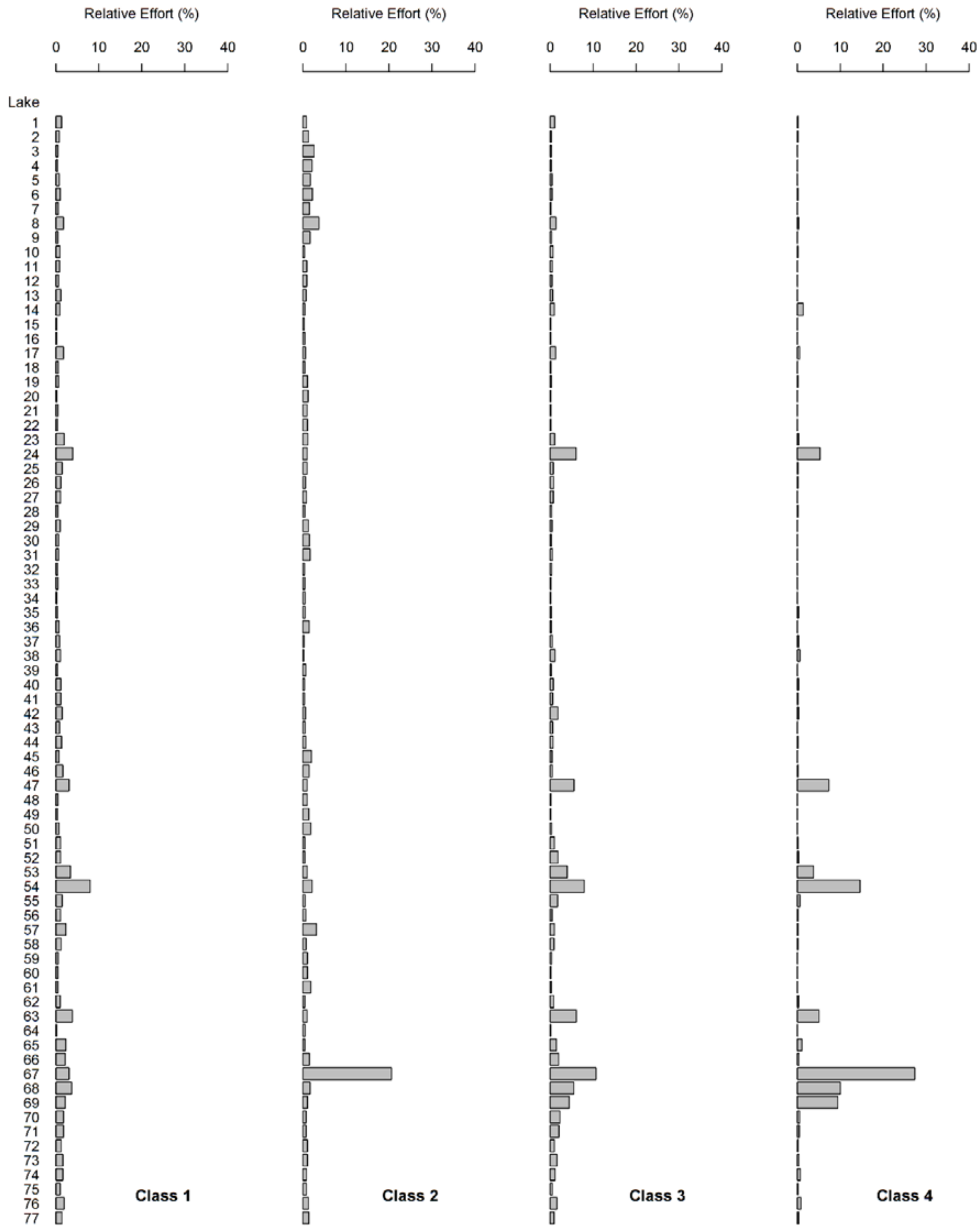

Figure B19. 4C-INT - Sensitivity Analysis: Class Effort with Catch Efficiency SD = 0

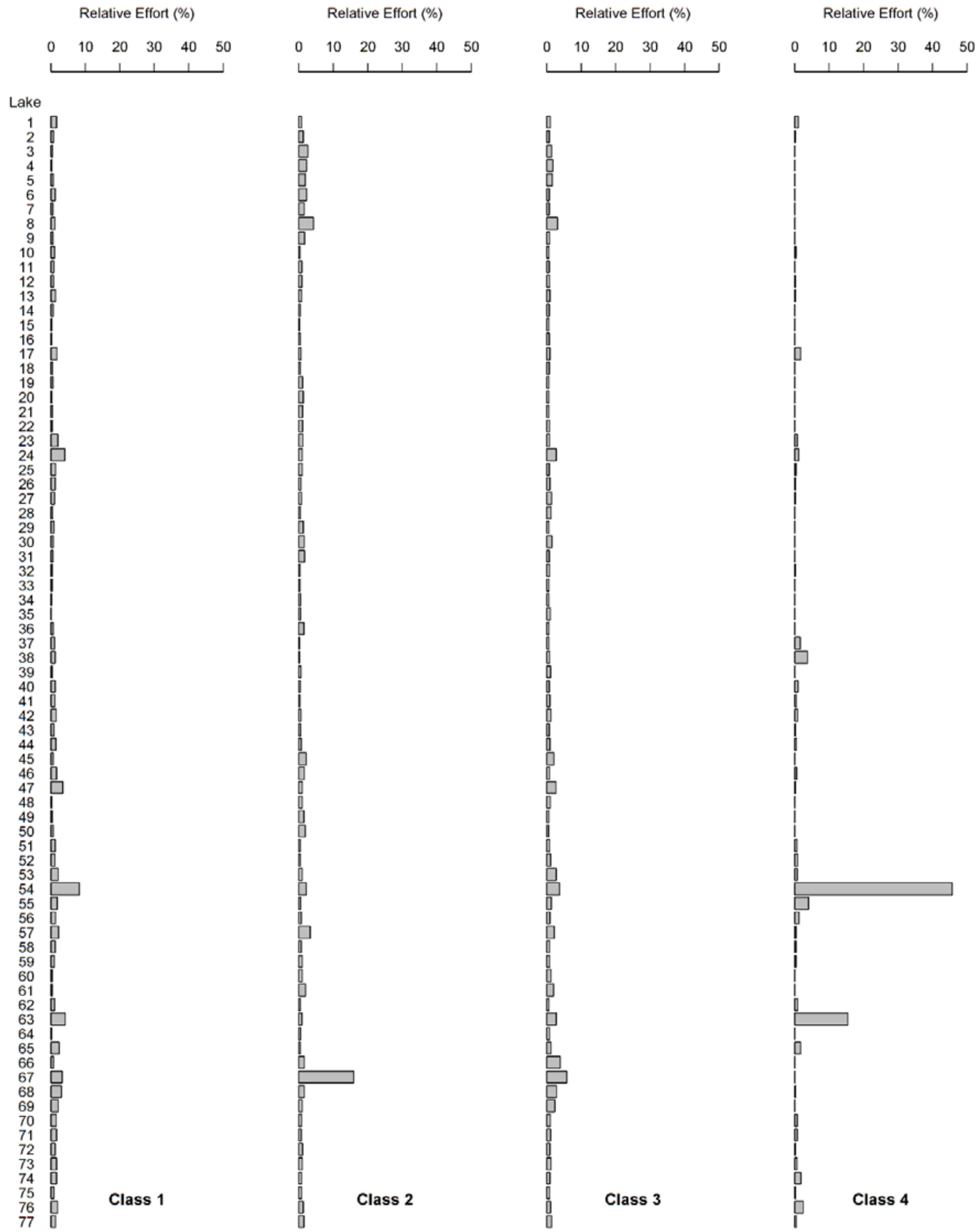

Figure B20. 4C-INT - Sensitivity Analysis: Class Effort with Catch Efficiency SD = 9

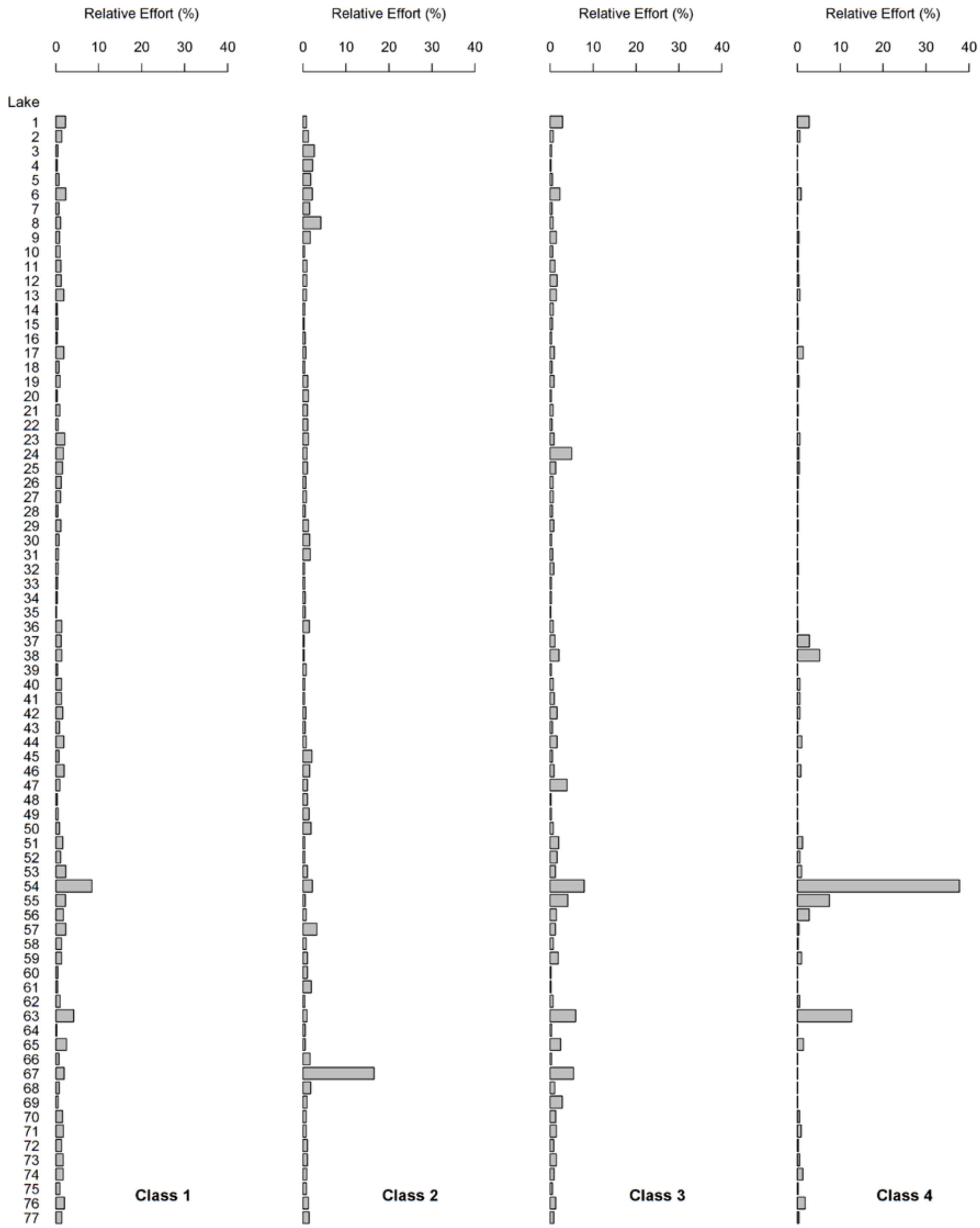

Figure B21. 4C-INT - Sensitivity Analysis: Class Effort with RT Pop. 50% of Initial Value

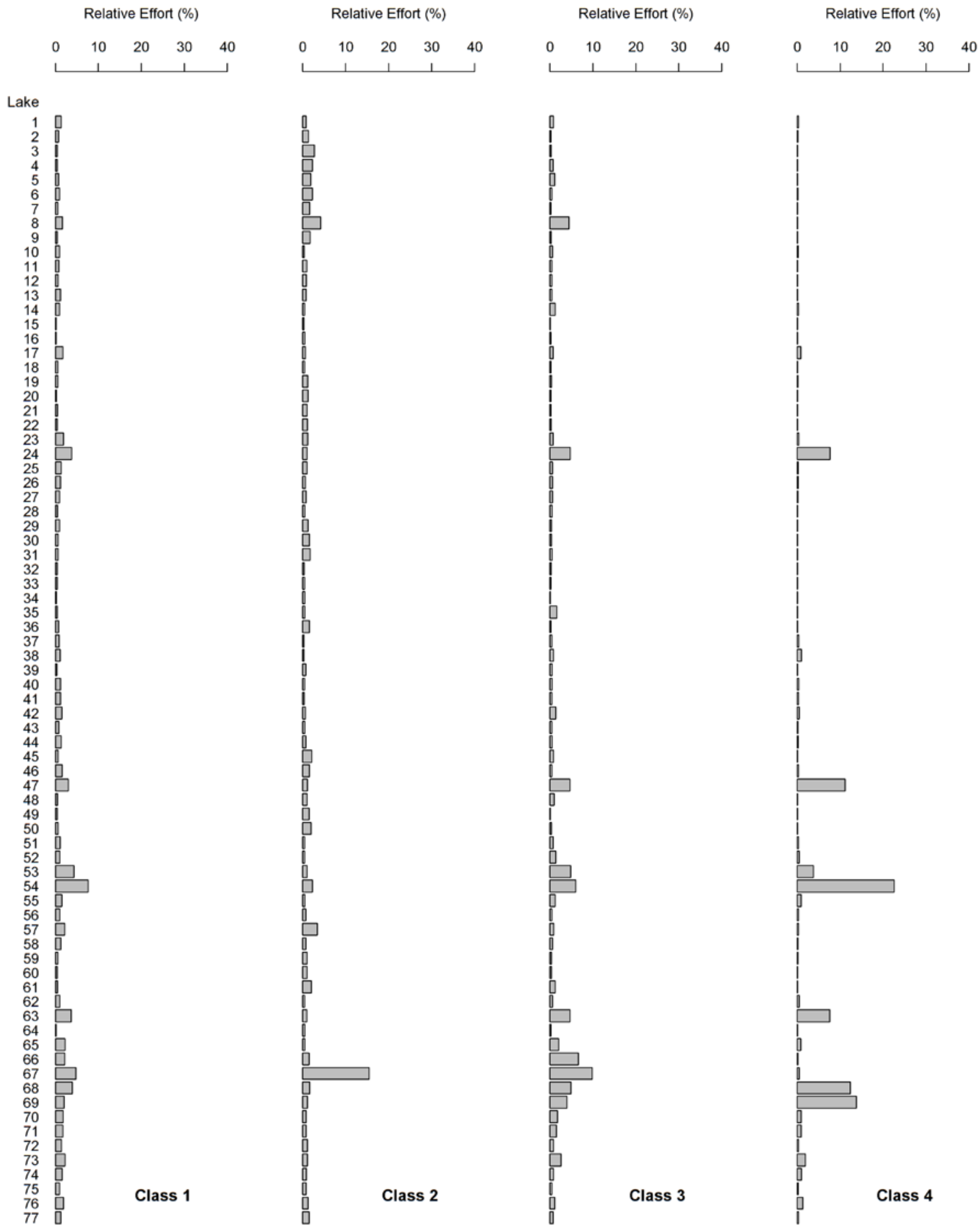

Figure B22. 4C-INT - Sensitivity Analysis: Class Effort with RT Pop. 200% of Initial Value

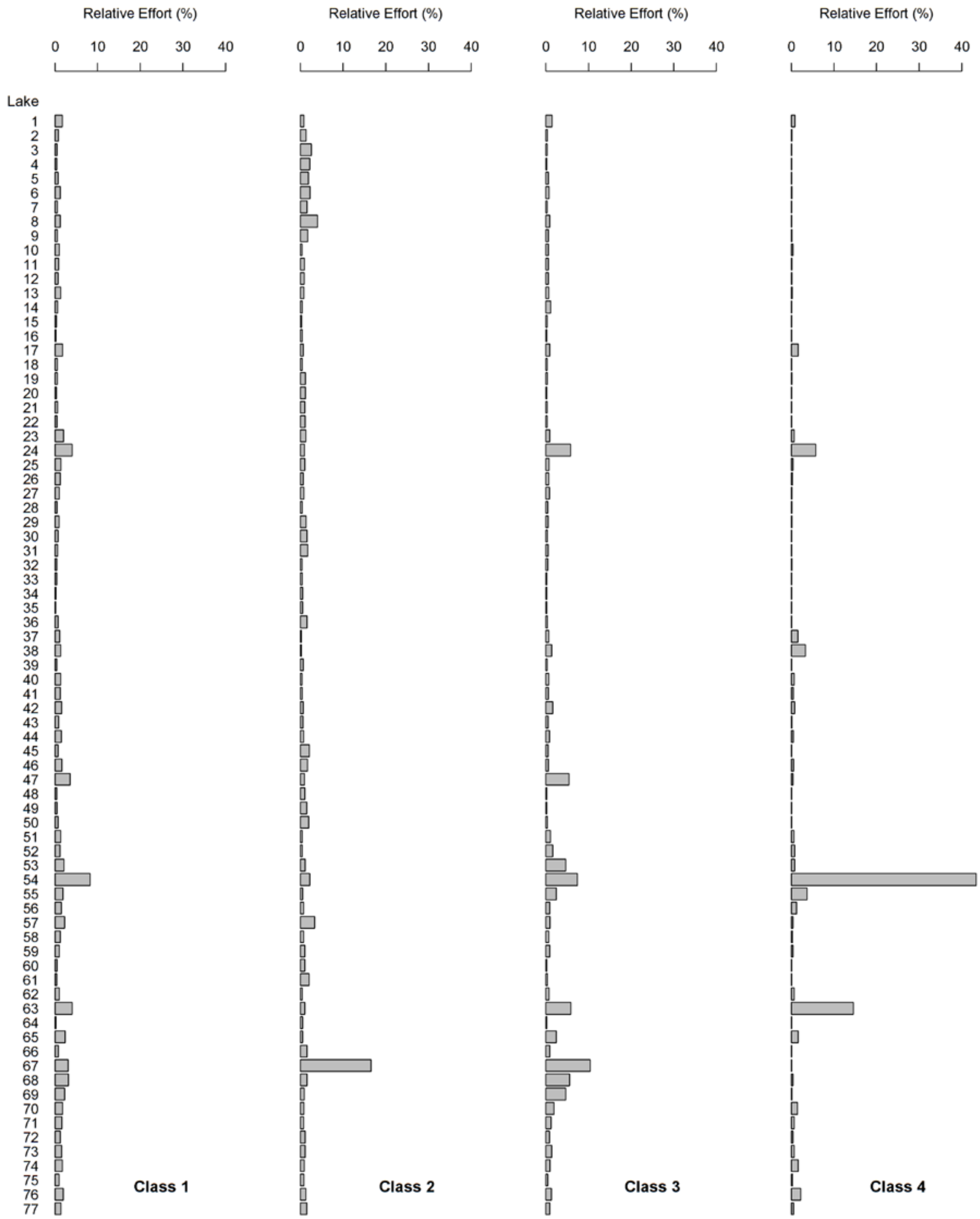

Figure B23. 4C-INT - Sensitivity Analysis: Class Effort with Exploitable Area = 5ha

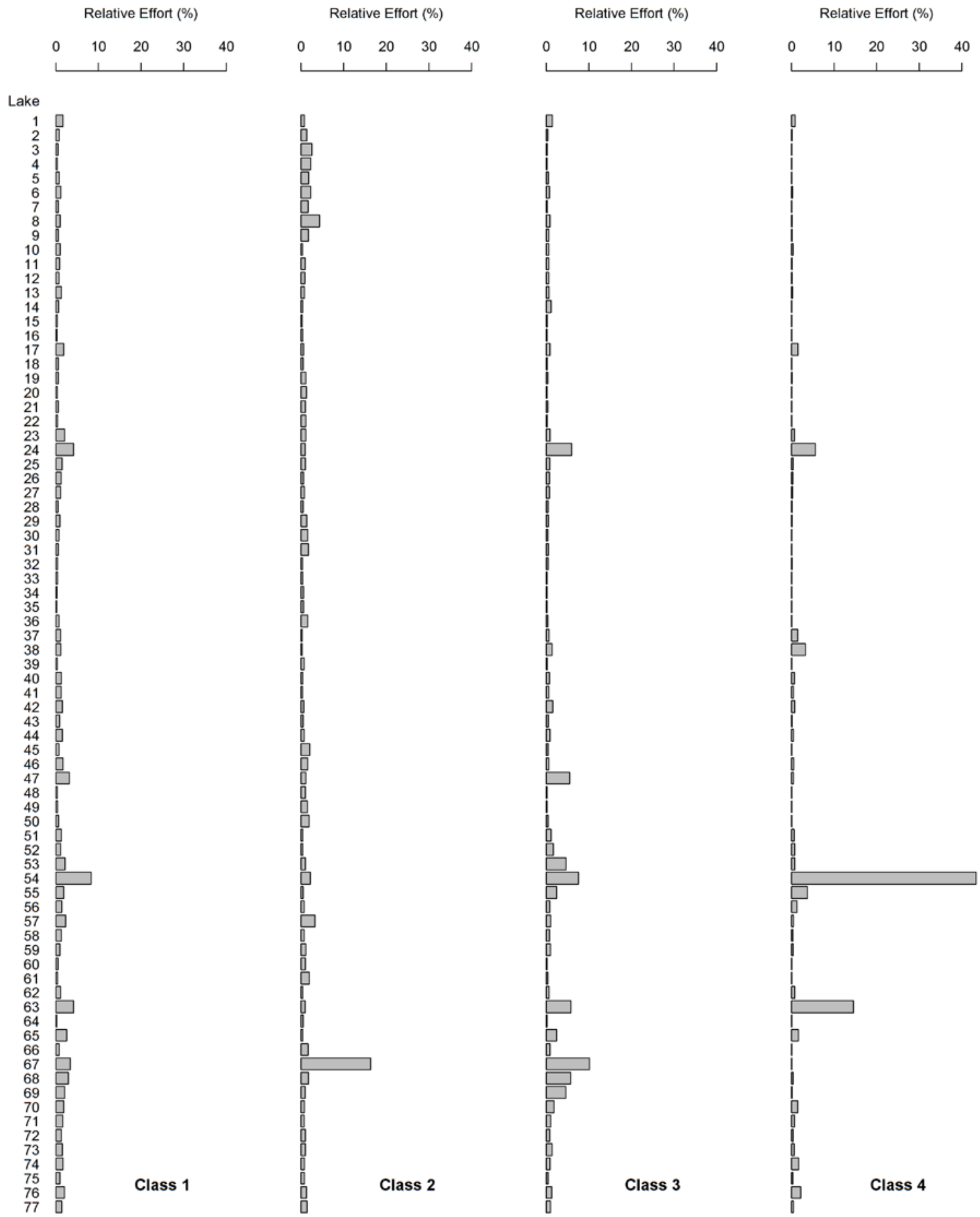

Figure B24. 4C-INT - Sensitivity Analysis: Class Effort with Exploitable Area = 20ha

Instantaneous Fishing Mortality Rate

Table B2. Range of Instantaneous Mortality Rate (F) Relative to Initial Value

	4C-ME	3C-INT	4C-INT
Initial Value	0.5270	1.6460	0.9430
Catchability (SD=0)	0.0939	1.2703	0.6546
Catchability (SD=9)	1.0545	1.8591	0.9805
Rainbow Trout Pop 50% of Initial Value	0.4458	1.6971	1.8774
Rainbow Trout Pop. 200% of Initial Value	0.3232	2.0163	0.7470
Exploitable Area (5ha)	0.5868	1.6637	0.9274
Exploitable Area (20ha)	0.5689	1.7013	0.9722

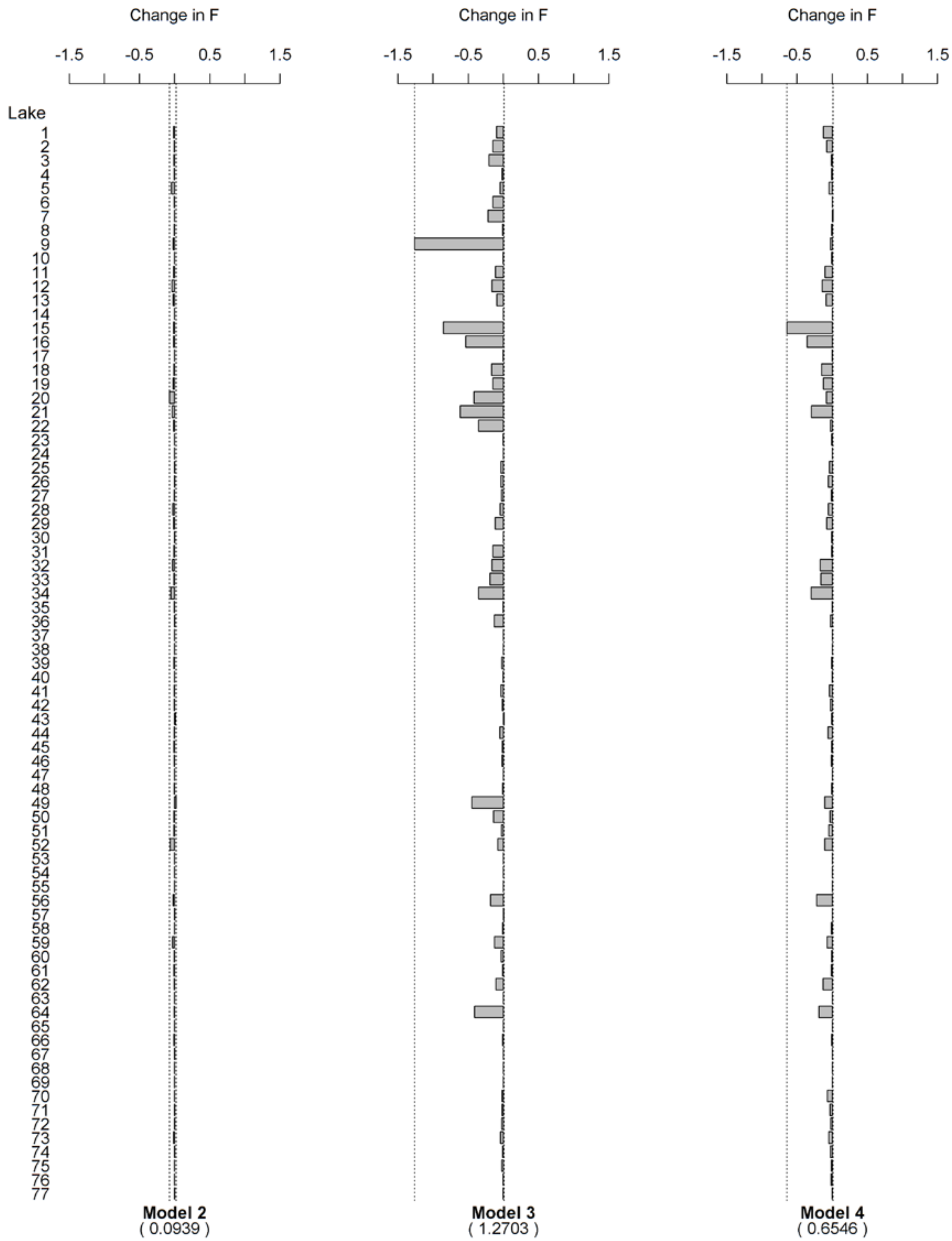

Figure B25. Sensitivity Analysis: Range of F with Specialization SD = 0

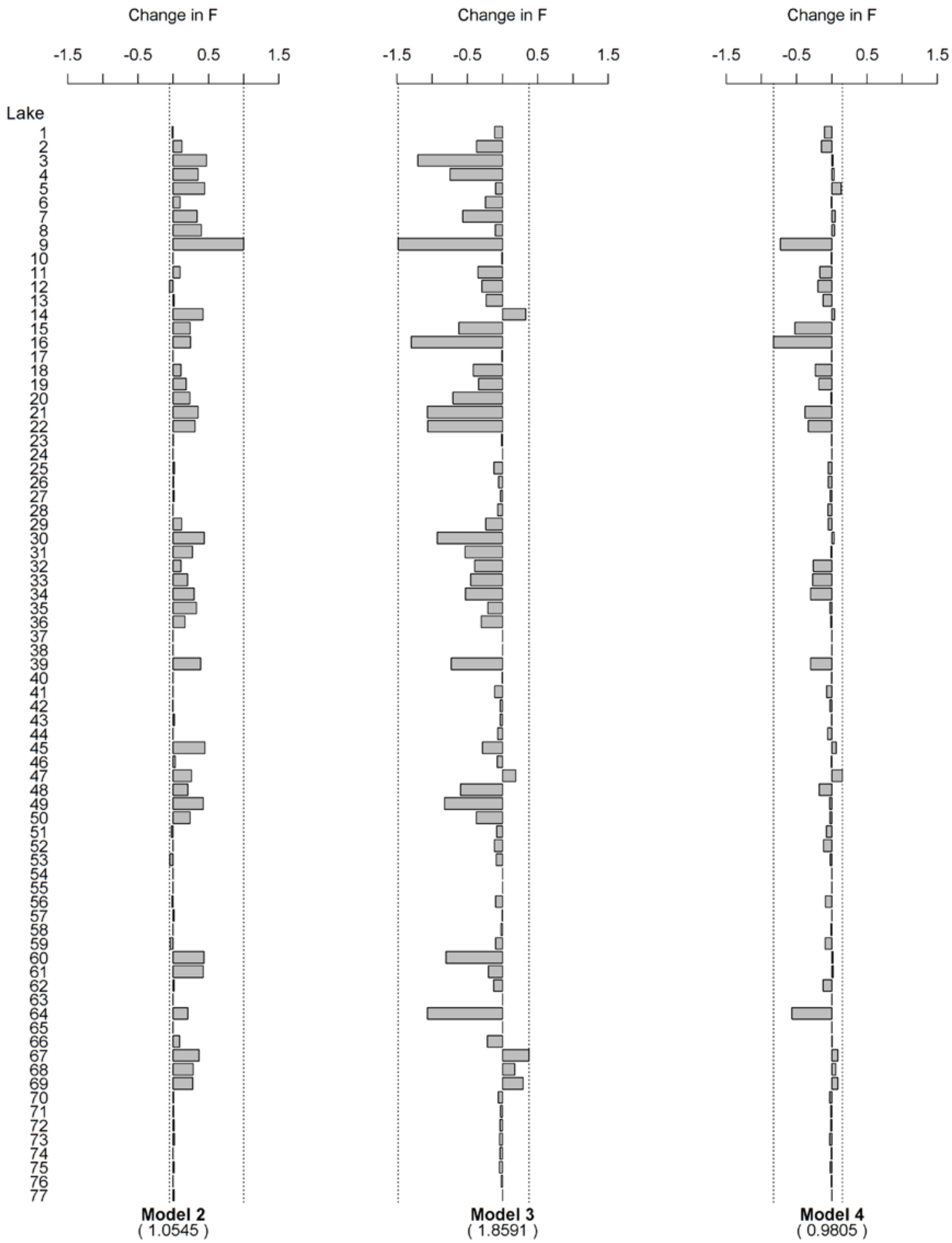

Figure B26. Sensitivity Analysis: Range of F with Specialization SD = 9

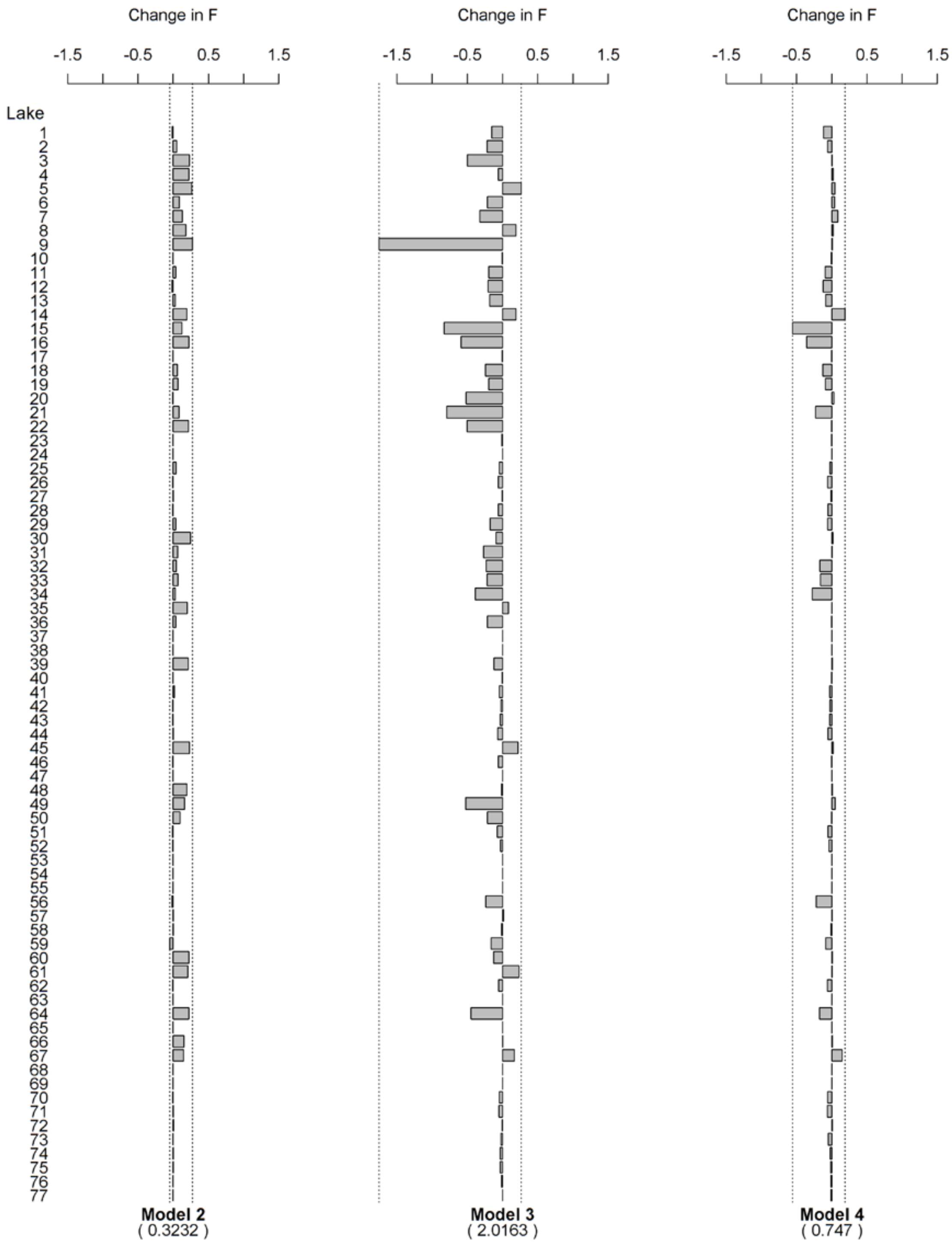

Figure B27. Sensitivity Analysis: Range of F with RT Pop. 50% of Initial Value

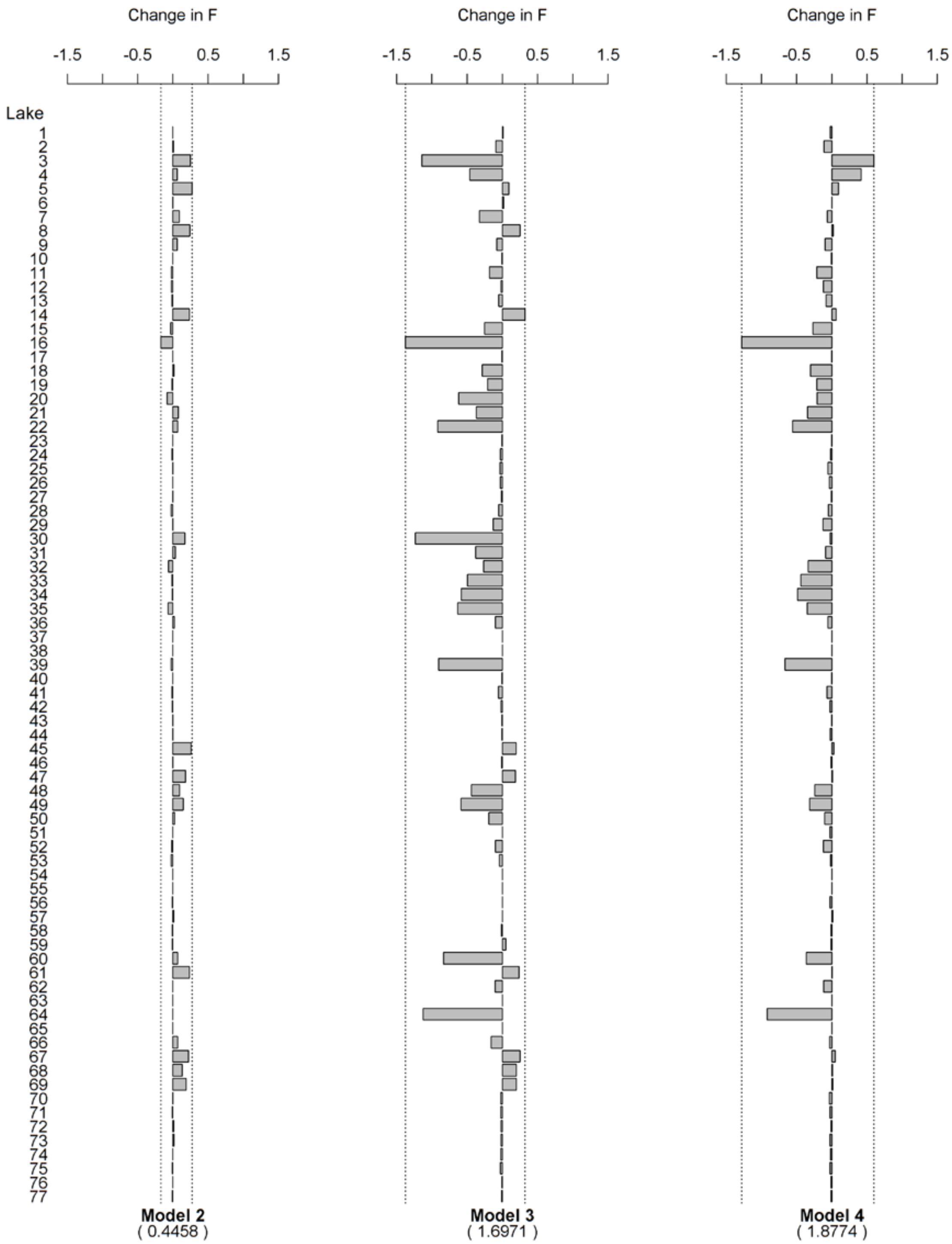

Figure B28. Sensitivity Analysis: Range of F with RT Pop. 200% of Initial Value

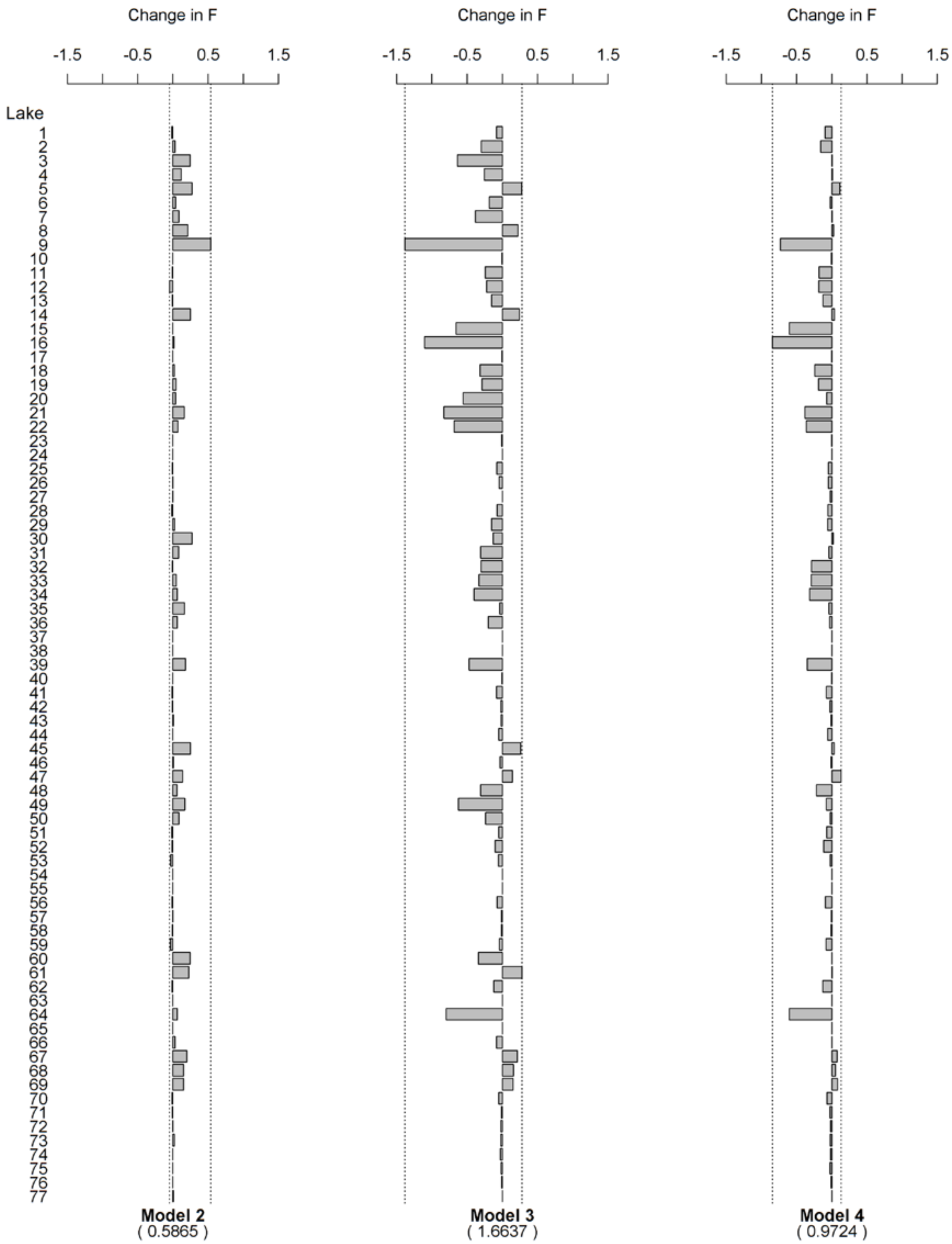

Figure B29. Sensitivity Analysis: Range of F with Exploitable Area = 5ha

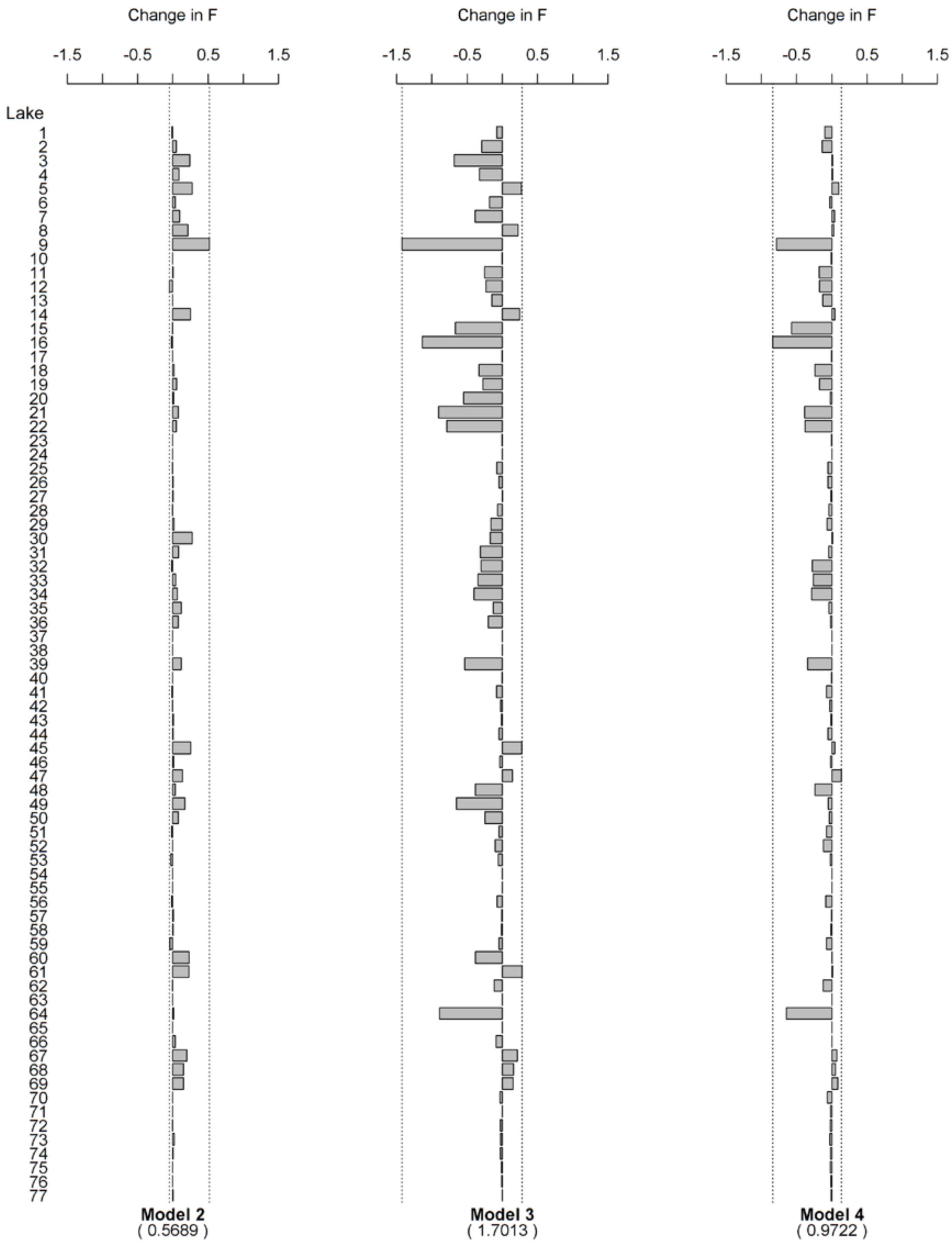

Figure B30. Sensitivity Analysis: Range of F with Exploitable Area = 20ha

Appendix C.

Choice Model Parameters

Table C1. Choice Model Parameter Codes

Code	Name	Description
SP*XXX	Species	Interaction between attribute (XXX) and species (Rainbow Trout) †
DUR*XXX	Duration	Interaction between attribute (XXX) and whether trip was single or multiple day
GEO*XXX	Geography	Interaction between attribute (XXX) and whether anglers were from the Lower Mainland
SI*XXX	Specialization	Interaction between attribute (XXX) and angler specialization score

† The DCE accounted for variation in target species (Rainbow Trout or Kokanee) with Kokanee as the baseline. My model is limited to Rainbow Trout anglers so preferences included interactions with Species.

Table C2. MNL Parameters

Attributes	Class1	s.e.	z-value
Intercept	0.838	0.025	33.745
Species	0.395	0.024	16.403
Catch	0.067	0.017	3.965
Size	0.429	0.023	18.786
Take	0.400	0.042	9.475
Gear (lvl 0)	0.054	0.022	2.488
Gear (lvl 1)	-0.048	0.024	-2.013
Gear (lvl 2)	0.131	0.024	5.415
Gear (lvl 3)	-0.137	0.025	-5.504
Lake	0.100	0.013	7.670
Motor (lvl 0)	0.042	0.018	2.326
Motor (lvl 1)	0.061	0.015	3.931
Motor (lvl 2	-0.103	0.018	-5.597
Boat (lvl 0)	-0.071	0.021	-3.381
Boat (lvl 1)	0.026	0.018	1.419
Boat (lvl 2)	0.045	0.016	2.805
Crowding	-0.067	0.018	-3.830
Distance	-0.803	0.045	-17.991

Table C3. 4C-ME Parameters

Attributes	Class1	s.e.	z-value	Class2	s.e.	z-value	Class3	s.e.	z-value	Class4	s.e.	z-value
Intercept	3.485	0.208	16.795	-0.571	0.055	-10.311	1.288	0.190	6.771	0.842	0.053	15.919
Species	0.124	0.043	2.883	0.472	0.064	7.386	2.137	0.200	10.712	0.327	0.051	6.475
Catch	0.085	0.032	2.678	0.004	0.042	0.087	0.117	0.079	1.483	0.103	0.037	2.770
Size	0.397	0.044	9.030	0.562	0.056	10.026	1.190	0.142	8.355	0.155	0.050	3.118
Take	0.394	0.080	4.947	0.792	0.107	7.404	0.590	0.299	1.973	0.466	0.089	5.241
Gear (lvl 0)	0.079	0.040	2.001	0.071	0.054	1.326	-0.171	0.105	-1.625	0.117	0.048	2.463
Gear (lvl 1)	0.033	0.047	0.704	-0.157	0.054	-2.914	-0.172	0.117	-1.470	0.013	0.052	0.255
Gear (lvl 2)	0.080	0.045	1.775	0.108	0.056	1.918	0.104	0.101	1.026	0.220	0.054	4.073
Gear (lvl 3)	-0.192	0.047	-4.105	-0.022	0.058	-0.386	0.239	0.118	2.023	-0.350	0.056	-6.210
Lake	0.086	0.025	3.433	0.121	0.033	3.611	0.095	0.064	1.499	0.086	0.028	3.077
Motor (lvl 0)	0.038	0.032	1.191	0.072	0.044	1.647	0.140	0.100	1.398	0.057	0.038	1.497
Motor (lvl 1)	0.084	0.028	3.012	-0.038	0.038	-1.010	0.093	0.070	1.324	0.080	0.033	2.400
Motor (lvl 2	-0.122	0.033	-3.670	-0.034	0.045	-0.764	-0.233	0.111	-2.098	-0.137	0.039	-3.501
Boat (lvl 0)	-0.147	0.039	-3.736	0.043	0.051	0.831	-0.125	0.099	-1.261	0.022	0.045	0.493
Boat (lvl 1)	0.066	0.033	1.975	-0.047	0.045	-1.053	-0.032	0.082	-0.395	-0.018	0.040	-0.466
Boat (lvl 2)	0.081	0.030	2.743	0.004	0.041	0.107	0.157	0.075	2.102	-0.004	0.035	-0.105
Crowding	-0.125	0.031	-3.978	0.062	0.042	1.472	-0.136	0.087	-1.554	-0.083	0.037	-2.230
Distance	-0.810	0.086	-9.446	-1.060	0.112	-9.447	-1.253	0.233	-5.368	-1.192	0.098	-12.205

Table C4. 3C-INT Parameters

Attributes	Class1	s.e.	z-value	Class2	s.e.	z-value	Class3	s.e.	z-value
Intercept	3.114	0.163	19.156	-0.648	0.101	-6.413	2.372	0.242	9.815
Species	0.427	0.062	6.888	0.560	0.095	5.881	1.314	0.213	6.163
Catch	0.141	0.038	3.701	0.028	0.059	0.481	0.192	0.128	1.502
Size	0.455	0.082	5.538	0.769	0.126	6.086	0.497	0.218	2.282
Take	0.485	0.086	5.665	0.655	0.130	5.028	0.261	0.350	0.746
Gear (lvl 1)	-0.011	0.050	-0.227	-0.055	0.064	-0.848	-0.451	0.137	-3.298
Gear (lvl 2)	0.121	0.045	2.677	0.078	0.058	1.349	0.004	0.130	0.029
Gear (lvl 3)	-0.175	0.045	-3.922	-0.066	0.060	-1.116	0.179	0.138	1.297
Lake	0.129	0.027	4.857	0.069	0.041	1.697	0.002	0.088	0.024
Motor (lvl 1)	0.057	0.030	1.915	0.061	0.048	1.258	0.380	0.107	3.566
Motor (lvl 2	-0.066	0.034	-1.927	-0.246	0.061	-4.036	-0.212	0.113	-1.872
Boat (lvl 1)	0.111	0.034	3.290	-0.042	0.055	-0.755	0.056	0.111	0.508
Boat (lvl 2)	0.103	0.034	3.021	0.034	0.055	0.617	-0.006	0.097	-0.059
Crowding	-0.122	0.040	-3.037	0.016	0.055	0.294	-0.077	0.113	-0.681
Distance	-1.087	0.093	-11.632	-1.475	0.152	-9.723	-2.128	0.392	-5.425
SP*Catch	0.017	0.039	0.442	0.103	0.058	1.787	-0.310	0.127	-2.443
SP*Size	0.107	0.090	1.185	-0.205	0.126	-1.632	0.470	0.217	2.168
SP*Take	0.220	0.101	2.173	0.181	0.138	1.308	1.806	0.301	5.996
SP*Gear	0.032	0.032	0.995	-0.070	0.051	-1.385	-0.007	0.096	-0.070
SP*Lake	-0.030	0.024	-1.245	0.068	0.039	1.745	0.067	0.068	0.977
SP*Motor (lvl 1)	0.040	0.029	1.383	-0.110	0.046	-2.402	-0.322	0.087	-3.694
SP*Motor (lvl 2)	-0.113	0.036	-3.098	0.171	0.060	2.862	-0.001	0.091	-0.006
SP*Motor (lvl 3)	-0.038	0.034	-1.119	-0.078	0.055	-1.432	-0.079	0.093	-0.853
SP*Boat	-0.055	0.036	-1.546	0.041	0.055	0.754	-0.125	0.086	-1.452
SP*Crowding	-0.043	0.042	-1.020	-0.034	0.053	-0.636	0.333	0.104	3.206
SP*Distance	-0.061	0.078	-0.783	-0.178	0.129	-1.382	0.322	0.344	0.937
Duration	0.271	0.095	2.846	0.200	0.048	4.147	0.226	0.097	2.331
SP*Duration	0.094	0.035	2.704	0.013	0.064	0.197	0.082	0.095	0.865
DUR*Catch	0.021	0.025	0.843	0.027	0.041	0.653	-0.066	0.069	-0.957
DUR*Size	0.081	0.035	2.310	0.060	0.053	1.126	0.035	0.089	0.394
DUR*Take	0.185	0.062	2.982	-0.039	0.107	-0.369	0.158	0.165	0.960
DUR*Gear (lvl 1)	-0.065	0.038	-1.706	-0.096	0.052	-1.834	0.154	0.092	1.675
DUR*Gear (lvl 2)	0.069	0.037	1.874	0.088	0.054	1.632	0.117	0.090	1.293
DUR*Gear (lvl 3)	0.002	0.039	0.039	0.019	0.055	0.350	-0.214	0.099	-2.169
DUR*Lake	-0.019	0.019	-1.017	0.022	0.032	0.706	-0.051	0.048	-1.074
DUR*Motor (lvl 1)	0.031	0.023	1.367	0.027	0.037	0.727	0.007	0.054	0.119
DUR*Motor (lvl 2)	-0.054	0.027	-1.974	-0.048	0.044	-1.101	0.024	0.066	0.355
DUR*Boat (lvl 1)	0.008	0.027	0.301	0.064	0.044	1.451	-0.004	0.065	-0.059
DUR*Boat (lvl 2)	-0.039	0.024	-1.637	0.006	0.039	0.148	0.012	0.062	0.200
DUR*Crowding	-0.030	0.026	-1.148	-0.006	0.041	-0.133	-0.008	0.066	-0.126
DUR*Distance	0.797	0.074	10.777	1.228	0.115	10.651	0.710	0.195	3.643

Attributes	Class1	s.e.	z-value	Class2	s.e.	z-value	Class3	s.e.	z-value
Geography	0.377	0.125	3.021	0.276	0.060	4.600	0.955	0.207	4.611
SP*GEO	-0.133	0.041	-3.263	0.148	0.070	2.111	1.083	0.168	6.463
GEO*Catch	0.012	0.028	0.439	-0.040	0.044	-0.897	0.408	0.094	4.324
GEO*Size	-0.073	0.038	-1.894	-0.082	0.058	-1.407	0.883	0.140	6.299
GEO*Take	0.096	0.068	1.420	0.311	0.113	2.740	-1.196	0.321	-3.728
GEO*Gear (lvl 1)	0.032	0.042	0.770	0.083	0.056	1.480	-0.388	0.124	-3.128
GEO*Gear (lvl 2)	-0.011	0.041	-0.269	-0.109	0.057	-1.900	-0.027	0.138	-0.196
GEO*Gear (lvl 3)	-0.090	0.042	-2.126	0.012	0.059	0.206	0.774	0.141	5.485
GEO*Lake	-0.006	0.021	-0.266	-0.034	0.034	-1.009	-0.073	0.073	-1.006
GEO*Motor (lvl 1)	0.019	0.024	0.758	0.052	0.039	1.343	0.088	0.080	1.097
GEO*Motor (lvl 2)	0.009	0.029	0.304	0.058	0.046	1.247	-0.155	0.103	-1.511
GEO*Boat (lvl 1)	0.046	0.030	1.556	0.038	0.046	0.834	0.024	0.093	0.253
GEO*Boat (lvl 2)	-0.074	0.026	-2.890	0.052	0.043	1.199	-0.010	0.083	-0.121
GEO*Crowding	0.008	0.028	0.271	-0.008	0.044	-0.191	-0.256	0.096	-2.655
GEO*Distance	0.145	0.087	1.676	0.207	0.135	1.533	0.140	0.317	0.440
Specialization	0.272	0.127	2.136	0.118	0.057	2.094	-0.044	0.130	-0.339
SI*SP	-0.098	0.039	-2.497	0.019	0.075	0.252	0.636	0.162	3.926
SI*Catch	0.029	0.028	1.038	0.106	0.049	2.183	0.044	0.081	0.541
SI*Size	0.139	0.038	3.618	0.600	0.065	9.218	0.009	0.107	0.081
SI*Take	-0.217	0.068	-3.203	0.119	0.124	0.957	0.265	0.222	1.192
SI*Gear (lvl 1)	-0.083	0.041	-2.020	-0.003	0.060	-0.051	-0.007	0.099	-0.075
SI*Gear (lvl 2)	0.053	0.040	1.307	-0.128	0.063	-2.031	0.029	0.111	0.260
SI*Gear (lvl 3)	0.098	0.042	2.320	0.275	0.063	4.393	-0.136	0.112	-1.214
SI*Lake	-0.034	0.021	-1.609	-0.006	0.037	-0.153	0.031	0.060	0.519
SI*Motor (lvl 1)	-0.037	0.024	-1.514	-0.007	0.041	-0.163	-0.012	0.064	-0.191
SI*Motor (lvl 2)	-0.028	0.030	-0.943	0.094	0.049	1.906	-0.047	0.076	-0.614
SI*Boat (lvl 1)	-0.037	0.030	-1.254	0.031	0.049	0.636	-0.008	0.078	-0.100
SI*Boat (lvl 2)	0.069	0.026	2.698	0.002	0.048	0.036	-0.031	0.074	-0.425
SI*Crowding	-0.041	0.028	-1.444	-0.040	0.047	-0.855	0.285	0.078	3.649
SI*Distance	0.107	0.075	1.443	-0.024	0.104	-0.230	0.292	0.259	1.127

Table C5. 4C-INT Parameters

Attributes	Class1	s.e.	z-value	Class2	s.e.	z-value	Class3	s.e.	z-value	Class4	s.e.	z-value
Intercept	4.5528	0.3053	14.9118	0.4394	0.129	3.4073	0.1065	1.6308	0.0653	-1.2864	0.201	0.0653
Species	0.2191	0.0636	3.448	0.0888	0.1042	0.8513	4.0492	1.6335	2.4789	1.0417	0.1955	2.4789
Catch	0.1084	0.039	2.7766	0.0963	0.0688	1.4003	0.5583	0.155	3.6025	-0.2504	0.1171	3.6025
Size	0.3354	0.088	3.8116	0.5458	0.136	4.0144	0.7429	0.2737	2.7144	0.7937	0.3083	2.7144
Take	0.5336	0.0925	5.7685	0.7862	0.1547	5.083	1.134	0.3589	3.1599	0.7522	0.2426	3.1599
Gear (lvl 1)	0.0493	0.0555	0.8869	-0.2646	0.0824	-3.2099	-0.3104	0.1967	-1.5777	0.2764	0.1115	-1.5777
Gear (lvl 2)	0.1022	0.0496	2.0593	0.2097	0.0844	2.4855	-0.0967	0.1143	-0.8462	-0.0095	0.0964	-0.8462
Gear (lvl 3)	-0.2357	0.0502	-4.7004	-0.3954	0.0936	-4.2227	0.4058	0.1295	3.1327	0.1404	0.0952	3.1327
Lake	0.0582	0.0286	2.0298	0.1188	0.0476	2.498	0.3493	0.091	3.8366	-0.0178	0.0834	3.8366
Motor (lvl 1)	0.0534	0.0313	1.7031	0.1374	0.0552	2.4908	0.3497	0.1441	2.4271	0.14	0.1068	2.4271
Motor (lvl 2	-0.051	0.0359	-1.4192	-0.1936	0.0708	-2.7342	-0.5257	0.1705	-3.0837	-0.415	0.1488	-3.0837
Boat (lvl 1)	0.0718	0.036	1.9964	-0.0049	0.064	-0.0761	0.7878	1.5879	0.4961	0.1048	0.1055	0.4961
Boat (lvl 2)	0.0791	0.0366	2.1627	0.0313	0.0624	0.5009	1.2745	1.5886	0.8023	-0.037	0.1145	0.8023
Crowding	-0.0775	0.0415	-1.8675	-0.1237	0.0682	-1.812	-0.1572	0.1483	-1.0601	0.2361	0.1151	-1.0601
Distance	-0.9159	0.0996	-9.1924	-2.1775	0.1812	-12.0198	-2.4193	0.372	-6.5031	-0.8431	0.3145	-6.5031
SP*Catch	0.0388	0.0415	0.9346	-0.0725	0.0656	-1.1057	-0.3378	0.1579	-2.139	0.3694	0.1214	-2.139
SP*Size	0.1864	0.0992	1.878	-0.5401	0.1377	-3.9221	0.4187	0.2795	1.4981	0.3365	0.2922	1.4981
SP*Take	0.3128	0.1081	2.8948	0.9254	0.1704	5.4307	-1.0272	0.3789	-2.7107	0.2025	0.2551	-2.7107
SP*Gear	0.022	0.0344	0.6395	0.1437	0.063	2.2811	0.0639	0.1737	0.3681	-0.3202	0.0961	0.3681
SP*Lake	0.0268	0.0261	1.0239	0.0361	0.0436	0.8277	-0.3002	0.0819	-3.6673	0.2308	0.081	-3.6673
SP*Motor (lvl 1)	0.0536	0.0303	1.7706	-0.0638	0.0526	-1.2113	-0.3698	0.1386	-2.6691	-0.2319	0.1079	-2.6691
SP*Motor (lvl 2)	-0.1611	0.0373	-4.3224	-0.0961	0.0606	-1.5857	0.5123	0.1659	3.0882	0.4654	0.1474	3.0882
SP*Motor (lvl 3)	-0.0244	0.0359	-0.6798	-0.0584	0.0602	-0.9709	-0.9536	1.5867	-0.601	-0.0409	0.1021	-0.601
SP*Boat	-0.0226	0.0382	-0.5899	0.0621	0.0598	1.0387	-1.276	1.5894	-0.8028	-0.0413	0.1142	-0.8028
SP*Crowding	-0.0743	0.0424	-1.7509	0.2669	0.0673	3.964	0.0915	0.1422	0.6433	-0.1699	0.1065	0.6433
SP*Distance	-0.1998	0.0878	-2.2766	-0.0254	0.1493	-0.1702	0.6839	0.296	2.3103	-0.9268	0.2759	2.3103

Attributes	Class1	s.e.	z-value	Class2	s.e.	z-value	Class3	s.e.	z-value	Class4	s.e.	z-value
Duration	0.6563	0.2626	2.4994	0.3483	0.0644	5.4042	0.1198	0.1253	0.9565	0.1188	0.0831	0.9565
SP*Duration	0.1154	0.0357	3.2352	-0.0019	0.0672	-0.0281	0.2052	0.1531	1.3403	0.0306	0.1091	1.3403
DUR*Catch	0.048	0.0275	1.7478	-0.0206	0.0485	-0.4255	-0.0152	0.0659	-0.2303	0.0451	0.0655	-0.2303
DUR*Size	0.0393	0.0375	1.046	0.1172	0.0639	1.8337	0.1833	0.1073	1.7074	0.0762	0.0882	1.7074
DUR*Take	0.2035	0.0657	3.097	0.0839	0.1192	0.7037	0.1595	0.224	0.712	-0.0753	0.1789	0.712
DUR*Gear (lvl 1)	-0.0753	0.0421	-1.787	-0.0668	0.0664	-1.0057	0.0793	0.1016	0.7806	-0.0832	0.0818	0.7806
DUR*Gear (lvl 2)	0.0513	0.0406	1.2639	0.1785	0.0694	2.5741	0.1209	0.0859	1.4079	0.0258	0.0841	1.4079
DUR*Gear (lvl 3)	0.0232	0.0429	0.5406	-0.0538	0.0777	-0.6931	-0.1058	0.0908	-1.1649	0.0864	0.0832	-1.1649
DUR*Lake	-0.0109	0.0211	-0.5167	0.0159	0.0384	0.4145	-0.0666	0.0477	-1.3952	-0.0099	0.0509	-1.3952
DUR*Motor (lvl 1)	0.0238	0.0244	0.9765	0.0915	0.0445	2.0576	-0.0275	0.0589	-0.4668	-0.0244	0.0586	-0.4668
DUR*Motor (lvl 2)	-0.0267	0.0294	-0.9104	-0.0592	0.0544	-1.0888	-0.0385	0.0794	-0.4854	-0.0405	0.07	-0.4854
DUR*Boat (lvl 1)	0.019	0.0294	0.6462	0.0331	0.0515	0.6422	-0.0752	0.0711	-1.0577	0.0602	0.069	-1.0577
DUR*Boat (lvl 2)	-0.0501	0.0257	-1.9507	0.0574	0.0475	1.2087	0.0252	0.0635	0.3974	-0.061	0.0623	0.3974
DUR*Crowding	-0.0261	0.0281	-0.9282	0.0337	0.0504	0.6687	-0.0112	0.0683	-0.1646	-0.0651	0.0675	-0.1646
DUR*Distance	0.8956	0.0819	10.9308	1.4305	0.1459	9.805	0.3678	0.2014	1.8266	0.83	0.163	1.8266
Geography	0.2498	0.2064	1.21	0.3737	0.0798	4.6838	1.2862	0.2028	6.3434	0.0206	0.1143	6.3434
SP*GEO	0.0726	0.0408	1.7782	0.0157	0.0807	0.1946	-0.4297	0.1987	-2.1623	0.6093	0.1443	-2.1623
GEO*Catch	0.0327	0.0303	1.0783	0.1779	0.0557	3.1943	0.0229	0.0852	0.2688	-0.1253	0.0749	0.2688
GEO*Size	-0.0264	0.042	-0.6293	0.1237	0.0727	1.7028	0.1059	0.1439	0.7361	-0.2124	0.1066	0.7361
GEO*Take	0.0519	0.072	0.7212	0.0985	0.1314	0.7493	-0.7799	0.2783	-2.8023	0.1467	0.202	-2.8023
GEO*Gear (lvl 1)	0.0181	0.0456	0.3964	0.0563	0.0718	0.7842	-0.0699	0.1227	-0.5698	0.0924	0.087	-0.5698
GEO*Gear (lvl 2)	0.0606	0.0454	1.3361	-0.0097	0.0775	-0.1256	-0.1961	0.107	-1.8327	-0.2685	0.0962	-1.8327
GEO*Gear (lvl 3)	-0.0542	0.0465	-1.1643	-0.0236	0.0853	-0.2774	0.3999	0.1228	3.2574	0.1772	0.0943	3.2574
GEO*Lake	0.0284	0.0235	1.2078	0.0147	0.0432	0.3391	-0.0902	0.0598	-1.5098	-0.0427	0.0547	-1.5098
GEO*Motor (lvl 1)	0.0294	0.0264	1.113	-0.0224	0.0491	-0.4567	0.033	0.0739	0.4457	0.13	0.0639	0.4457
GEO*Motor (lvl 2)	-0.0172	0.0318	-0.5411	0.0812	0.0612	1.3257	-0.0844	0.0949	-0.8896	0.0426	0.0734	-0.8896
GEO*Boat (lvl 1)	0.0671	0.0318	2.1142	0.0587	0.0561	1.0461	0.0089	0.084	0.1062	0.0354	0.0733	0.1062

Attributes	Class1	s.e.	z-value	Class2	s.e.	z-value	Class3	s.e.	z-value	Class4	s.e.	z-value
GEO*Boat (lvl 2)	-0.0517	0.0285	-1.8153	0.0806	0.0537	1.5002	-0.0627	0.0755	-0.8295	0.0947	0.0698	-0.8295
GEO*Crowding	-0.0088	0.0304	-0.2889	-0.1257	0.0555	-2.2653	0.106	0.0848	1.2496	0.0468	0.0759	1.2496
GEO*Distance	0.1925	0.0915	2.104	0.2535	0.1629	1.5568	0.4127	0.2831	1.4579	0.5365	0.2217	1.4579
Specialization	0.3468	0.234	1.4817	0.0524	0.0698	0.7512	0.3697	0.1683	2.1964	0.1507	0.0949	2.1964
SI*SP	-0.0908	0.0395	-2.2963	0.143	0.0777	1.8402	0.3871	0.1951	1.9846	0.1216	0.1339	1.9846
SI*Catch	-0.021	0.0316	-0.664	0.1439	0.0507	2.839	0.0892	0.084	1.0621	0.193	0.0821	1.0621
SI*Size	0.1858	0.0444	4.184	0.1352	0.0693	1.9521	0.0571	0.1363	0.4193	1.1899	0.1197	0.4193
SI*Take	-0.1308	0.0727	-1.7986	0.0719	0.1303	0.5517	-0.2451	0.2612	-0.9385	0.1826	0.2126	-0.9385
SI*Gear (lvl 1)	-0.0713	0.0486	-1.4678	-0.0273	0.0694	-0.3934	-0.0411	0.1098	-0.3746	-0.1265	0.0972	-0.3746
SI*Gear (lvl 2)	0.0404	0.0462	0.8729	-0.1312	0.0753	-1.7413	0.2222	0.1114	1.9951	-0.0069	0.1062	1.9951
SI*Gear (lvl 3)	0.0875	0.0505	1.7328	0.2205	0.0827	2.6673	-0.0712	0.1169	-0.6092	0.1852	0.1024	-0.6092
SI*Lake	-0.0102	0.0242	-0.4206	0.0798	0.0421	1.8974	-0.1829	0.0602	-3.0379	-0.0694	0.0579	-3.0379
SI*Motor (lvl 1)	-0.0098	0.0271	-0.3622	-0.0757	0.0477	-1.5857	0.0025	0.0725	0.0342	0.0546	0.0692	0.0342
SI*Motor (lvl 2)	-0.0537	0.0328	-1.6364	0.0008	0.0602	0.0135	0.1783	0.0935	1.9067	0.1437	0.0821	1.9067
SI*Boat (lvl 1)	-0.0145	0.0333	-0.434	0.0737	0.0526	1.4012	-0.1978	0.0873	-2.2662	0.0219	0.0766	-2.2662
SI*Boat (lvl 2)	0.0424	0.0299	1.4144	0.0349	0.051	0.6848	0.1932	0.0756	2.5541	-0.027	0.0746	2.5541
SI*Crowding	-0.0294	0.0314	-0.9339	-0.0963	0.0539	-1.7872	0.1693	0.0794	2.1326	-0.0052	0.0812	2.1326
SI*Distance	0.074	0.089	0.8315	0.0987	0.1244	0.7934	0.4384	0.2577	1.7009	-0.2782	0.1724	1.7009